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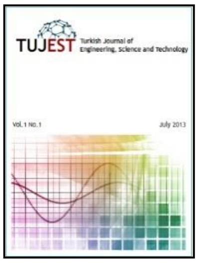

Using Fuzzy Hopfield Neural Network for Diagnosis of the Hepatitis Disease

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Abstract

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 article, a fuzzy Hopfield neural network has been used for determination of severity of the famous disease of hepatitis. This disease is one of the most common and dangerous diseases which endangers 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. The data was extracted from UCI and it has 19 fields and 155 records. After training and testing the fuzzy Hopfield neural network and the comparison of its performance with various neural networks Multilayer Perceptron (MLP) structure trained by standard back propagation, Radial Basis Function (RBF) network structure trained by OLS algorithm, GRNN, BNNF, BNND and HNN, it was found that it has a good performance and was able to diagnose the severity of hepatitis with 92.05% accuracy.

1. Introduction

Hepatitis B has a virus cause. Its size is 42 nanometers and its active part is in its central region. The Australian antigen or the HB surface antigen (HbsAg) itself is on virus surface. This virus with going through liver cells makes them produce similar viruses. It is considered an infected individual when there are (HbsAg) in one's blood. The most sensitive patient's blood tests which consider viruses' spread in body are PCR and HBNDNA. If the test consequence is positive, it can be deduced that the person has been infected with HB virus but determining the person pathology status and the rate of disease improvement involve modern and complicated tests.

According to the recent world health organization (who) reports, there are nearly 400 million HB infected in the world and 50 million persons are added to them increasing annually. This figure is 2 million people in Iran [1]. This disease ranked as the third infectious one. The significance of surveying and designing an intelligence system has been sensed in this field. Some of the works that have been done in this field -using a data bank comprised 19 fields taken from the site UCI- have gotten various resulting [2].

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The rest of the paper is arranged as follows. Section 2 gives the background information including hepatitis disease classification problem, previous research in corresponding area and brief introduction to natural. We described the procedure in Section 3 with subtitles of suggested a new medical diagnosis method and measures for performance evaluation. In each subsection of that section, the detailed information is given. The results acquired in applications are given in Section 4. This section also comprises the discussion of these results in specific and general manner. Accordingly in Section 5, we infer the paper with summarization of results by emphasizing the significance of this study and mentioning about some future work.

2. Background

2.1. Hepatitis Disease Dataset

Hepatitis B is caused by a virus that attacks the liver. The virus, which is called hepatitis B virus (HBV), can bring about lifelong infection, cirrhosis (scarring) of the liver, liver cancer, liver failure, and death. In 2003, an estimated 73,000 people were infected with HBV. People of all age's group get hepatitis B and about 5000 die per year of sickness affected by HBV. HBV is spread when blood from an infected person enters the body of a person who has an uninfected person's body. Healthcare staffs who have received hepatitis B vaccine and improved immunity to the virus are at virtually no risk for 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 annual yearly number of professional infections has reduced 95% since hepatitis B vaccine became ready for use 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 requires determination of whether patients with hepatitis will either live or die. It was contributed by Jozef Stefan Institute, Yugoslavia. The used data source in this study was taken from UCI machine learning repository. The goal of the dataset is to anticipate the presence or absence of hepatitis disease given the results of different medical tests carried out on a patient. This database includes 19 attributes, which have been extracted from a larger set of 155. Hepatitis dataset it is contained 155 samples belonging to two various classes (32 ''die'' cases, 123 ''live'' cases). There are 19 attributes, 13 binary and 6 attributes with 6–8 discrete values. Attributes of symptoms that are obtained from patient are as follows (UCI Machine Learning Repository):

Table 1 Attributes of symptoms that are obtained from patient

#	Name	Value
1	Age	10, 20, 30, 40, 50, 60, 70, 80
2	Sex	Male, Female
3	Steroid	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	Ascites	No, Yes
13	Varices	No, Yes
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	No, Yes

2.2. Previous Research

With regards to other clinical diagnosis problems, classification systems have been used for hepatitis disease diagnosis problem. When the studies in the literature related with this classification application are examined, it can be seen that a great variety of procedures were used which were reached high classification accuracies using the dataset taken from UCI machine learning repository. Among these, while Karol Grudzin´ ski has acquired 92.9%, 90.2% and 89.0%, respectively [39], using weighted 9-NN, 18-NN, and stand. Manhattan and 15-NN, stand. Euclidean algorithms, Rafał Adamczak has obtained 89.7%, 88.5%, 79.0% and 77.4%, respectively [40], using FSM with rotations, FSM without rotations, RBF and MLP + BP algorithms. While, Stern & Dobnikar have obtained 86.4%, 86.3%, 85.8%, 85.3%, 85.0%, 84.5%, 83.2%, 82.7%, 82.1%, 82.0% and 81.9%, respectively, using LDA (linear discriminate analysis)[41], Naive Bayes and Semi- NB, QDA (quadratic discriminate analysis), 1-NN, ASR, Fisher discriminate analysis, LVQ, CART (decision tree) MLP with BP, ASI and LFC algorithms, Norbert Jankowski has obtained 86% using IncNet algorithm. Ozyılmaz L. and Tu¨lay Y. have obtained 74, 37%, 83, 75% and 80, 0% using MLP, RBF and GRNN algorithms [40].

It is worth mentioning, researcher Dr. Plot had an major role in the diagnosis of hepatitis is better 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 [11-12].

The best reported resulting in this field has been Sartakhdi [45]. This test using hybridizes support vector machine (SVM) and simulated annealing (SA) could have diagnosed the HB to the accuracy of %96.2. No report has been seen in the field of appointing the rate HB intensity and the research is a new work in this field.

Table 2. Algorithms Classification Accuracy

Algorithms	Classification Accuracy	Reference
CSFNN	90.0	[37]
C4.5	83.6	
NB	87.8	
BNND	90.0	
BNNF	88.7	
Weighted 9NN (10*FC)	92.9	[39]
18NN, stand manhattan (10*FC)	90.2	
15NN, stand manhattan (10*FC)	89.0	
FSM without ratations	88.4	[40]
RBF(tooldaig) (10*FC)	79.0	
MLP+BP (tooldaig) (10*FC)	77.4	
LDA , (10*FC)	86.4	[41]
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	[37]
GRNN (5* FC)	80.0	[40]
FS- fuzzy – AIRS (50*50%)	81.8	[43]
FS-AIRS with fuzzy res. (10*FC)	92.5	[42]
FS- fuzzy – AIRS (10*FC)	94.1	[44]
LDA-ANFIS (10* FC)	94.1	[41]
MLNN(MLP)+LM(10*FC)	91.8	[38]
CORE	92.4	[42]
PGA-LSSVM	95.0	[43]
GA-SVM	89.6	[42]
SVM-SA	96.2	[45]

3. Method

3.1.* Hopfield *Neural Network

The Hopfield neural network has been studied widely with its feature of simple architecture and potential for parallel implementation. Hopfield neural network (HNN) is a biologically inspired mathematical tool and was proposed by Hopfield [14] in 1982.The Hopfield neural network is a famous technique which is used for solving optimization problem based on energy function. The HNN, a feedback auto –association network, which has several traits [15] including:

- Synaptic weights are accumulated in advance.
- Nonlinear threshold operations are used in each layer to produce new states.
- States feedback is utilized to that the states of neuron can be operatively updated.
- The objective function is minimized until the network converges to a fixed state.

The benefit of using HNN over more traditional optimization techniques lies in its potential for rapid computational power when implemented in electronic hardware, and the inherent parallelism of the network. There are two kinds of Hopfield networks, discrete and continuous models, which allow various values for neuron states.

Biological modeling of human brain is tried by utilizing a fully inter –connected system of N neurons. Assume neuron *i* has internal state U_i and output level V_i. The internal state U_i incorporates a bias current symbolized by I_i and the weighted sum of the output from all other neurons. Assume the weight, which determines the strength of the connection from neuron *i* to neuron *j* is given by W_{ij}. The relationship between the internal state U_i of a neuron and its output level V_i is determined by an activation function G (U_i) i.e. V_i =G (U_i). The nature of this activation function is used to determine that the Hopfield neural network is discrete or continuous .an example of an activation function, in a uninterrupted case, is shown as following.

$$V_i = G(U_i) = \frac{1}{2}\left(1 + \tanh\left(\frac{U_i}{\lambda}\right)\right)$$

Where λ is a parameter used to control the gain of the active function. For discrete Hopfield neural network, the activation function is usually a discrete threshold function .the following is an example for which the threshold value is setting to zero.

$$V_i = G(U_i) = \begin{cases} 1 & U_i > 0 \\ 0 & U_i \le 0 \end{cases}$$

The states of the neurons on the network are updated themselves sequentially according to the following rules.

$$U_i(t+1) = U_i(t) + \Delta t\left(\sum_{j=1}^{N} W_{ij} V_j + I_i\right)$$

$$V_i(t+1) = G(U_i(t+1))$$

Where Δt is represented as a constant time-step. The network of neurons will be converged to a local minimum of the following energy function over time.

$$E = -\frac{1}{2}\sum_i \sum_j V_i W_{ij} V_j + \sum_i I_i V_i$$

Provided the weights are symmetric i.e. $W_{ij} = W_{ji}$ [14]. If neurons of the network are updated in synchronously, then the possibility of the convergence exists.

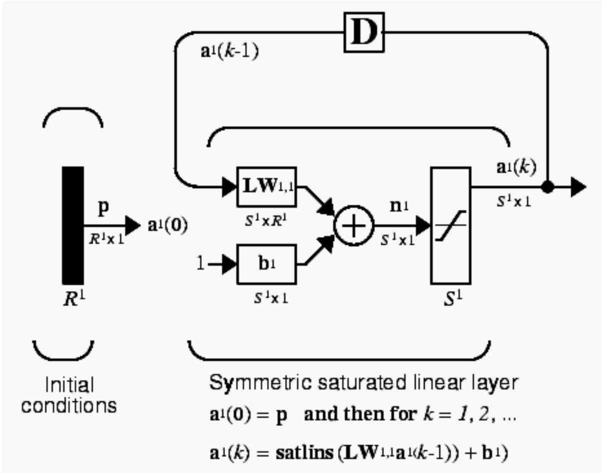

Figure 1. Applied Hopfield network for diagnosing disorders

Since the data are in a six dimensional space, three dimensional Hopfield must be used so that the network labels each datum regarding to three fields. Then redo this action to compute other three fields. Resultant of these two labeled amounts is the certain amount of each datum.

Energy function is defined as following formula:

$$E = \frac{A}{2}\sum_i\sum_j\sum_k\sum_l\sum_p\sum_q D(i,j,k)V_{ij}V_{kl}V_{pq}$$
$$+\frac{B}{2}\sum_i\sum_j\sum_k V_{ij}(V_{kl}-1)^2 + \frac{C}{2}\sum_i\sum_j (V_{ij}-1)$$

In function of energy equation Function D is defined as below:

$$D(i,j,k,l,p,q) = \begin{cases} 1 & V_{ij}V_{kl}V_{pq} overlap \\ 0 & V_{ij}V_{kl}V_{pq} not\ overlap \end{cases}$$

In a three-dimension space Hopfield differential equation is calculated based on formula 8:

$$\frac{\partial U_{ij}}{\partial t} = -\frac{U_{ij}}{C_i}\sum_k\sum_l W_{ij,kl} + V_{ij} + I_{ij}$$
$$\frac{\partial U_{kl}}{\partial t} = -\frac{U_{kl}}{C_k}\sum_p\sum_q W_{kl,pq} + V_{kl} + I_{kl}$$
$$\frac{dU_{ij}}{dt} = -\frac{U_{ij}}{\tau_i} - \frac{\partial E}{\partial V_{ij}} = -\frac{U_{ij}}{\tau_i} - A\sum_k\sum_l\sum_p\sum_q D(i,j,k,l,p,q).$$
$$V_{KL}V_{pq} - B\sum_k\sum_l V_{kl}\delta_{ij,kl} - C\sum_p\sum_q V_{pq}\delta_{kl,pq} + C$$
$$W_{ij,kl,pq} = -AD(i,j,k,l,p,q) - B\delta_{ij,kl,pq}$$
$$I_{ij} = B$$
$$\delta_{ij,kl,pq} = \begin{cases} 1 & (i,j)=(k,l)=(p,q) \\ 0 & otherwise \end{cases}$$

Network can be built after calculating the weights. By first measuring in each level output of the network's neurons is produced. The proper activating function in Hopfield network is sigmoid function which used in this research. Outputs of each level are utilized as the inputs of the next level in order to keep the network steady. After network training, testing level should be done. In this research, the network was trained and tested by different parts of data. Outcomes are discussed and examined in experimental results part.

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 [46]. In addition, this network had many applications in solving different medical problems including electrocardiogram signal modeling and its noise reduction [47].

3.2. Fuzzy hopfield neural network

The concept of fuzzy Hopfield has shown a very advantageous function through optimization, clustering and pattern recognition. By the combination of fuzzy logic and Hopfield network; ability, flexibility and accuracy of network has been developed and rather than outputs 0 and 1 Dependency rate of each datum upon the appointed class is calculated [16-19].

Fuzzy C-Means is used for determining information collection of X, choosing the number of the class, choosing the amount of M which is always upper than 1 as the power of weighting, determining the $\varepsilon > 0$ as the error rate of algorithm's output, determining the standard matrix of stimulus A and primary measuring the dividing matrix [16].

The algorithm implemented for liver disorders diagnosis using fuzzy Hopfield network is discussed in ten levels. Using this method, dependency rate of each record which in fact is the result of suspect's examinations, is calculated regarding patients and healthy people collection. Then final decision is made about the suspect.

3.2.1. The history

An idea of fuzzy Hopfield neural network with the computational functions of fuzzy logic is defined .this led us to in the Hopfield neural model in order to undrestand automatic, accurate tuning of the network coefficients. In the suggested merging the set of fuzzy rules is determined on the basis of example extracted from the experience we have obtained in different Hopfield network applications in several fields [20].the rules were acquired through a supervised learning process, as described in [21].

During the last few years, the fuzzy Hopfield neural network has been studied widely with its features of simple architecture and potential for parallel implementation .the fuzzy Hopfield neural network is the combination of fuzzy c-means clustering and Hopfield neural network clustering network and it has been widely used in several kinds of unsupervised pattern recognition and specific image segmentation problems. Cheng et al. proposed a competitive Hopfield neural network for medical image segmentation. Furthermore; Chung et al. applied a competitive Hopfield neural network for polygonal approximation. The winner-take-all rule has been adopted in the two dimensional discrete Hopfield neural network to get rid of the need for finding weighting cause in the energy function. lin et al. proposed the segmentation of signal and multi-spectral medical image using a fuzzy Hopfield neural network [22,23,24]. Moreover, an edge detection algorithms based on the Hopfield neural network were proposed by chao et al.[25]. Additionally, endocardial boundary detection using the Hopfield neural network was depicted by Tsai et al .[26].amatur et al.[27] used the two dimensional Hopfield neural network for segmentation of multi-spectral MR images. fuzzy possibilistic neural network to vector quantize in frequency domains was proposed by Lin[28].Fuzzy Hopfield neural network with fixed weight for medical image segmentation was proposed by chang and ching[29].robust segmentation of medical image using competitive Hopfield neural network as a clustering tool was proposed by roozbahani et al.[30]. In additional, medical image segmentation using a contextual constraint based Hopfield neural cube was proposed by chang and chung [31].besides, a new image clustering and compression method based on fuzzy Hopfield neural network was proposed by Kaya [32] and Image Clustering and Compression Using An Annealed Fuzzy Hopfield Neural Network [35], stochastic stability analysis of fuzzy Hopfield neural network with time varying delays was proposed by He Huang [36].

3.2.2. Algorithm

1) Classifying the data fuzzy C-Means.

2) Normalizing the data (calculating each of the fields' averages and variances and determining the unity coefficient of fields in order to omit the sick field if recognized. [33])

3) Primary centering $V_{i=0}$

4) Computing the distance between each data and appointed class

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

5)Calculating the primary dividing matrix

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

6) Computing the new cluster's centroid

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

7) Calculating the input for each neuron (I, k)

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

8) Calculating the new dividing 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 $\left| J^{t+1} - J^t \right| < \varepsilon$ go to level 6 else go to end.

11) End

3.2.3. 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 explained in detail in the next section
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

The related flowchart is as follows:

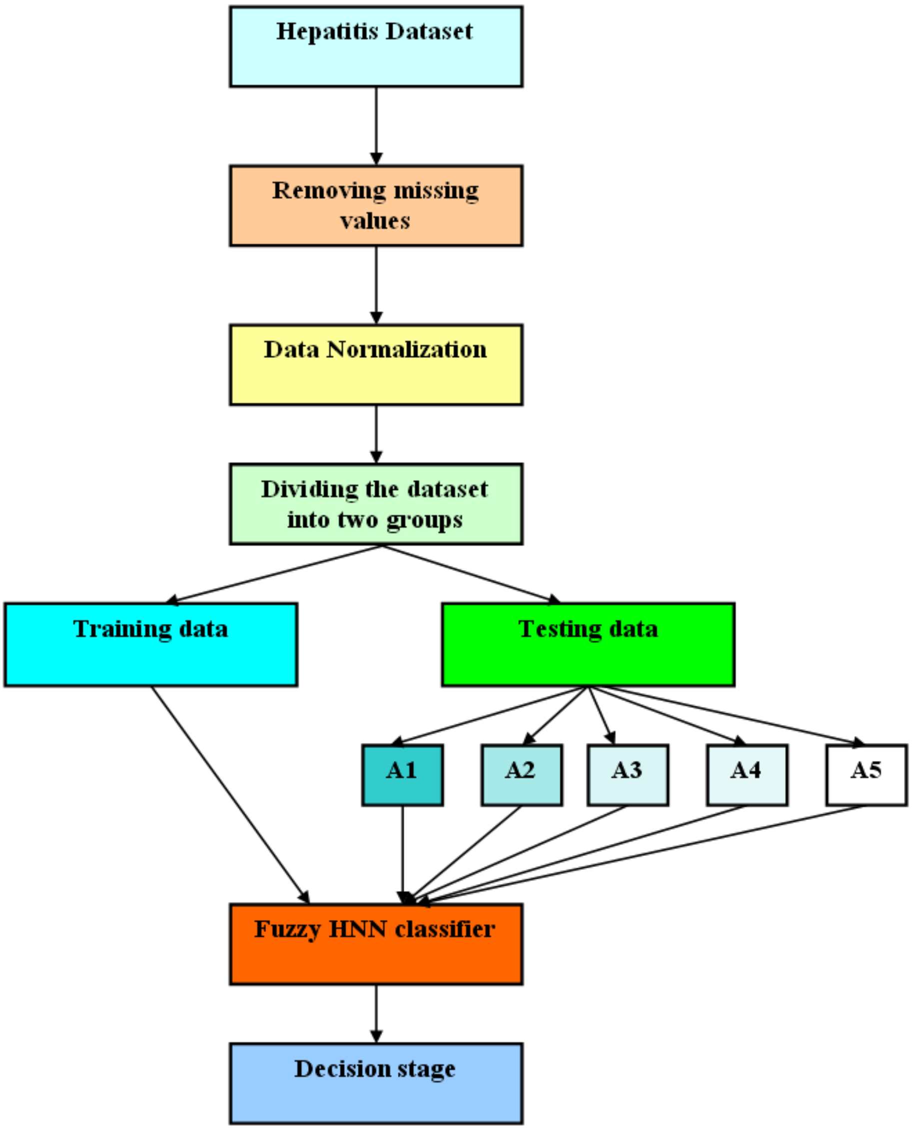

Figure 2. Flowchart of proposed method

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, *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 (DIE) and 62 samples of the second class (LIVE). To make the testing and evaluation steps even more accurate, after normalization in MATLAB, 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 (DIE) 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.

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

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

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

Clearly, it seems that the proposed method is faster compared with other methods working based on clustering. 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 Hopfield neural network and forms the base of the mentioned Hopfield fuzzy network. This new function is in fact the same energy function of Hopfield network 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.

6. Conclusion

In this research, we tried to diagnose hepatitis more accurately using 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 results. According to the results, fuzzy hopfield neural network 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).

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