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Chronic Kidney Disease Diagnose using Radial Basis Function Network (RBFN)

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ABSTRACT

Fast and accurate diagnosis of the diseases consider one of the major challenges in giving proper treatment. Different techniques have their own limitations in terms of accuracy and time. Neural network technique used as a powerful discriminating classifier for tasks in medical diagnosis for early detection of diseases. It had already been applied in diagnose many diseases, like chronic kidney disease (CKD) which is one of the leading causes of death contributed by other illnesses such as diabetes, hypertension, lupus, anemia or weak bones that lead to bone fractures. In this paper, a deep learning method to perform a both feature extraction and the classification for CKD detection using Radial Basis Function Network as activation function . This network has great ability of accurate and speed diagnosing, so it is useful to use it in medicine to give the doctors or medical team the right diagnoses. Better performance in terms of accuracy, specificity and sensitivity will be selected as classification model. To test the performance of RBF model, a CDK dataset is employed which contains the clinical manifestations of six diseases as a sample. After applying training method, the network will match these manifestations with the manifestations obtained from sample patients to decide right disease which was entered to the program, the result, shows good performance, low error ratio, high accuracy.

KEYWORDS: Radial Basis Function Network, CDK , Clinical Manifestation, Feature Extraction, Error Ratio.

1. Introduction

In the recent years, the huge development occurs into computer and its techniques, but sometimes the traditional programming cannot solve some complex problems which cannot be formulated or found a general framework within these techniques [1]. These problems led the researchers to delve deeper into finding efficient algorithms help in finding appropriate and optimal solutions for complex problems with the speed of access to solutions, storage and retrieval, and neural networks. [2]

For example, of such problems is medical diagnosis of diseases, which means the act of identifying a disease from its signs and symptoms [3]. One of the most common diseases is chronic kidney diseases (CDK). The kidneys are a pair of bean-shaped organs contained in all vertebrates. They are able to remove waste products from the body, also they can maintain balanced electrolyte levels, and regulate blood pressure. [4]

In proposed algorithm, we will take six CDK diseases as a sample, the symptoms of these diseases store in a dataset. The input of the of the network will be the clinical manifestation received from the patient. The sample of six diseases manipulate in this research are:

- Renal Cell Carcinoma : this kind of cancer is occurred while the cancer cells form in the kidneys. Over 90 % of kidney cancers are renal cell carcinomas which start in the tubules of the kidneys.[5]
- Glomerulonephritis: a category of disorders affecting the part of kidney which is responsible of filtering the blood (called glomeruli). Two forms of glomerulonephritis—acute and chronic.[7]

- Nephrotic Syndrome: refers to a clinical syndrome clarified by a lot of proteinuria (more than 40 mg/m2 per hour) that is responsible for hypoalbuminemia (less than 30 g/L), and result edema, hyperlipidemia, and various complications.[6]
- Kidney Failure: the disease occurs when the kidneys lose the ability of sufficiently filtering waste from the blood.[7]
- Polycystic Kidney Disease: refers to inherited disorder when develop the clusters of cysts within the kidneys primarily. [8]
- Kidney stone disease: refers to a crystal concretion which formed within the kidneys. This kind is increased urological disorder of human health, and it is affecting about 12% of the world population.[17]

2. Artificial Neural Networks ANN

ANN general term which includes different systems and various types of approaches, both from statistics and computer science. [9] It considers one of the technologies that helps in finding alternative solutions to these dilemmas through its ability to process data without the need for a specific pre-formation or structure, which simulates in its construction and operation the mechanism of the device Nervous system in humans. The Radial Basis Function Network distinguished from the other neural networks because of their universal approximation and faster learning speed. So it is one of the most important artificial neural networks that is characterized by with hybrid characteristics compared to other networks, in addition, its ability to adapt and modify.

2.1 Radial Basis Functions Network

RBFN is specialized for non-linear classification tasks and relies on the integration of the Radial Basis Function which commonly used for function approximation problems. Radial basis function networks are distinguished from other neural networks due to their universal approximation and faster learning speed [19]. RBFN is a type of feed forward neural network composed of three layers, an input layer, a hidden layer, and an output layer as shown in Figure 1, each layer consists of a set of neurons. uses Radial Basis Function neurons, each of which evaluates the input vector by comparing its stored training value to the input and calculating a similarity measure. then multiplied each similarity value by weights and summed in the output layer. A measure of the Euclidean distance between the input and training data will used to compute any new input easily [10]. Each cell in any layer is associated with all cells in other layer by weights as shown in the following figure:

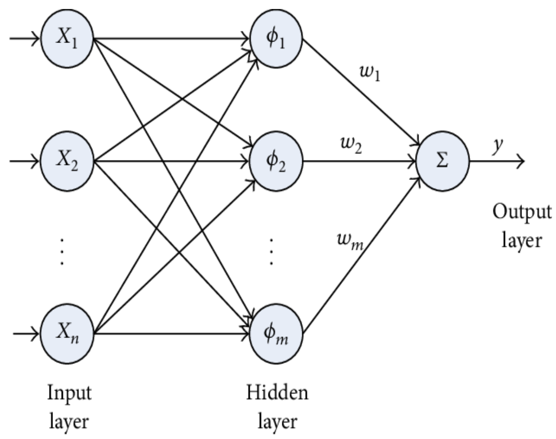

Figure 1: Architecture of RBF Network

2.2 Mechanism of Radial Basis Function Network

Many activation functions used in RBFN as follows:

- Gaussian Activation Functions: define a receptor = t, then draw confronted maps around the receptor, after that apply Gaussian Activation Functions for RBF (confrontal mapping). The radial distance defined as:

  r = ||x- t||, where x is the input vector for the network.[11]

  Gaussian Radial Function:

  $\emptyset(r) = \exp(-r^2/2\sigma^2)$ 1

  Where σ > 0

$\emptyset(r)$: Represents the real output and the value of the output is limited between [0-1] as shown in figure 2:

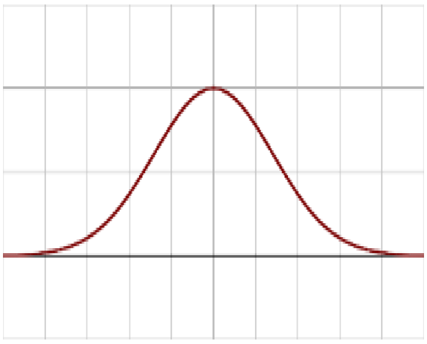

Figure 2: Gaussian Activation Functions

- Signum Activation Function: used by the original Perceptron. If the input sum is above a certain threshold (always 0), then output will be a certain value (1), and if the input sum is below a certain threshold (0), then output will be (-1). as shown below:[12][16]

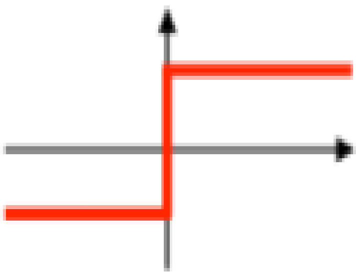

Figure 3: Signum Activation Function

$f(x) = +1$ if $x >= 0$

$f(x) = -1$ if $x < 0$

3. Proposed Algorithm

3.1 Train the Network

To train the network, many steps were used as follows:

i. Selected small primary values randomly for the weights of each cell in Radial Base Function Network.

ii. Determine the fixed value of the σ and this value is limited between [0-1].

iii. Calculating the output (Oj) for the hidden layer through the Gaussian Radial Function.

iv. Calculate the activation level (real output Oj) for the output layer Through the following equations:

$NET_j = \sum_{i=1}^{N} Xi \ . Wi$ …………2

$Oi = f\,(NET_j)$ …………..3

v. If the desired output is not achieved, then change weights through the next equation:

$\Delta Wij = Xi * Ej * C$ ………….4

Where:

Xi: Inputs of cell j.

C: Ratio of learning in the network.

Ej: : Ratio of error which calculated as following:

$Ej = T_j - O_j$ ……………5

T_j: The desired output of the cell j.

Oj: Real output of cell j.

The values of new weights resulting from the next stage the process is retained in the output layer.

vi. Repeat the steps from step four to step five until the desired solution is reached. The flowchart of training algorithm is shown in figure 4:

3.2 Calculate the Weights

The initial weights of the first treatment layer (Hidden layer) as well as the output layer are configured as random generated numbers limited between [1-0]. The changing weights has been done as follows:[18]

- 1-Hidden layer: the weights don't change because the training in them is non-indicative.
- 2- Output layer: Weights are changed when the required output is not obtained through mathematical equations described in the radial base function algorithm.

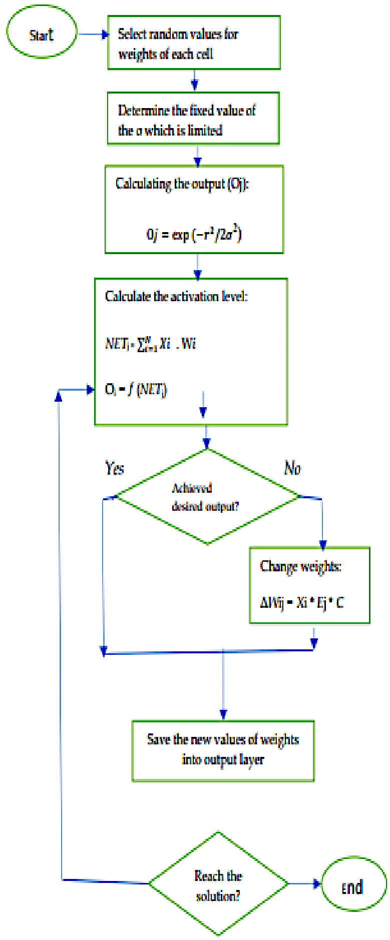

Figure 4: Training Flowchart of RBFN

3.3 Design and Implementation of RBFN

In Radial Basis Functions Network, the values from all cells in the hidden layer are multiplied by a specific weight associated with the neurons and transferred to an output neuron. [13][14]. The RBFN that is designed in proposed algorithm has one hide layer and a bias cell in the input layer, as well as a bias cell in the output layer to speed up the work of the network and approach the right solution. The input to the bias cell is (1).

Diseases diagnosed in this algorithm do not depend on analyses or x-rays, but depends on the apparent pathological symptoms which input to the RBFN received from the patient. In this paper six diseases of kidney were considered as a case study, in the future work the number of diseases may be any number. The Radial Base Function Network will diagnose these diseases according to the input symptoms (dataset) which consists of a group of cells whose number is according to the number of disease symptoms which is in table 1) and through the algorithm training the RBFN will match the disease.

The RBFN used consists of three Layers:

1-input layer: equal here to (24) satisfactory width, so number of cells in a layer is (24) as well as bias cell. During the execution of main program, symptoms are selected and determine the number of middle level cells as well as the learning ratio of the network. After inserting pathological symptoms, find out which disease has these symptoms, if the symptoms chosen are identical to one of the diseases specified in the program, it will be the result of diagnose test. If the symptoms chosen are not entirely identical to any diseases specified in the program, the result will be more than one disease or anything else with certain error rate. [15]

2- hidden layer: number of cells in the hidden layer is (N+1), i.e. (24+1) with the addition of the bias cell in this layer.

3- output layer: represents number of diseases specified in the research, i.e., 6.

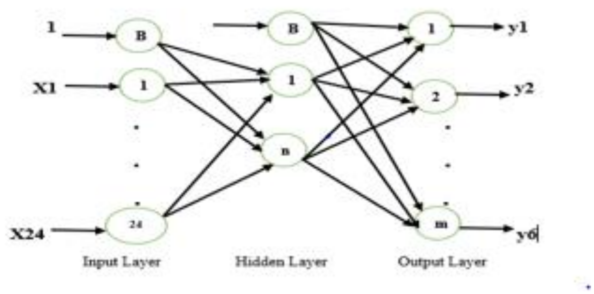

Figure 5: Design of RBFN

Table (1) shows the pathological symptoms with the diseases corresponding to those symptoms.

Table 1: Input and Output in RBFN for Diagnose CDK

Input-RBFN		**Output-RBFN**	
Clinical Manifestation	Input Node	Diseases	Output Node
Urine with blood	X1		

lump in the abdomen	X2	Renal Cell Carcinoma	Y1
pain in the side that doesn't go away	X3		
Loss of appetite	X4		
Weight loss for no known reason	X5		
Anemia	X6		
puffiness of the face in the morning	X7	Glomerulonephritis	Y2
Brown urine (or Urine with blood)	X1		
urinating less than usual	X8		
short of breath and cough because of extra fluid in the lungs	X9		
Edema (swelling) due to buildup of extra fluids and salt in your body	X10	Nephrotic syndrome	Y3
Blood pressure is high	X11		
hyperlipidemia (higher levels of cholesterol)	X12		
reduced amount of urine	X13	Kidney failure	Y4
unexplained shortness of breath	X14		
confusion	X15		
persistent nausea	X16		
pain or pressure in the chest	X17		
excessive drowsiness or fatigue	X18		
Urine with blood	X1	Polycystic kidney disease	Y5
Headaches	X19		
Urinary tract infection	X20		
Cysts in the kidneys and other organs	X21		
Pain in the lower sides and back	X22		
pain on either side of the lower back	X3	Kidney stones	Y6
urinary outflow obstruction	X23		
Urine with blood, nausea or vomiting	X1, X24		

4. Results

Through the network training process according to the proposed algorithm, satisfactory results were obtained close to the real output. The error ratio which obtained after execution the practical part of the algorithm, was low as shown in table (2), and this promise high accuracy.

Table 2: Error Ratio in proposed algorithm

Disease	Error Ratio
Renal Cell Carcinoma	0.33
Glomerulonephritis	0.53
Nephrotic syndrome	0.66
Kidney failure	0.71
Polycystic kidney disease	0.73
Kidney stones	0.91

4.1 Effect of Learning Ratio on the RBFN Training Times

Determination of the number of cells in the hidden layer is very important in RBF networks because it affects the network complexity and the generalizing capability of the network. If the number of the cells in the hidden layer is insufficient, the RBF network cannot learn the data adequately; on the other hand, if the cell number is too high, poor generalization or an overlearning situation may occur [20]. When RBFN use learning ratio during the training process, limited between [0-1], so it will affect the number of training network times. if this ratio is very small will be unappropriated.

Assume the number of hidden layer cells is 2 the effect can be observed as shown in table (3) and figure (6) when the ratio is decreased the number of trainings will be increased.

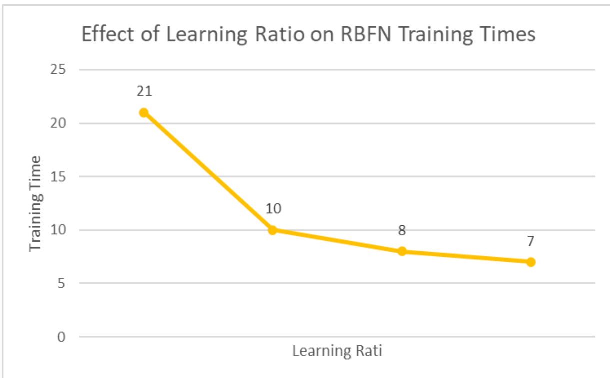

Figure (6): Effect of learning ratio on RBFN training times

4.2 Effect Number of Hidden Layer Cells on the Number of Training Times

The number of hidden layer cells has an effect on the number of times it takes to access to the desired results, when increased number of hidden layer cells, the network training times will increase also. This effect can be seen through the following table:

Table (3): Effect of learning ratio on RBFN network training times

No. of Hidden Layer Cells	No. of Training Times	Learning Ratio
2	7	0.4
4	8	0.4
6	9	0.4
8	10	0.4

Table 4: Effect number of hidden layer cells on number of training times

No. of Hidden Layer Cells	No. of Training Times	Learning Ratio
2	21	0.1
2	10	0.2
2	8	0.3
2	7	0.7

5. CONCLUSION

Using RBF network provided better precision and accuracy diagnosis for some groups of patients than using other methods. The sensitivity and specificity of neural network models had a better predictive power compared to logistic regression, this promises the possibility of diagnosing many diseases such as CDK, Diabetes with different symptoms with low error ratio. Also, we can decrease this ratio by through Changing the weights.

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