Diagnosis of Glomerulonephritis by an ANN Based on Physical Symptoms and Clinical Observations of the Blood Samples

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Abstract-An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. Neural networks provide significant benefits in medical research. They are actively being used for such applications as locating previously undetected patterns in mountains of research data, controlling medical devices based on biofeedback, and detecting characteristics in medical imagery. The main purpose of this study is to construct an Artificial Neural Network for the differential diagnosis of kidney disease, glomerulonephritis based on the physical symptoms and clinical tests conducted on blood samples of different individuals in the lab. In this study multilayered feed forward neural network is constructed, trained and tested using back propagation learning rule.

Index Terms—Artificial Neural Network, Kidney, Glomerulonephritis, Clinical Tests, Computer-Aided Medical Diagnosis, Multilayer Feed Forward Neural Network

I. INTRODUCTION

Glomerulonephritis is inflammation of the tiny filters in the kidneys (Glomeruli). Glomeruli remove excess fluid, electrolytes and waste from the blood stream and pass them into the urine, also called glomerular disease. glomerulonephritis can be acute (a sudden attack of inflammation) or chronic (coming on gradually). If glomerulonephritis occurs on its own, it's known as primary glomerulonephritis. If another disease, such as lupus or diabetes. is the cause, it's called secondary glomerulonephritis. If severe or prolonged, the inflammation associated with glomerulonephritis can damage your kidneys.

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Broadly we can divide the causes as follows

A. Autoimmunity

When the body's immune system functions properly, it creates protein-like substances called antibodies and immunoglobulins to protect the body against invading organisms. In an autoimmune disease, the immune system creates auto antibodies, which are antibodies or immunoglobulins that attack the body itself. Autoimmune diseases may be systemic and affect many parts of the body, or they may affect only specific organs or regions.

B. Heredity

Sometimes this disease runs in families – This kind often shows up in young men who may also have hearing loss and vision loss.

C. Infective

Glomerular disease sometimes develops rapidly after an infection in other parts of the body. Acute Post-Streptococcal Glomerulonephritis (PSGN), HIV etc.

D. Sclerotic Disease

This means scarring of the glomeruli by various systemic and local causes. Eg: Diabetes, Lupus disease etc.

Symptoms

Signs and symptoms of glomerulonephritis may depend on whether the person is having acute or chronic form and the cause. The first indication that something is wrong may come from symptoms or from the results of a routine urinalysis. Signs and symptoms may include:

- Pink or cola-colored urine from red blood cells in your urine (hematuria)
- Foamy urine due to excess protein (proteinuria)
- High blood pressure (hypertension)
- Fluid retention (edema) with swelling evident in your face, hands, feet and abdomen
- Fatigue from anemia or kidney failure

The NCHS and CDC for research in US estimates that nearly 39,480 people were dying with glomuronephritis in each year. 13.9 people per 1, 00,000 population died from nephritis, nephrotic syndrome and nephrosis each year in the US. Kidney disease was ranked the ninth leading cause of death in the US. In India the children above 10 years, glomerulonephritis was the leading cause (16%) of Acute Renal Failure.

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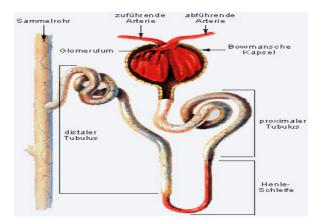


Fig 1. Structure of Glomeruli

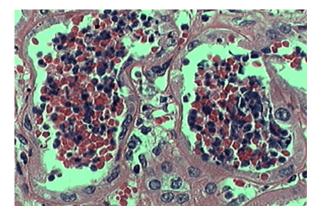


Fig 2. Postinfectious Glomerulonephritis

II. CLINICAL DIAGNOSIS OF GLOMERULONEPHRITIS

Most of the symptoms described above are non-specific and can be caused by many other diseases. A detailed history and medical examination is first done by the doctor and inflammation of the kidney is suspected then further tests like Urine test, Blood Test, Imaging Test or Kidney biopsy may be done.

A. Urine Test

A urinalysis may show red blood cells and red cell casts in urine, an indicator of possible damage to the glomeruli. Urinalysis results may also show white blood cells, a common indicator of infection or inflammation, and increased protein, which may indicate nephron damage. Other indicators, such as increased blood levels of creatinine or urea, are red flags.

B. Blood Test

These can provide information about kidney damage and impairment of the glomeruli by measuring levels of waste products, such as creatinine and blood urea nitrogen.

C. Imaging Tests

If the doctor detects evidence of damage, he or she may recommend diagnostic studies that allow visualization of the kidneys, such as a kidney X-ray, an ultrasound examination or a computerized tomography (CT) scan.

D. Kidney Biopsy

This procedure involves using a special needle to extract small pieces of kidney tissue for microscopic examination to help determine the cause of the inflammation. A kidney biopsy is almost always necessary to confirm a diagnosis of glomerulonephritis.

III. ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An ANN is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s). You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. This is primarily because the solution is not restricted to linear form. Neural Networks are ideal in recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. Neural networks learn by example so the details of how to recognize the disease is not needed. Based on the way they learn, all artificial neural networks are divided into two learning categories: supervised and unsupervised. In supervised learning, the network is trained by providing it with input and output patterns. During this phase, the neural network is able to adjust the connection weights to match its output with the actual output in an iterative process until a desirable result is reached. An ANN of the unsupervised learning type, such as the self-organizing map, the neural network is provided only with inputs, there are no known answers. The network must develop its own representation of the input stimuli by calculating the acceptable connection weights. That is self-organization by clustering the input data and find features inherent to the problem. Medical Diagnosis using Artificial Neural Networks is currently a very active research area in medicine and it is believed that it will be more widely used in biomedical systems in the next few years.

A. Multilayered Neural Network

A widely used Neural Network model called the Multi Layered Neural Network (MLNN) is shown in Fig 1. The MLNN consists of one input layer, one or more hidden layers, and one output layer. Each layer employs several neurons, and each neuron in a layer is connected to the neurons in the adjacent layer with different weights.

Signals flow into the input layer, pass through the hidden layer(s), and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer. The incoming signals (x_{ij}) are multiplied by the weights (v_{ij}) and summed up with the bias (b_j) contribution. The output of a neuron is determined by applying an activation function to the total input (net_j) is calculated by the equation as follows.

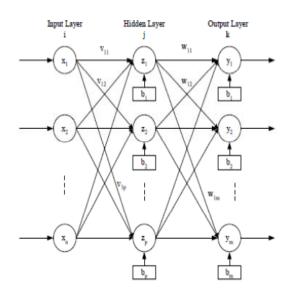


Fig.1: Architectural structure of an MLP with one hidden layer

$$n = \sum_{i=1}^{n} \sum_{i=1}^{n} \sum_{i=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n}$$

where,

- netj = total input of the hidden layer neuron j
- xi = input to the hidden layer neuron j from input layer neuron i
- vij = weight between the input layer neuron i and hidden layer neuron j
- bj = bias of the hidden layer neuron j
- n = number of neurons in the input layer

Multi-layer networks use a variety of learning techniques, the most popular being back-propagation. Here, the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small. In this case, one would say that the network has learned a certain target function. To adjust weights properly, one applies a general method for nonlinear optimization that is called gradient descent. For this, the derivative of the error function with respect to the network weights is calculated, and the weights are then changed such that the error decreases (thus going downhill on the surface of the error function). For this reason, backpropagation can only be applied on networks with differentiable activation functions.

In general, the problem of teaching a network to perform well, even on samples that were not used as training samples, is a quite subtle issue that requires additional techniques. This is especially important for cases where only very limited numbers of training samples are available. The danger is that the network over fits the training data and fails to capture the true statistical process generating the data. Computational learning theory is concerned with training classifiers on a limited amount of data. In the context of neural networks a simple heuristic, called early stopping, often ensures that the network will generalize well to examples not in the training set.

Other typical problems of the back-propagation algorithm are the speed of convergence and the possibility of ending up in a local minimum of the error function. Today there are practical solutions that make back-propagation in multilayer perceptrons the solution of choice for many machine learning tasks.

B. Activation Functions

Activation functions for the hidden units are needed to introduce nonlinearity into the network. Without nonlinearity, hidden units would not make MLPs more powerful than just plain networks which do not have any hidden layer units, just input and output units. The sigmoid functions, such as logistic and hyperbolic tangent functions, are the most commonly used activation functions in networks trained by Back Propagation. The logistic function with the output amplitude lying inside the range [0.0 to1.0] by the following equation.

$$Zj = f(netj) = 1/1 + e^{-netj}$$

The output amplitude of the hyperbolic tangent function lies inside the range [-1.0 to 1.0] by the following equation.

$$Z_i = f(net_i) = tanh(net_i)1 - e^{-2net_i}/1 + e^{-2net_i}$$

IV. CONSTRUCTION, TRAINING, LEARNING PROCESS OF ANN

A. Materials

The data required for this module is collected from the hospitals or from the Clinical Labs. The parameters that are used to diagnose the glomerulonephritis are the Physical signs, symptoms, and measurements that are obtained from the patients during physical examination and results obtained from the clinical examination of the blood samples collected from the patients. In the present study 50 samples are used. Each sample is having a set of 16 input nodes as given in the Table 1 and one output node. The input nodes represent the obtained physical, clinical evaluation features and the output node represents the diagnosis classification result in terms of abnormal or normal.

B. Construction of MLNN

A three layered feed forward neural network is constructed Back Propagation Learning rules are applied. It consists of 16 input neurons [x1, x2...x16] in the input layers which are the Physical symptoms and the results obtained from the clinical examination of the blood samples collected from individuals, 8 hidden neurons in the hidden layer and one output in the output layer. The network is trained using Back Propagation techniques. The activation function used in this model is the sigmoid logistic function. Once the network is trained, then it can be used to perform the diagnosis classification automatically for a new pattern.

	ATTRIBUT	ES AND THEIR DESCRIPTI	ION
S.No	Attribute Name	Description	Allowed Values
1	Age	Age of the Patient	Continuous
2	Gender	Gender of the Patient	Binary
3	Fatigue	Feeling very tiredness due to loss of blood	Binary
4	Nausea and vomiting	Vomiting sensation and uneasiness in the body	Binary
5	Shortness of breath	Unable to take normal breath	Binary
6	Disturbed vision	Vision disturbance or giddiness	Binary
7	Hyper- tension	High blood pressure	Binary
8	Diabetics	Abnormal sugar levels	Continuous
9	Weight gain	Abnormal gain of weight due to edema	Binary
10	Bloody Urine	Presence of RBC turn the urine reddish color	Binary
11	Smoky or Foamy Urine	Presence of proteins causing foamy or smoky urine	Binary
12	Edema	Swelling of the body, especially noted in the face, hands, feet, and ankles	Binary
13	Create-nine	Excess createnine levels	Continuous
14	Blood urea nitrogen	Excess Waste products in the blood	Continuous
15	Anemia	Less RBC count	Continuous
16	Phosphorus	Excess Phosphorus levels	Continuous

TABLE I RIBUTES AND THEIR DESCRIPT

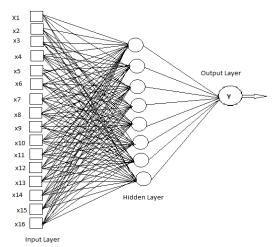
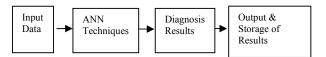


Fig4.Multilayer Nueral Network

C. Training and Learning of MLNN

A neural network is built with 16 input nodes, 8 hidden nodes and one output node. The supervised network is trained using Back Propagation Learning techniques. The data collected from 50 patients are used to train and test the

ISBN: 978-988-19252-8-2 ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online) network. Among these samples, 75% of the data used for training and remaining 25% of the data are used for testing purposes. While testing the network, various data sets are applied to its input layer. Then the network generates the output which is compared with the desired outputs. In the training process weights are adjusted till the target is reached. When the output result is matched with the original resultant with minimum error and then the training is stopped. The most iterative times were set to 4000 epochs, and the output error of the validation was set to less than 0.01. The output value is in between the range (0.0 to 1.0). If the obtained output value is near to 1.0 then the patient is normal person or the obtained output value is near to 0.0 then the person is diagnosed with glomerulonephritis. Once the Network is trained using these samples then it does the classification automatically for a new pattern. The Mean square error (MSE) is then calculated. The remaining 25% of the data is used for testing. The output results in normality and abnormality of the patient.



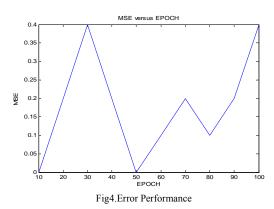
D. Result Analysis

TABLE II COMPARISON OF ACTUAL DATA WITH OUTPUT RESULT

Sample No.	Actual Result	Output Value	Result
10	GN	0.213	GN
16	Normal	0.946	Normal
21	Normal	1.001	Normal
25	GN	0.014	GN
30	GN	0.024	GN

* GN - Glomerulonephritis

The data collected from 50 patients are given as input data and resultant output data is compared with the actual resultant. Out of 50 Samples 28 samples were normal and the remaining 22 samples were diagnosed with glomerulonephritis. The samples were chosen randomly and given as input data as shown in the Table:2. In overall training and testing only 10% of data is mismatched and the total accuracy is 90%. The result kept the accuracy in overall classification.



The Fig shows the Error performance (Mean Squared Error) of the training network. The MSE value decrease with the increase of the epoch values. The least MSE value of this approach is 0.010.

V. CONCLUSION

To reduce misdiagnosis, a reliable computerized diagnostic program needs to be developed. The artificial neural network proposed for the diagnosis of glomerulonephritis gives more accurate results without the aid of Physical practitioner. To meet the growing demands of increasing population Doctors need additional support to diagnose the disease more perfectly to avoid misdiagnoses of the disease. If the disease is diagnosed it is easy to go for further investigation and to treat the patient without time delay.

References

- [1] B.Yegnanarayana, Artificial Neural Networks by Prentice Hall.
- [2] Laurene Fausett, Florida Institute of Technology, Fundamentals of Neural Networks Architectures, Algorithm, and Applications. Pearson Publications.
- [3] S.N.Sivanandam, S.Sumathi, S.N.Deepa, Introduction to Neural Networks using MATLAB6.0, TATA McGRAW HILL.
- [4] http://labtestsonline.org/understanding/conditions/kidney/start/3
- [5] Oxford, UK. Box, G.E.P. and Jenkins, G.M. (1970) *Time Series Analysis, Forecasting and Control*, Holden Day, San Francisco, CA.
- [6] Walter A.Hunt , Kidney Diseases, A Guide for Living, Forwarded by Ronald D.Perrone, M.D. Tufts Medical Center.
- [7] Artificial Neural Networks Methodological Advances and Biomedical Applications, Edited by Kenji Suzuki, ISBN 978-953-307-243-2, hard cover, 362 pages, Publisher: InTech, Published: April 11.
- [8] Clinical Applications of Artificial Neural Networks. Edited by Richard Dybowski King's College London Edited by Vanya Gant University College London Hospitals NHS Trust, London.
- [9] Comprehensive Clinical Nephrology by Jurgen Floege, Richard J. Johnson, MD and John Feehally.
- [10] B.Sumathi and Dr.A.Santhakumaran "Pre-Diagnosis of Hypertension using Artificial Neural Networks", Global journal of Computer Science and Technology, Volume 11, issue2 version 1.0 Feb, 2011