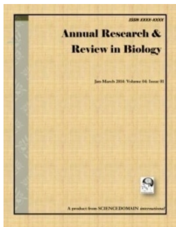

Annual Research & Review in Biology
4(17): 2709-2721, 2014

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Diagnosing Hepatitis Disease by Using Fuzzy Hopfield Neural Network

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Authors' contributions

This research was carried out in collaboration between all authors. Author MN designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors AM and MR managed the analyses of the study. Author HJ managed the literature searches. All authors read and approved the final manuscript.

Original Research Article

Received 25th January 2014
Accepted 29th March 2014
Published 6th May 14 2014

ABSTRACT

Aims: Nowadays, computational intelligence is frequently used in diagnosis and determination of the severity of various diseases. In fact, different tools of computational intelligence help physicians as an assistant to diagnose with fewer errors. In this paper, a fuzzy Hopfield neural network has been used as the determination of severity of the famous disease of hepatitis.
Study Design: This disease is one of the most common and dangerous diseases which endanger the lives of millions of people every year. Diagnosing this disease has always been a serious challenge for physicians and thus we hope this study to be helpful.
Place and Duration of Study: Department of Medicine, Mashhad University and hospital of imam reza, department of liver biopsy, Mashhad, Iran.
Methodology: The data was extracted from University of California, Irvine (UCI) and it has 19 fields with 155 records. It was used the fuzzy Hopfield neural network and the comparison of its performance with various neural networks Multilayer Perceptron (MLP). This trained by standard back propagation, Radial Basis Function (RBF) network, the structure trained by Orthogonal Least Squares (OLS) algorithm, General Regression Neural Networks (GRNN), Bayesian Network with Naïve Dependence and Feature

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selection (BNNF), Bayesian Network with Naïve Dependence (BNND) and Hopfield Neural Network (HNN).
Results: it was found that it has a good performance and was able to diagnose the severity of hepatitis with 92.05% accuracy.
Conclusion: In this article, it is tried to diagnose hepatitis more accurately by fuzzy Hopfield neural network. This network has a high convergence speed and does not have the main problem of the Hopfield network which may converge on another model different from the input data. The use of a suitable pre-processing tool on the data has contributed greatly to the better training of the networks. The training data was not used in network testing in order to get more realistic consequences.

Keywords: Hepatitis; diagnosis disease; fuzzy logic; fuzzy neural network; fuzzy hopfield neural network.

1. INTRODUCTION

World health organization says reports, there are closely 400 million HB who are infected in the world and 50 million the number of them is growing exponentially each year for instance this figure is 2 million persons in Iran [1]. The disease is ranked as the third infectious one. In recent decade, using some different artificial intelligence (AI) methods in medical diagnosis is extremely efficient. In fact, these methods can be used as assistant by experts and practitioners; in addition, these tools can be helped them, so those have a precise diagnosis and more accurate. One of the most important tools in AI is Neural Networks (NN). They have simulated performance of the human brain and have tried to learn models which are in the data And a set of rules from the data are extracted. First of all, Neural networks are trained and learned then can be tested their accuracy. Hopfield neural networks with combination of fuzzy logic are is one of the most flexible NN which can perform well in diagnosing in different samples. The importance of survey and design of an intelligent system has been sensed in this field. Some of the actions that were done in this field -using a data bank comprised 19 fields which were taken from the site UCI- have gotten various results [2-4].

The rest of the paper was arranged as follows. The second section gives the background information including classification problem of hepatitis disease, preceding research was in similar area and short summery of natural. We described the procedure in third Section with alternative suggestion of new medical diagnosis method and measures for evaluating performance. In each subsection of that section, the itemized information is given. The acquired results in applications are given in fourth section; in addition, it also includes the discussion of these results in specific and general manner. Accordingly in fifth section, we infer the paper with summarization of results by emphasizing the importance of this study and mentioning about some future actions.

2. BACKGROUND

2.1 Hepatitis Data Set

Hepatitis B is created by a virus that attacks the liver. It which is named hepatitis B virus (HBV) can bring about continuous infection, cirrhosis (scarring) of the liver, liver cancer, liver failure and death. By 2003, it is estimated that 73,000 persons were infected with HBV. They with all age groups suffer from get hepatitis B and about 5000 persons die annually from illness are affected by HBV; consequently, it is spread when blood from an infected person enters the body of a person who has an uninfected person's body. Healthcare staffs that have received hepatitis B vaccine and improved immunity to the virus are not at risk any infection. For a susceptible person, the risks from a single needle stick or cut exposure to HBV Infected blood ranges from 6% to 30%. The yearly number of professional infections has decreased by 95% as hepatitis B vaccine became ready for using in 1982, from >10,000 in 1983 to <400 in 2001 (http://www.cdc.gov/ncidod/dhqp/ bp_hepatitisb.html, last arrived: 20 January 2006).

This hepatitis disease data set needs the determination of whether patients with hepatitis will either live or DEAD. There are two different classes in Hepatitis Disease: firstly, Patients who have survived due to hepatitis (LIVE), secondly, unfortunately Hepatitis patients who were died by this virus. It was given by Jozef Stefan Institute, Yugoslavia [4]. The data sources used in this study was taken from UCI machine learning database. The aim of the set is to anticipate the attendance or absence of hepatitis disease by considering the given results of different medical tests that are carried out on a patient. This database includes 19 attributes, which were extracted from a larger set of 155 samples. Hepatitis data set is contained 155 samples owned by two different groups (32 ''DEAD'' cases, 123 ''live'' cases). The number of attributes is 19 that are 13 binary and 6 attributes with 6–8 discrete values according to the Table 1. Symptoms attributes which are acquired from patient are as is explained in the coming section:

Table 1. Data set of Hepatitis disease

#	Name	Value
1	Age	10, 20, 30, 40, 50, 60, 70, 80
2	Sex	Female ,Male
3	Steroid	Yes ,No
4	Antivirals	Yes ,No
5	Fatigue	Yes ,No
6	Malaise	Yes ,No
7	Anorexia	Yes ,No
8	Liver Big	Yes ,No
9	Liver Firm	Yes ,No
10	Spleen Palpable	Yes ,No
11	Spiders	Yes ,No
12	Ascites	Yes ,No
13	Varices	Yes ,No
14	Bilirubin	0.39, 0.80, 1.20, 2.00, 3.00, 4.00
15	Alk Phosphate	33, 80, 120, 160, 200, 250
16	Sgot	16.: 13, 100, 200, 300, 400, 500
17	Albumin	2.1, 3.0, 3.8, 4.5, 5.0, 6.0
18	Protime	10, 20, 30, 40, 50, 60, 70, 80, 90
19	Histology	Yes ,No

2.2 Previous Research

With regards to other clinical diagnosis difficulties, classification systems have been applied for diagnosing the problems of .hepatitis disease When the studies in the literature related to this classification application are examined, it can be seen that a great variety of procedures were used which were reached high classification accuracies by using the data set taken from UCI machine learning repository.

It is worth mentioning, researcher Dr. Plot had a major role in the diagnosis of hepatitis and had proper and more accurate results, they are noticeably results. He suggests a new method that is unequaled in its methods and widened capabilities in solving other problems as well [5-6].

One of the best reports of outcome in this research has been Sartakhdi [7]. This test utilize hybridizes SVM and simulated annealing (SA) could have been diagnosed the HB to the accuracy of %96.2. Report has not been seen in the field of appointing the rate HB intensity and the study is a new function in this issue. It can be seen in the Table 2, a brief history of several different methods in diagnosis of Hepatitis disease.

Table 2. Previous Research of Hepatitis disease

Algorithms	Classification accuracy	Reference
CSF NN	90.0	[8]
C4.5	83.6	
NB	87.8	
B NND	90.0	
B NNF	88.7	
Weighted 9NN(10*FC)	92.9	[9]
18NN,stand manhattan(10*FC)	90.2	
15NN,stand manhattan(10*FC)	89.0	
FSM without ratations	88.4	[10]
RBF(tooldaig) (10*FC)	79.0	
MLP+BP(tooldaig)(10*FC)	77.4	
LDA,(10*FC)	86.4	[11]
Naïve Bayes and Semi-NB(10*FC)	86.3	
QDA(10*FC)	85.8	
ASR(10*FC)	85.0	
Fisher Discriminant analysis(10*FC)	84.5	
LVQ(10*FC)	83.2	
CART(Decision tree)(10*FC)	82.7	
MLP with BP(10*FC)	82.1	
ASI(10*FC)	82.0	
MLP(5*FC)	74.3	[8]
GRNN(5*FC)	80.0	[10]
FS-fuzzy AIRS(50*50%)	81.8	[13]
FS-AIRS with fuzzy res(10*FC)	92.5	[12]
FS- fuzzy–AIRS(10*FC)	94.1	[14]
LDA-ANFIS(10* FC)	94.1	[11]
MLNN(MLP)+LM(10*FC)	91.8	[15]
CORE	92.4	[12]
PGA-LSSVM	95.0	[13]
GA-SVM	89.6	[12]
SVM-SA	96.2	[7]

3. METHODS

3.1 Fuzzy Hopfield Neural Networks

The Hopfield neural network (HNN) has been investigated extensively with its simple architecture specification and potential for parallel performance. HNN is a biologically influenced from mathematical instrument and was suggested by Hopfield [16]. The HNN is a well-known technique which is used for solving the problem of optimization dependent upon energy function. The HNN, an auto return of part of the output associated network that has some characteristics [17].

Due to its certain properties, this network has been used in different areas. As a sample, an adaptive Hopfield network was used for solving one of the most significant concerns of power systems which was minimizing the operating costs based on economic load dispatch (ELD) method [18]. In addition, this network had many applications in solving different medical problems including electrocardiogram signal modeling and its noise reduction [19].

Fuzzy Hopfield's concept (FHNN) has demonstrated a very advantageous profitable function through via optimization, pattern recognition and clustering. The capability, flexibility and accuracy of network have been developed by the joining of Fuzzy Logic and HNN; rather than results 0 and 1 dependency rate of every factual information on the nominated class is computed [20-23]. An idea of fuzzy Hopfield neural network with the computational functions of fuzzy logic is explained defined. It led to have automatic understanding and accurate tuning of the network coefficients based on the Hopfield neural model. This led us to in the HNN model so that understand operating by itself, accurate tuning of the network coefficients. In the proposed suggested merging the set of fuzzy rules are determined based on samples extracted from the experience that are acquired in various HNN applications in some areas .the rules were obtained through a supervised learning process, as explained in [24]. This Neural network has more application in medical examination and it is a good help in diagnosis of different disease such as Liver disease [25], Breast cancer and so on.

Fuzzy C-Means is applied for determining information gathering of X, selecting the number of the class, selecting the quantity of M that is often higher than 1 as the power of weighting, determining the $\varepsilon > 0$ as the algorithm's results of error rate, the standard matrix of stimulus A and original measuring is determined and also dividing matrix [20].

The algorithm performed for diagnosing liver disorders by using FHNN is considered in ten parts. Utilizing this proposed, dependency rate of every record that in fact is the outcome of suspect's tests, is computed considering the collection of patients and collection of healthy people afterwards final decision would be made about the suspect.

During the last decades, the FHNN has been investigated broadly with its characteristic of uncomplicated structure and potential for parallel execution. Meanwhile, it is the union of fuzzy c-means clustering and HNN; additionally, it has been extensively utilized in some types of unsupervised pattern recognition and particular image segmentation and clustering problems. Cheng et al. Suggested a competitive HNN for image segmentation of medical; Furthermore, they have used a competitive HNN for polygonal estimation. The winner-take-all rule has been adopted in the two dimensional discrete it to go away from the need for finding weighting cause in the function of energy by lin et al. Suggested signal segmentation and multi-spectral medical image by applying a FHNN [26-28]. Moreover, an edge detection algorithms based on the HNN were suggested by chao et al. [29]. Additionally, use of endocardial boundary detection in using the HNN was described by Tsai et al. [30]. Amatur et al. used the two dimensional HNN for segmenting of multi-spectral MR images [31]. fuzzy possibilistic neural network to vector quantize in frequency domains was proposed by Lin [32]. Another application of FHNN in image processing is a new combination of it with stable weight for the segmentation of medical image which was suggested by chang and ching [33,34] and also other new method of medical image segmentation using involving competition HNN likes a clustering way was suggested by roozbahani et al. [35]. In addition, segmentation of medical image processing with helping a contextual restriction based on HNN cube was recommended by them [36]. In addition to, a novel method of image compression and clustering established upon FHNN was suggested by Kaya [37] and there is another similar method of it with the use of Annealed FHNN [38]. Finally, the FHNN stochastic model of stability analysis with time changing postponements was suggested by He Huang [39].

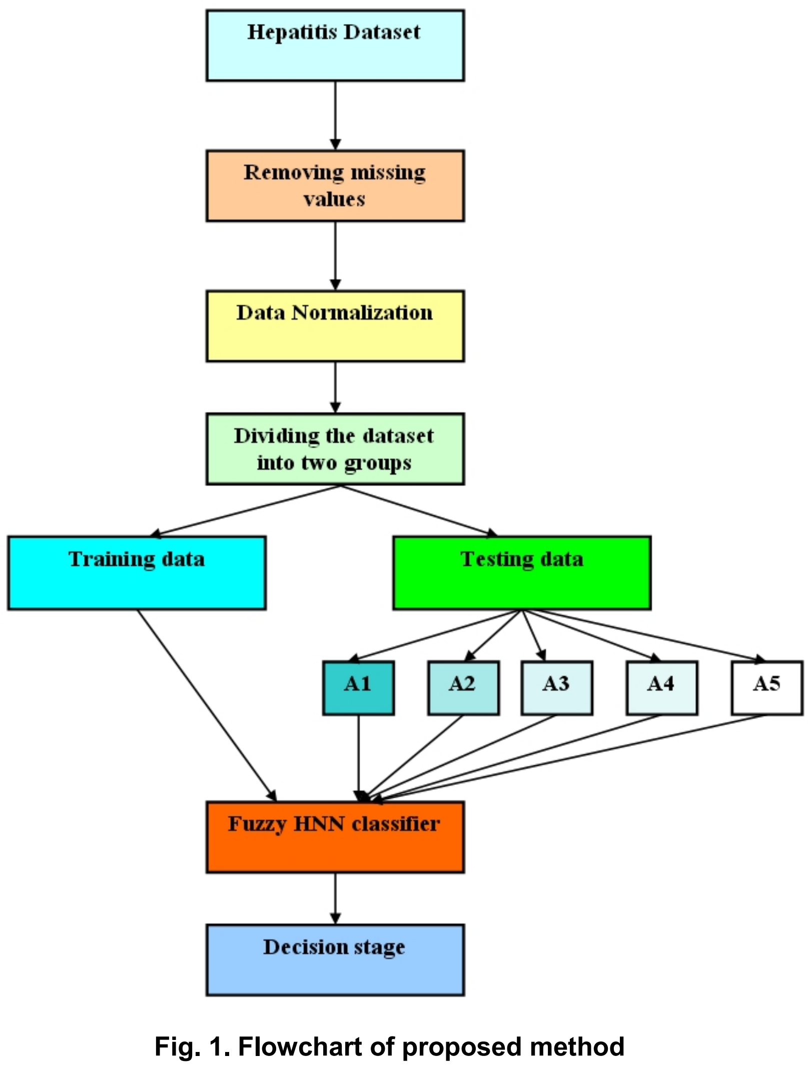

Fig. 1. Flowchart of proposed method

3.2 Algorithm

1) The data of fuzzy C-Means are classified.
2) The data are normalized (every of the fields' averages, variances are calculated; furthermore, the unity constant factor of fields in order to delete the sick field are determined if identified [40].
3) Primary centering $V_{i=0}$
4) distance between every data and nominated class are computed

$$D = (x_k - v_i)^T A(x_k - v_i), 1 \le i \le c, 1 \le k \le N$$

5) The initial dividing matrix is calculated

$$U^{(0)} = \mu_{i,k}^{(0)} = \frac{1}{\sum_{j=1}^{c} \left(D_{ikA} \big/ D_{jkA} \right)^{2/(m-1)}}$$

6) New cluster's centroid are computed

$$v_i = \sum_{f=1}^{n} \frac{1}{\sum_{h=1}^{n} \mu_{i,h}^{m}} x_f \mu_{i,f}^{m}$$

7) Input for each neuron (I, k) are calculated

$$Net_{i,k} = \left[x_k - \sum_{f=1}^{n} \frac{1}{\sum_{h=1}^{n} \mu_{i,h}^{m}} x_f \mu_{i,f}^{m} \right]^2$$

8) Can be calculated the new separating matrix (fuzzy C-Means)

$$\mu_{i,k} = \left[\sum_{j=1}^{c} \left(\frac{Net_{i,k}}{Net_{j,k}} \right)^{2/m-1} \right]^{-1}$$

9) Calculate J^t

$$J^t = \frac{1}{N} \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{i,k}^{m} D_{i,k}^{2}$$

10) If $\left| J^{t+1} - J^t \right| < \varepsilon$ intend to level 6 else intend to finish.
11) Finish

3.3 Proposed Method

In overall, this study has the following steps:

1. Removing the missing data
2. Data normalization
3. Dividing the dataset into a training group (75 records) and a test group (80 records)
4. Dividing the test data into 5 groups (A1,A2,A3,A4,A5) which is described in detail in the next segment
5. Training the fuzzy Hopfield neural network
6. Testing the network with the data from 5 groups
7. Comparison of the results of Hopfield fuzzy network with 6 other neural networks

All details can be seen in the above Fig. 1. In fact, this flowchart is an overall aspect of this proposal.

4. PREPROCESSING DATA

Data analyzing process starts with data loading and progressed by separation of good data from noise data or preprocessing. This is the first step of data preprocessing and has a considerable influence on next steps efficiency increase.

As described in section2, hepatitis dataset is a 155×19 matrix. In order to survey missing data in MATLAB (its version is MATLAB 7.0.4 Release Notes), *isnan* function has been used to define the number of missing data for each column. The output from this function is zero that shows the absence of missing data in it.

In next step one should detect outliers (irrelevant data). These data differ from other data pattern considerably. These values generally form as a result of measurement fault or could be the provider of special characteristics in data set. A general method to know these data is to use data mean and standard deviation. Data greater than $\mu + n\sigma$ would be eliminated, which μ is mean, σ is standard deviation and n is a coefficient that is defined by expert's diagnosis.

Finally, the existence of noise caused data to have some fluctuation around the predicted values. To eliminate these unwanted fluctuations and maintain the main features, data should be smoothed pre processing. In smoothing process of data, there are two assumptions:

1) The relation between independent variable and reply is smooth.
2) The smoothing algorithm provides a better estimation from predicted valued via noise reduction.

To smooth data in MATLAB, two functions of filter and *convn* could be used. We used *convn* in this research. The value of smoothing is under control by S variable. The greater the window size, the more data smoothing.

5. EXPERIMENTAL RESULT

In this study, the proposed network (FHNN) was compared with various neural networks including Multilayer Perceptron neural network, RBF, BNND, BNNF, HNN; the results indicate the good performance of the proposed network. All data have been divided into two main groups of *TESTD* and *TRAIND* for network training and testing. The *TESTD* data group has 80 samples of 155 bank records including 18 samples of the first class (DEAD) and 62 samples of the second class (LIVE). To make the testing and evaluation steps even more accurate, after normalization in MATLAB 7.0.4, the data are divided into 5 groups. Each one of A1, A2 and A3 subgroups have 4 samples of the first class and 12 samples of the second class. The subgroups A4 and A5 also contain 3 samples of the first class and 13 samples of the second class. In addition, there is no noise or missing data in the test data. The reason for the combination of classes in the 5 subgroups is the number of samples in the first class (DEAD) with respect to their number in second class (LIVE) which is equal to 0.26. 75 samples will be used for training the networks. It must be kept in mind however, that due to lack of overlapping between training and test data, the results of networks are less efficient, but closer to reality. Because in all groups have same number of each class, so there are not redundant data for testing system. And also each group has special attribute that its result is interesting after test which can be shown in the Tables 3 and 4.

Table 3. The results for testing A1 subset with different Neural Network

Neural networks	Average classification accuracy (%)	Min classification accuracy (%)	Max classification accuracy (%)	Testing error
MLP	76.04	69.16	80.71	0.2971
RBF	85.15	80.92	87.50	0.1953
GRNN	86.07	75.12	89.66	0.1873
BNND	87.41	79.33	90.68	0.1784
BNNF	90.96	84.52	92.07	0.1573
HNN	90.00	86.50	91.41	0.1477
FHNN	92.01	90.00	94.66	0.1305

Table 4. The results for testing A2 subset with different Neural Network

Neural networks	Average classification accuracy (%)	Min classification accuracy (%)	Max classification accuracy (%)	Testing error
MLP	78.36	75.6	80.73	0.2816
RBF	79.21	71.68	81.97	0.2018
GRNN	86.91	80.12	89.23	0.1741
BNND	88.43	81.74	90.39	0.1685
BNNF	90	86.57	91.71	0.1514
HNN	90.29	87.00	91.00	0.1449
FHNN	92.31	90.12	95.16	0.1295

Clearly, it seems that the proposed method is faster compared with other methods working based on clustering according to the Tables 5, 6 and 7. Moreover, along with the proposed algorithm, a new objective function has been presented as well. This objective function has been minimized by the Lyapunov Energy Function which is the base of HNN and forms the base of the mentioned Hopfield fuzzy network. This new purpose is in fact the same energy function of HNN which has been optimized and established based on the average distance between the samples and the data cluster center. Another specific feature of this method is fewer numbers of iterations and fast convergence to the model.

Table 5. The results for testing A3 subset with different Neural Network

Neural networks	Average classification accuracy (%)	Min classification accuracy (%)	Max classification accuracy (%)	Testing error
MLP	76.14	70.72	79.48	0.2908
RBF	83.28	79.4	85.33	0.2311
GRNN	86.83	77.21	90.03	0.1746
BNND	87.92	80.03	91.72	0.1691
BNNF	89.25	85.08	91.15	0.1573
HNN	90.05	85.22	92.17	0.1495
FHNN	91.93	89.75	92.46	0.1375

Table 6. The results for testing A4subset with different Neural Network

Neural networks	Average classification accuracy (%)	Min classification accuracy (%)	Max classification accuracy (%)	Testing error
MLP	81.42	75.4	83.15	0.2457
RBF	82.77	78.4	83.49	0.2301
GRNN	87.02	82.36	90.17	0.1702
BNND	88.7	82.59	91.35	0.1655
BNNF	90.22	87.06	92.44	0.1529
HNN	90.45	87.51	92.19	0.1439
FHNN	92.68	90.69	95.44	0.1255

Table 7. The results for testing A5 subset with different Neural Network

Neural networks	Average classification accuracy (%)	Min classification accuracy (%)	Max classification accuracy (%)	Testing error
MLP	63.25	61.41	65.73	0.3804
RBF	83.31	79.17	85.86	0.2341
GRNN	84.21	74.57	85.72	0.1897
BNND	85.98	77.49	90.71	0.1795
BNNF	89.05	82.75	90.84	0.1665
HNN	90.05	85.00	91.45	0.1507
FHNN	91.35	89.37	92.19	0.1381

Finally, Table 8 shows to compare among seven different method of neural networks that can be seen the best result by proposed method.

Table 8. Results for 5-fold cross validation Method

Type of NN	Classification accuracy (%)
MLP	75.04
RBF	82.54
GRNN	86.2
BNND	87.69
BNNF	89.9
HNN	90.17
FHNN	92.05

6. CONCLUSION

In this article, we experimented to diagnose hepatitis more accurately utilizing FHNN. This network has a high convergence speed and does not have the main problem of the Hopfield network which may converge on another model different from the input data. The use of a suitable pre-processing tool on the data has contributed greatly to the better training of the networks. The training data was not used in network testing in order to get more realistic results. According to the results, FHNN has the ability to diagnose hepatitis with the average accuracy of 92.05% which is a better performance compared with the six other neural networks (MLP, RBF, GRNN, BNND, BNNF, HNN).

ACKNOWLEDGMENTS

It is outstanding to regard highly all the guidance and efforts given by nurses and doctors of Imam Reza hospital, department liver biopsy, Mashhad Iran.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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