**DIAGNOSIS OF LIVER DISEASE INDUCED BY HEPATITIS VIRUS USING ARTIFICIAL NEURAL NETWORKS**

Sana Ansari1, Imran Shafi1, Aiza Ansari2, Jamil Ahmad1, Syed Ismail Shah1

1Department of Computing and Technology, Iqra University, Islamabad Campus,

sanaansari165@yahoo.com, [imranshafi@iqraisb.edu.pk](mailto:imranshafi@iqraisb.edu.pk), [aizaansari@hotmail.com](mailto:aizaansari@hotmail.com), [jamil@iqraisb.edu.pk](mailto:jamil@iqraisb.edu.pk), [ismail@iqraisb.edu.pk](mailto:ismail@iqraisb.edu.pk)

2 Shifa College of Medicine, Islamabad

*Abstract* **This paper presents an artificial neural network based approach for the diagnosis of hepatitis virus. The dataset used for this purpose is taken from the UCI machine learning database. Both supervised and unsupervised neural network models have been analyzed with different architectures, learning and activation functions. It is concluded that the supervised model performed better than the unsupervised one. The paper also compares the results of the previous studies on the diagnosis of hepatitis which use the same dataset.**

***Key Words: Artificial Neural Networks, Hepatitis, Feedforward, Generalized Regression, Self Organizing Maps***

1. INTRODUCTION

One of the most critical features in medicine is the diagnosis of a disease. Diagnosis is defined as the analysis of the physiological or biochemical cause of a disease [1]. It is a complicated task and involves certain level of expertise on the part of a doctor. A sophisticated system is needed to assist doctors for diagnosing a disease accurately and efficiently. The use of technology, especially Artificial Intelligence (Al), can minimize cost, time, human expertise and incorrect diagnosis. Artificial Neural Networks (ANN) is a type of AI which has extensively been applied to solve medical problems. They have been used in multiple applications like diagnosis, forecasting, image analysis etc [2, 3, 4, 5, 11]. The ANNs are systems made up of neurons which work in a similar way as the brain. Hepatitis is considered as one of the most deadly diseases. Early detection increases the chances of recovery manifold. Hepatitis causes inflammation and destruction of hepatocytes (liver cells). Hepatitis can be caused due to viruses, bacteria, drugs, etc. This disease can be categorized as Acute or Chronic. Acute hepatitis is the rapid, sharp, and painful onset of the disease. Acute symptoms are more painful for patients but it has a limited course and rarely lasts beyond 1 or 2 months. Usually, there is only minimal liver cell damage and little evidence of immune system activity. Chronic hepatitis is inflammation of the liver that persists more than six months. Chronic inflammatory cell infiltrates comprising lymphocytes, plasma cells and sometimes lymphoid follicles are usually present in the portal tracts [7, 8]. There are five different types of hepatitis viruses A, B, C, D and E. Hepatitis A and E are of acute type whereas Hepatitis B, C and D are of chronic type. The chronic hepatitis leads to cirrhosis which causes destruction of liver parenchymal cells.

The purpose of this paper is to use the UCI dataset for the diagnosis of hepatitis using both supervised and unsupervised ANNs. We have used three types of networks out of which two belong to the supervised category; the Feedforward Backpropagation Neural Network (FFNN) and Generalized Regression Neural Network (GRNN) and one belongs to the unsupervised type; Self Organizing Map (SOM). A performance comparison has also been shown between the networks we used and the results were also compared with the previous studies that used the same dataset for the diagnosis and classification of hepatitis.

Rest of the paper is organized in five sections. Section II presents the Literature review, Section III presents the proposed method and the material used for the diagnosis of hepatitis virus. Section IV discusses the architecture of ANN used in the research. Section V provides the discussion on experimental results. Section VI provides comparison of the results with previous studies. Section VII finally concludes the paper.

1. Literature Review

Nowadays, ANNs have significantly been used in the field of medicine. They have been applied in the area of pathology, radiology, cardiology, oncology [1, 2 3, 5, 11, 18].

The ANN have also been used for the diagnosis and classification of various diseases. Bascil et al. used both the Multilayer Perceptron (MLP) with Levenberg Marquardt training algorithm and Probabilistic Neural Network (PNN) for the diagnosis of hepatitis and used the UCI dataset for this purpose [12, 13]. Jilani et al. used MLP with backpropagation algorithm for the classification of hepatitis C virus using the dataset from UCI machine learning repository [14]. Uttreshwar et al. used both the GRNN and SOM for the diagnosis of hepatitis B using the same UCI dataset [1, 15]. Liang et al. used the ANN for the visualization and classification of Emphysema [16]. ANN is also used for the Classification of Impulse Oscillometric Patterns of Lung Function in Asthmatic Children [17].

1. Proposed Method for Diagnosing Hepatitis
2. *Methodology*

The method used for the diagnosing consists of three stages. The stages are shown in fig. 1.

Stage 1: Pre-Processing

In this stage the data is first collected and the targets of each training sample are set. After this the entire data set is divided into the training and testing sets. In case of the validation set the training set is further divided into two parts; one for training and the other for validation. After this the data is ready to be presented to the ANNs.

Stage 2: ANN Processing

The training and validation set which includes both the training samples along with their target values are presented to the ANN. The trained ANN then diagnoses the hepatitis virus correctly.

Stage 3: Post-Processing

The results of the ANN belong to one of the two classes either live or dead. In this stage the results of the ANN are converted into a more understandable form.

Scrutinizing the data

Creating the training, validation and test set

Setting the targets

**Stage 1**

Creating the network

Training the models for Diagnosing hepatitis

**Stage 2**

Testing the models

1. Artificial Neural Networks Approach

**Stage 3**

Interpretation of the ANN results

Figure 1. ANN Methodology

1. *Material*

The dataset that is used for diagnosing hepatitis is taken from the UCI machine learning database. It comprises of 155 samples which includes both the positive and negative cases for hepatitis virus. All samples have 19 attributes, which are presented in Table 1. Out of these 19 attributes 13 have binary values (either it is No or Yes) and the rest 6 have a range of values. These 19 attributes includes 12 physical examination tests, 5 Liver Function Tests (LFT’s) and 2 general attributes of a patient.

TABLE I. Attributes and their values

|  |  |  |  |
| --- | --- | --- | --- |
| **Input Attributes** | | | |
| **S. No** | | **Attributes** | **Values** |
| 1 | | Age | 10-80 Years |
| 2 | | Gender | Male, Female |
| 3 | | Steriod | No, Yes |
| 4 | | Antivirals | No, Yes |
| 5 | | Fatigue | No, Yes |
| 6 | | Malaise | No, Yes |
| 7 | | Anorexia | No, Yes |
| 8 | | Liver Big | No, Yes |
| 9 | | Liver Firm | No, Yes |
| 10 | | Spleen Palpable | No, Yes |
| 11 | | Spiders | No, Yes |
| 12 | | Ascities | No, Yes |
| 13 | | Varices | No, Yes |
| 14 | | Bilirubin | 0.39 - 4.00 |
| 15 | | Alkaline Phosphatase | 33, 80 - 250 |
| 16 | | SGOT | 13,100 - 500 |
| 17 | | Albumin | 2.1-6.0 |
| 18 | | Prothrombin Time | 10 - 90 |
| 19 | | Histology | No, Yes |
| **Output Class** | | | |
| 1 | Class | | Die, Live |

The entire dataset is divided into two sets one is used for training the ANNs and the other to test them. The training set consists of 100 samples. These 100 samples contains samples from both the classes (live or die). The test set contains 55 samples. These samples are used to check the performance of the networks. Table 2 gives the details of the training and test samples.

TABLE II. Samples used to train and test the ANNs

|  |  |  |  |
| --- | --- | --- | --- |
| **Dataset** | **Total Samples** | **Class** | |
| ***Live*** | ***Die*** |
| ***Training Set*** | 100 | 87 | 13 |
| ***Test set*** | 55 | 36 | 19 |

1. Architecture of Artificial Neural Networks

The ANNs are made up of simple processing units called neurons. They have the ability to store knowledge and utilize it for decision making. The ANN uses the learning function to modify its weights to achieve the desired results [6].

We have analyzed both supervised and unsupervised neural network models with different architectures, learning and activation functions. Supervised models are those in which at each instant of time, when the input vector is applied the desired response (target value) is provided to the network as well. In case of the unsupervised learning the desired response is not known and so explicit error information cannot be used to improve network behavior [6, 9]. The three networks that we selected on the basis of performance evaluation are explained as under.

1. *Feedforward Backpropagation Neural Network*

FFNN is a type of supervised network and belongs to the category of MLP. The architecture we used for FFNN includes 19 neurons in the input layer (as there are 19 attributes used to diagnose hepatitis), the two hidden layers contain 10 neurons each and the output layer has only one neuron. The network was trained using both the training and validation set. Validation set stops the training process by monitoring the error. The error is calculated at the output layer which is the difference between the desired output and the output produced by the neuron.

ej (n)=dj(n)-yj(n)

Where ej is the error of the output neuron j after the activation of the neuron, dj is the desired output of the j neuron and yj is the output produced by the network after every epoch.

We have used Levenberg-Marquardt back propagation algorithm for training the FFNN. This algorithm is based on the error correction learning rule.

The calculated error is then sent back to the network to update the weights in order to achieve the desired results. The performance of the network (to minimize the error) is calculated using the Mean Square Error (MSE) formula:

EAV=

Where EAV is the average of network error over the training examples, N is the total number of training examples and E (n) is the network error.

The weights are updated using the gradient descent with w/momentum weight/bias algorithms. For weight updation the formula used is

Where ∆wji is the weight of the output neuron, is the learning rate, dj-yj is the error, (Vj) is the input to the neurons and yi is the output to the neuron.

The activation function that we have used is the hyperbolic tangent sigmoid function.

The output of the network is either 0 which indicates that the virus is dead or 1 which means that the virus is alive.

The performance graph for the FFNN is shown in Fig. 2.

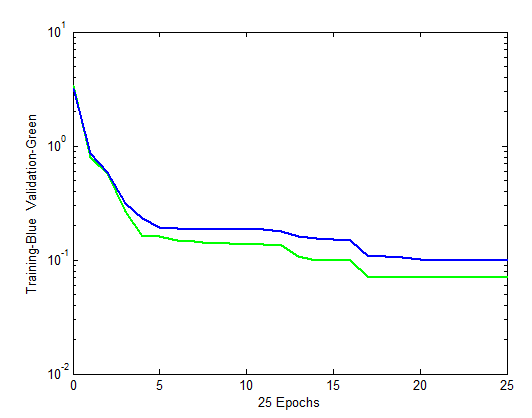


Figure 2. Performance graph for FFNN

1. *Generalized Regression Neural Network*

GRNN are a variant of Radial Basis Function networks. They are based on the one pass learning algorithm. GRNN consists of four layers: input layer, pattern layer, summation layer, and output layer. They are hypothetically reminiscent of K-Nearest Neighbor models. The idea behind GRNN is that an expected target value of a record entry is likely to be same as other entries that have adjacent values of the predictor variables. The distance is computed from the point being evaluated to each of the other points in order to predict the value. To calculate the weight at each point the kernel function is applied to the distance. The learning process is to find a surface in a multidimensional space that presents a best solution to the training data. The generalization is equivalent to the use of this multidimensional surface to interpolate the test data [1, 6, 10].

While implementing the GRNN the input layer has 19 neurons and the output layer has only one neuron. The radial basis transfer function (radbas) is used in the first layer whereas in the second layer we used the linear transfer function (purelin). Euclidean distance weight function (dist) is used calculate the weighted inputs. The output of the GRNN belongs to one of the two classes.

1. *Self Organizing Maps*

They are a type of unsupervised neural networks. SOMs use the competitive learning approach. The output neurons compete among themselves to be activated and as a result only one output neuron is on at one time [6, 10]. The winner neuron is selected on the basis of Euclidean distance. The neuron with the smallest distance is selected and its weights are updated using the following formula:

wij (new) = wij (old) + α [xi - wij (old)]

Where wij is the weight of the neuron, α is the learning rate and xi is the input vector.

The lattice we used has the dimension [5, 8]. The neurons are placed in the hexagonal topology. We used the link distance function (linkdist) to calculate the distance between the layer’s neurons. The learning function used is the Self organizing map weight learning function (learnsom) and the training function that is used is Random order incremental training function (trainr). The 19 attributes were presented to diagnose hepatitis. The SOM created two classes by looking at the dataset (without using the target set while training), one for positive results and the other for negative. The SOMs was tested after 500 training epochs.

The map created after the SOM is trained is shown in Fig. 3.

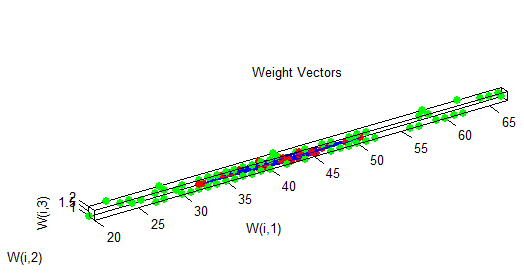


Figure 3. Output of the SOM after it was trained

1. Discussion on the Results

The first network we used is FFNN. Its results were 91% correct. After 300 epochs it correctly detects the state of hepatitis virus.

On the other hand, the GRNN provided better results than the FFNN. Its results were 92 % correct.

In case of SOM, it was not able to diagnose the hepatitis virus correctly using the UCI dataset.

The results of the three networks are presented in table 3 and their comparison is shown is fig 4.

TABLE III. Results of the ANNs

|  |  |  |
| --- | --- | --- |
| **Networks** | **Epochs** | **Results** |
| FFNN | 300 | 91% |
| GRNN | One pass learning | 92% |
| SOM | 500 | 2% |

Figure 4. Comparison of the three networks

1. Comparison with Previous Studies

A comparison has also been made between our study and the previous studies that used the UCI dataset for the diagnosis of hepatitis. The results of the old studies are presented in the table 4.

TABLE IV. Comparison of results with previous studies

|  |  |  |  |
| --- | --- | --- | --- |
| **Authors** | **Networks** | **Result Accuracy (%)** | **Year** |
| Jilani, Yasin and Yasin | MLP with BP | 89.6 | 2011 |
| Bascil and Oztekin | PNN | 91.25 | 2010 |
| Bascil and Temurtas | MLP (Levenberg Marquardt) | 91.87 | 2009 |
| Moein | MLP | 90 | 2008 |
| Uttreshwar and Ghatol | GRNN (Only Hepatitis B) | 86.32 | 2009 |
| Uttreshwar and Ghatol | SOM (Only Hepatitis B) | 97.34 | 2008 |
| Ozyilmaz and Yildirim | MLP | 81.375 | 2003 |
| Ozyilmaz and Yildirim | RBF | 85 | 2003 |
| Ozyilmaz and Yildirim | GRNN | 80 | 2003 |
| Stern and Dobnikar | MLP with BP | 82.1 | N/A |
| Adamczak | RBF | 79 | N/A |
| Adamczak | MLP with BP | 77.4 | N/A |
| **Proposed Method** | **FFNN** | **91.33** | **2011** |
| **Proposed Method** | **GRNN** | **92** | **2011** |
| **Proposed Method** | **SOM** | **Not able to diagnose** | **2011** |

The above table shows that our results are better than those achieved by other authors.

1. CONCLUSION

This paper presents an ANN based approach to diagnose hepatitis using the dataset from the UCI machine learning repository. Both supervised and unsupervised networks have been used for this purpose. We found that the supervised networks diagnosed the disease correctly and accurately as compared to the unsupervised network. Within the supervised category the GRNN outperformed the FFNN. Whereas, the SOM was unable to diagnose hepatitis virus correctly using the same dataset. Future approach could include research on using the LFTs and liver biopsy images for the diagnosis of the disease.

1. REFERENCES

[1] G. S Uttreshwar,. A. A. Ghatol, ‘Hepatitis B Diagnosis Using Logical Inference And Generalized Regression Neural Networks’, IEEE International Advance Computing Conference, IACC, pp.1587-1595, March 2009.

[2] D. Itchhaporia, P. B Snow, R. J Almassy and W. J Oetgen, “Artificial neural networks: current status in cardiovascular medicine,” Journal of the American College of Cardiology, vol.28, pp. 515-521, 1996.

[3] M. R. Raoufy, P. Vahdani, & S. M. Alavian, S. Fekri, P. Eftekhari and S. Gharibzadeh, “A Novel Method for Diagnosing Cirrhosis in Patients with Chronic Hepatitis B: Artificial Neural Network Approach,” J. S. Med July 2009 (Published Online).

[4] G. H. Haydon, R. Jalan, M. Ala-Korpela, Y. Hiltunen, J. Hanley, L. M. Jarvis, C. A. Ludlum and P. C. Hayes, “Prediction of cirrhosis in patients with chronic hepatitis C infection by artificial neural network analysis of virus and clinical factors,” Journal of Viral Hepatitis, 5(4), pp. 255-264, July 1998.

[5] C. M. Tiu, T. L. Jong, and C. W. Hsieh, “Self Organizing Map Neural Network with Fuzzy Screening for Micro-calcifications Detection on Mammograms,” IEEE Conference on Soft Computing in Industrial Applications, 2008.

[6] S. Haykin, Neural Networks A Comprehensive Foundation. India: Pearson Education, Inc., 1999.

[7] S.Davidson, Principles and Practice of Medicine. Churchill Living Stone, 20th edition, 2006.

[8] P.Kumar and M.Clark, Clinical Medicine. W.B. Saunders, 5th edition 2002.

[9] J. M. Zurada, Introduction to Artificial Neural Systems. Mumbai: Jaico Publishing House, 1994.

[10] S. N. Sivanandam, S. Sumathi and S. N. Deepa, Introduction to Neural Networks using Maltab 6.0. McGraw Hill, 2006.

[11] J. Yun, L. Zhanhuai , W. Yong and Z. Longbo, “A Better Classifier Based on Rough Set and Neural Network for Medical Images,” IEEE International Conference on Data Mining, IEEE Xplore, 2006.

[12] M. S. Bascil & F. Temurtas, “A Study on Hepatitis Disease Diagnosis Using Multilayer Neural Network with Levenberg Marquardt Training Algorithm,” Journal of Medical Systems, 16th October 2009 (Published online).

[13] M. S. Bascil and H. Oztekin, “A Study on Hepatitis Disease Diagnosis Using Probabilistic Neural Network,” Journal of Medical Systems, October 2010 (Published online).

[14] T. A. Jilani, H. Yasin and M. M. Yasin, “PCA-ANN for Classification of Hepatitis-C Patients,” International Journal of Computer Applications, Volume 14, No.7, pp. 1-6, February 2011.

[15] Uttreshwar, G. S., Ghatol, A. A., and B. Ambedkar, “Hepatitis B Diagnosis Using Logical Inference and Self-Organizing Map,” Journal of Computer Science, Volume 4, Issue 12, pp. 1042-1050, 2008.

[16] T. K. Liang, T. Tanaka, H. Nakamura, T. Shirahata and H. Sugiura, “An Automated Three-Dimensional Visualization and Classification of Emphysema using Neural Network,” [,42nd Asilomar Conference on](http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=5061475) Signals, Systems and Computers, pp. 1936 – 1940, October. 2008.

[17] M. Barúa, H. Nazeran, P. Nava, B. Diong,, and M. Goldman, “Classification of Impulse Oscillometric Patterns of Lung Function in Asthmatic Children using Artificial Neural Networks”, IEEE 27th Annual International Conference of the Engineering in Medicine and Biology Society, pp. 327-331, 2006.

[18] S. Moein, "Hepatitis Diagnosis by Training of an MLP Artificial Neural Network", in Proc. IC-AI, pp.291-294, 2008.