Artificial Neural Network System for Thyroid Diagnosis

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Abstract

Thyroid disease is one of major causes of severe medical problems for human beings. Therefore, proper diagnosis of thyroid disease is considered as an important issue to determine treatment for patients. This paper focuses on using Artificial Neural Network (ANN) as a significant technique of artificial intelligence to diagnose thyroid diseases. The continuous values of three laboratory blood tests are used as input signals to the proposed system of ANN. All types of thyroid diseases that may occur in patients are taken into account in design of system, as well as the high accuracy of the detection and categorization of thyroid diseases are considered in the system. A multilayer feedforward architecture of ANN is adopted in the proposed design, and the back propagation is selected as learning algorithm to accomplish the training process. The result of this research shows that the proposed ANN system is able to precisely diagnose thyroid disease, and can be exploited in practical uses. The system is simulated via MATLAB software to evaluate its performance.

Keywords: Artificial Neural Network (ANN), Neuron, Back propagation, Multilayer feedforward, Thyroid disease, Classification rate, Diagnosis.

الخلاصة

مرض الغدة الدرقية هو احد الاسباب الرئيسة للمشاكل الطبية الخطرة للبشر . لذا التشخيص الصحيح لمرض الغدة الدرقية يعتير من القضايا المهمة لتحديد العلاج المناسب للمرضى. هذا البحث يركز على استخدام الشبكة العصبية الصناعية كتقنية مهمة للذكاء الصناعي لتشخيص امراض الغدة الدرقية. القيم المستمرة لثلاث تحاليل دم مختبرية تستخدم كأشارات ادخال الى نظام الشبكة العصبية الصناعية المقترح. جميع انواع امراض الغدة الدرقية التي يمكن ان تحدث للمرضى تم اخذها بالحسبان في تصميم النظام، بالاضافة الى الدقة العالية في كشف وتصنيف امراض الغدة الدرقية تم اخذها بنظر الاعتبار في النظام. تم اختيار هيكلة متعدد الطبقات ذات التغذية الامامية للشبكة العصبية الصناعية في التصميم المقترح، وكذلك الانتشار العكسي استخدم كخوارزمية تعليمية لانجاز عملية التدريب. نتائج هذا البحث اظهرت ان التصميم المقترح قادر بدقة على تشخيص امراض الغدة الدرقية، ومن الممكن استغلاله في الاستخدمات العملية. ان النظام تم محاكاته بأستخدام برنامج الماتلاب وذلك لتقيم كفاءته.

الكلمات المفتاحية: الشبكات العصبية الصناعية، عصبية، الانتشار العكسي، متعدد الطبقات ذات التغذية الامامية، مرض الغدة الدرقية، نسبة التصنيف، التشخيص

1. Introduction

In recent years, artificial intelligence techniques are exploited for developing professional systems to diagnose different kinds of diseases with high accuracy. These systems assist staff in hospitals and medical centers to quickly diagnose patients and give them essential treatments without need for a specialist doctor. As a result, these systems decrease cost and time for diagnosis. Artificial Neural Network is the most important artificial intelligence technique that has been used to design diagnostic system for several diseases such as diabetes, heart disease, breast cancer, skin disease, and thyroid disease (Dey *et.al.,* 2008; Gharehchopogh & Khalifelu, 2011; Utomo *et.al.,* 2014; Kabari & Bakpo, 2009; Sharpe *et.al.,* 1993).

The thyroid gland is one of the most important organs in the human body. It produces two active hormones that are responsible for controlling metabolism, production of proteins, regulation of body temperature, and overall energy production (Nussey & Whitehead, 2001). Therefore, proper operation of thyroid gland is essential for every organ in the human body. However, thyroid diseases commonly occur and lead to produce too much or too little hormones. Severe case of thyroid disorders may lead to death. Hence, correct and fast diagnosis of thyroid diseases is necessary to provide patients the required cures in early stage of diseases.

To determine therapy for thyroid disease patient, it is very necessary to specify the type of disease. The thyroid diseases are mainly classified into two types: hyperthyroidism and hypothyroidism (Davidson & Haslett, 1999). Moreover, hyperthyroidism cases are subclassified into four types: primary, secondary, subclinical, and T3 thyrotoxicosis. On the other hand, hypothyroidism cases are subclassified into three types: primary, secondary, and subclinical. The classification of thyroid cases is illustrated in **Figure 1**.

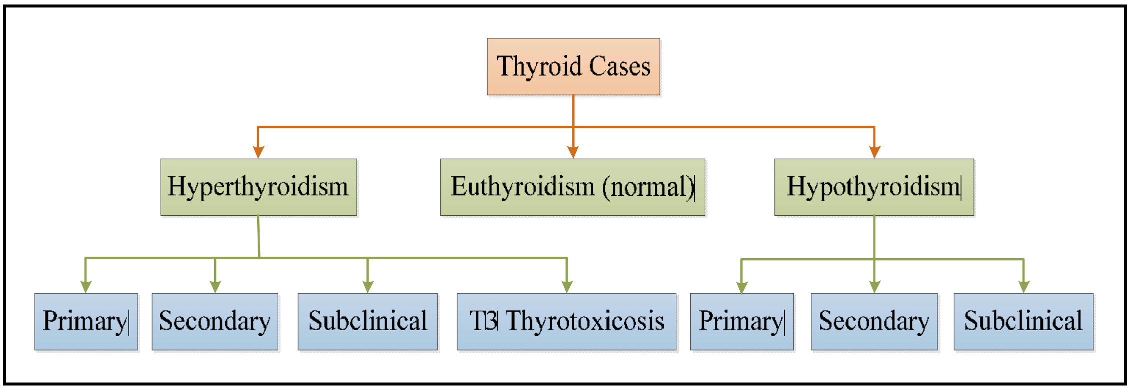


Figure 1: Classification of thyroid cases

Artificial Neural Network (ANN) is a powerful tool to solve classification and pattern recognition problems (Haykin, 2001; Graupe, 2013). Hence, ANN has been used to identify the type of thyroid disease. In recent years, there are many researches that have been focused in this area. Most of them used the data set from University of California, Irvine(UCI) repository of machine learning database (Lichman, 2013). In this data set, thyroid cases are only classified to three main types: euthyroidism (normal case), hyperthyroidism, and hypothyroidism based on five laboratory tests. However, cases are not subclassified to distinct seven types of thyroid disease. (Razia *et.al.* 2015) used UCI data set to compare performance of two ANN types: Multi-Layer Perceptron(MLP) and Radial Basis Function (RBF). Moreover, Temurtas (2009) presented a comparative study of several kinds of ANN using UCI data set. The achieved classification rates in this study are less than 95%. (Haddadnia *et.al.* 2013) proposed the use of Principle Component Analysis (PCA) to extract features from input samples of UCI data set. Then, Probabilistic Neural Network (PNN) is applied to classify thyroid cases. Furthermore,(Aziz ,2011) suggested to utilize ANN and genetic algorithms to design diagnosis system for thyroid diseases using the same data set. A genetic algorithm is exploited to find optimum number of neurons in hidden layer of ANN. On the other hand, several researchers used different data sets of thyroid diseases to create ANN diagnostic systems. Rouhani and (Mansouri,2009) performed thyroid diseases diagnosis using several ANN architectures, namely: RBF, PNN, Generalized Regression neural network (GRNN), Learning Vector Quantization Network (LVQ), and Support vector machines (SVM). They compared performance of these architectures via utilizing data set that has 221 cases. These cases are classified to normal, hyperthyroidism, hypothyroidism, subclinical hypothyroidism, and subclinical hyperthyroidism. Nevertheless, they used large number of input parameters. This will increase ANN complexity and enlarge response time. (Isa *et.al.*, 2010) provided in-depth comparison of using various activation functions of MLP architecture of ANN for thyroid disease classification. The best obtained classification rate in this study is only 94%.

In this work, automatic diagnostic system of thyroid diseases is designed based on neural network techniques. In addition to euthyroidism (normal case), all seven types of thyroid diseases are considered in the proposed system. The thyroid disease samples of real patients in Kerbala city are used in this work. These samples are applied as inputs to proposed ANN system to train and test it. The resulting ANN system is able to detect the abnormal state of thyroid gland and recognize type of the disease with high classification rate (99.2%). The system will help the medical staff to rapidly do essential treatments to patients and provide them suitable medicines.

The rest of this paper is organized as follows. In section two, a review of the structure and training process of the used kind of ANN is stated. The back propagation algorithm is utilized to train neural network. In section three, the data set which is used to achieve this work, is explained in details. While in section four, the problem of determining type of thyroid status is modeled to be solved by ANN. In section five, the proposed ANN system is simulated by Neural Network Toolbox in MATLAB environment. The performance of ANN is evaluated via calculating the classification rate. In addition, graphical user interface is programmed to facilitate dealing with the system by general users. Finally, in section six, the conclusion and main points of this work are stated.

2. Overview of Artificial Neural Network

Artificial neural network (ANN) is a well-known artificial intelligent technique for solving problems that are difficult to be solved by human beings or conventional computational algorithms (Graupe, 2013). ANN can learn and adjust itself to solve different nonlinear problems via modifying certain weights during training process with offline data. There are many existing architectures of ANN. In general, fundamental architectures of ANN are: single layer feedforward, multilayer feedforward, and recurrent (Haykin, 2001). In this work, a multilayer feedforward ANN is exploited to recognize the type of thyroid cases.

The structure and operation of ANN mimic the biological nervous system of human beings. A multilayer ANN has input layer, output layer, and one or more finite number of hidden layers. Each layer consists of individual elements called neurons or nodes. The number of neurons in each layer is chosen to be sufficient to solve a particular problem. Except the neurons of output layer, each neuron of a certain layer in feedforward network is connected to all neurons of a next layer by synaptic weights (Fine, 1999; Ham & Kostanic, 2001). The synaptic weights are initialized with random values. During training process, synaptic weights are modified via learning algorithm to make inputs produce the desired output. The structure of multilayer feedforward neural network is shown in **Figure 2**.

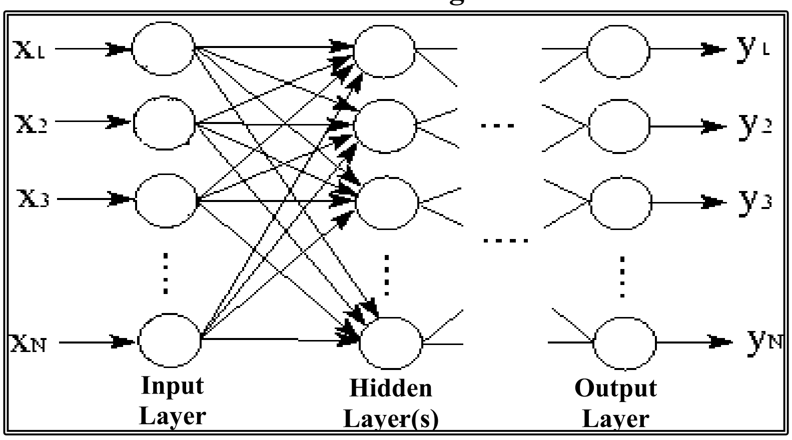


Figure 2: Structure of multilayer feedforward neural network (Fine, 1999)

In this work, back propagation is used as a learning algorithm to train ANN. At first, synaptic weights are initialized with random values. Then at each iteration of back propagation algorithm, one input sample is applied to ANN to produce the actual output. After that, the error is computed between the actual output and desired output. Depending on this error, the synaptic weights are updated as **Equation (1)** to minimize error.

$$W_{i+1} = W_i + \Delta W \tag{1}$$

Where W_{i+1} is updated value of the synaptic weights, W_i is current value of the synaptic weights, and ΔW is the updated change of weights, which is determined as **Equation (2)**.

$$\Delta W = \eta \frac{\partial E}{\partial W} \tag{2}$$

Where η is the learning rate parameter, and $\frac{\partial E}{\partial W}$ is the derivative of error with respect to value of the synaptic weights.

These processes are continued until the error reaches a very small value (approximately zero). At this time, the algorithm converges, and the training process is stopped (Fausett, 1994). The flowchart of back propagation algorithm is shown in **Figure 3**. After that, a test process is commenced to evaluate the performance of trained ANN via applying test samples that are not used in the training process. In this work, the ANN performance is computed by calculating the classification rate as **Equation (3)**.

$$Classification\ rate = \frac{Number\ of\ test\ samples\ that\ are\ correctly\ calssified\ by\ ANN}{Total\ number\ of\ test\ samples} \times 100 \tag{3}$$

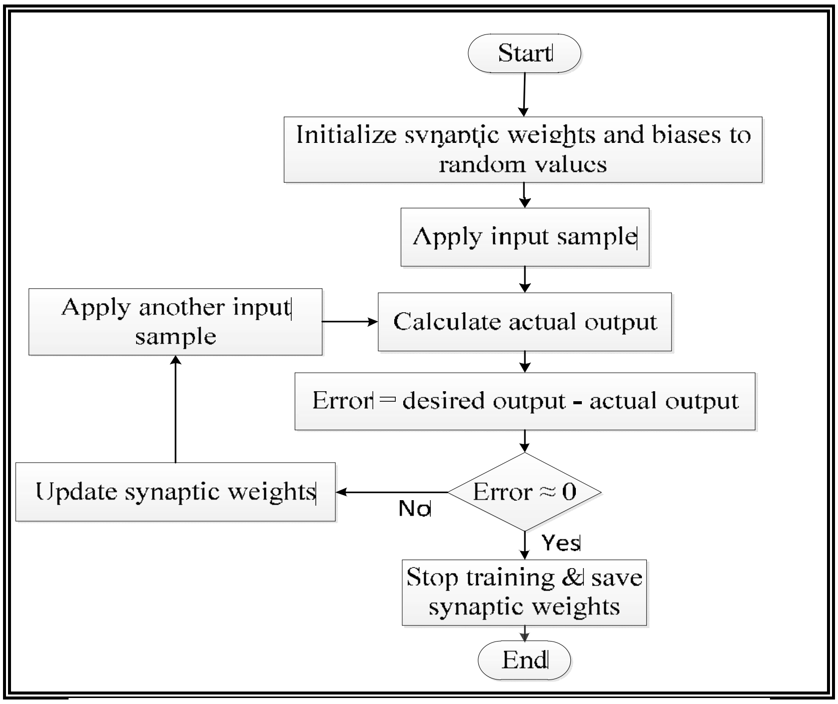


Figure 3: Flowchart of back propagation algorithm

3. Data Set

In order to design ANN system for thyroid diagnosis, we should have suitable data set that includes sufficient samples for each thyroid case. Therefore, we collected 655 samples of real patients from certified advanced hormones laboratory in Kerbala city. Each sample has three continuous values which are the result of laboratory blood tests that are done by modern device (miniVIDAS (Anon., n.d.)). These values represent:

1- Thyroid Stimulating Hormone (TSH).
2- Total serum thyroxin (T4)
3- Total serum triiodothyronine (T3)

Thus, each sample can be considered a vector of three entries. Furthermore, each sample is categorized into one of the eight thyroid cases. **Table 1** lists one sample example for each case. Moreover, numbers of samples for each thyroid case in the data set are demonstrated in **Table 2**. These samples are applied as input to ANN to train and test it. Most of samples (80%) are used to train ANN, and rest of samples (20%) are used to assess the performance of trained ANN.

Table 1: Examples of samples in the collected data set

No.	TSH	T4	T3	Thyroid case
1	3.29	102.35	1.67	Euthyroidism (normal)
2	0.07	142.81	3.11	Primary hyperthyroidism
3	7.05	222	3.9	Secondary hyperthyroidism
4	0.23	111.22	1.55	Subclinical hyperthyroidism
5	0.11	111	4.9	T3 thyrotoxicosis hyperthyroidism
6	29.44	23	0.55	Primary hypothyroidism
7	0.09	22	0.44	Secondary hypothyroidism
8	5.2	82.61	1.49	Subclinical hypothyroidism

Table 2: Number of samples for each thyroid case

No.	Thyroid case	Number of samples
1	Euthyroidism (normal)	328
2	Primary hyperthyroidism	44
3	Secondary hyperthyroidism	44
4	Subclinical hyperthyroidism	46
5	T3 thyrotoxicosis hyperthyroidism	40
6	Primary hypothyroidism	48
7	Secondary hypothyroidism	40
8	Subclinical hypothyroidism	65
	Total	**655**

4. ANN Design

In this work, a multilayer feedforward ANN is adopted to do the classification problem of thyroid cases because it is the most popular structure of ANN that is used for classification and pattern recognition problem (Pandya & Macy, 1995). In the data set, each sample is a vector of three entries (values of TSH, T4, and T3). Therefore, the designed ANN should have three neurons in the input layer. In contrast, the designed ANN should classify input samples into eight categories of thyroid cases. Thus, in the output layer, ANN should have eight neurons which are corresponding to these categories. As a result, inputs of ANN system are values of TSH, T4, and T3 for a certain sample, and output is the type of thyroid case for input sample as shown in **Figure 4**.

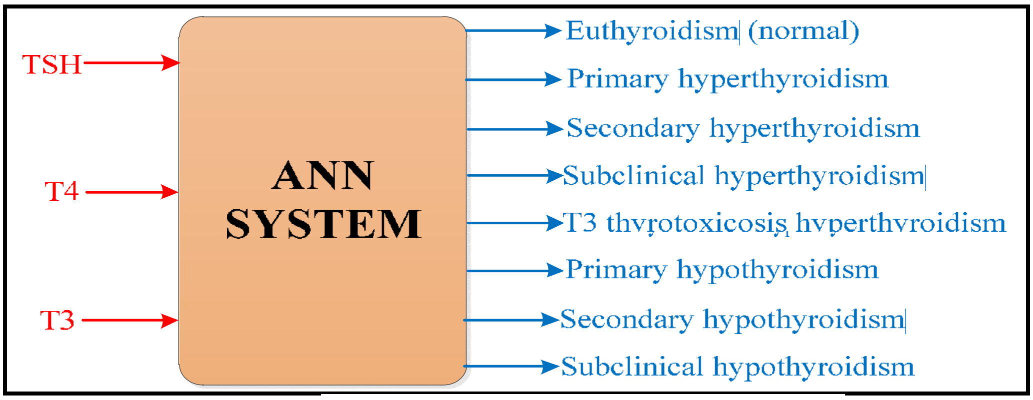


Figure 4: The ANN system for thyroid diagnosis

Number of hidden layers and number of neurons in each hidden layer are chosen based on trial and error technique. Moreover, number of hidden layers and number of neurons in each hidden layer should be as fewest as possible to reduce the complexity of ANN and response time. In this work, we consider a large number of networks with various combinations of hidden layers and different number of neurons in each hidden layer to search for the most suitable size network with best classification performance.

ANN is trained by back propagation algorithm. After training process, if inputs of a particular sample are applied to ANN, only one neuron of output layer will be active (its value is approximately one). In contrast, the values of the other seven will be roughly zero. The active neuron represents the category of thyroid case for input sample.

5. Simulation and Results

To evaluate performance of the proposed ANN system, we simulate it via using Neural Network Toolbox (NNT) in MATLAB environment (Beale, et al., 2015). First, we create ANN with one hidden layer. The tangent sigmoid is chosen as an activation function for hidden layer, while softmax is used for output layer. Then, we apply input samples in the data set and their target type of thyroid cases to train ANN with various number of neurons in the hidden layer. However, the efficiency of ANN depends on the initial value of synaptic weights. Furthermore, synaptic weights are initialized with random values. Therefore, we will obtain different result every time that ANN is trained. To solve this problem, we train ANN 10000 times. After that, we record the maximum, minimum, and average classification rates among 10000 trained ANNs with different number of neurons in the hidden layer as stated in **Table 3**.

Table 3: Classification rate of trained ANNs

Number of neurons in the hidden layer	Maximum classification rate %	Minimum classification rate %	Average classification rate %
1	74.81	50.38	64.29
2	96.95	50.38	85.01
3	98.47	58.02	91.82
4	98.47	58.78	94.17
5	99.24	62.60	95.08
6	99.24	70.99	95.54
7	99.24	78.63	95.81
8	99.24	80.15	96.04
9	99.24	83.97	96.17
10	99.24	85.50	96.26

It appears from **Table 3** that the classification rate increases as number of neurons in the hidden layer increases as illustrated in **Figure 5**. This means that classification rate and number of neurons in the hidden layer are directly proportional. Nevertheless, the maximum classification rate stops increasing when the number of neurons is more than 5. In other words, the maximum classification rate reaches saturated value when the number of neurons is 5.

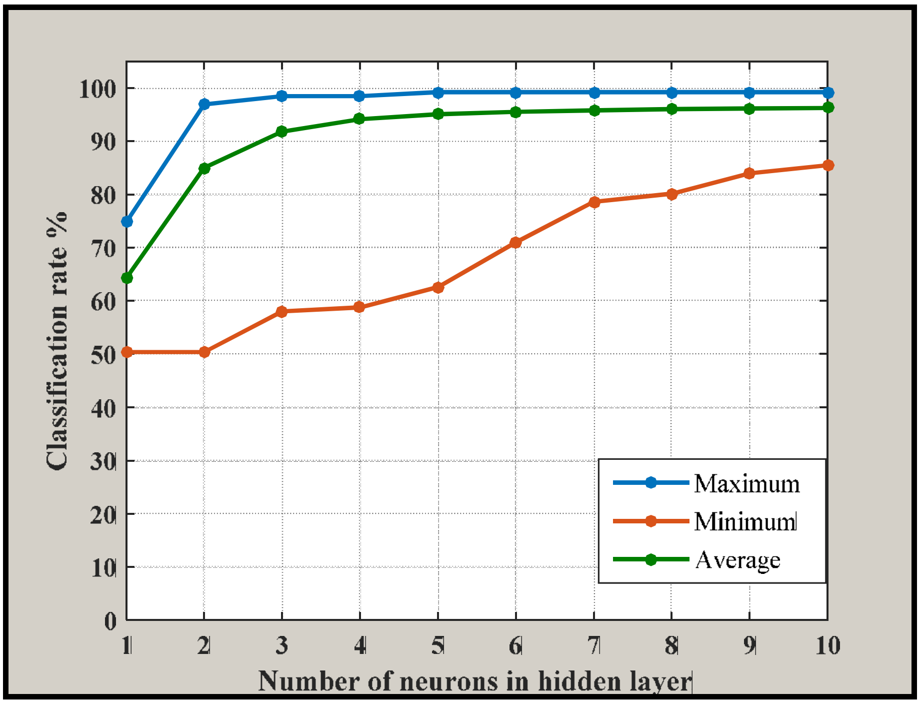
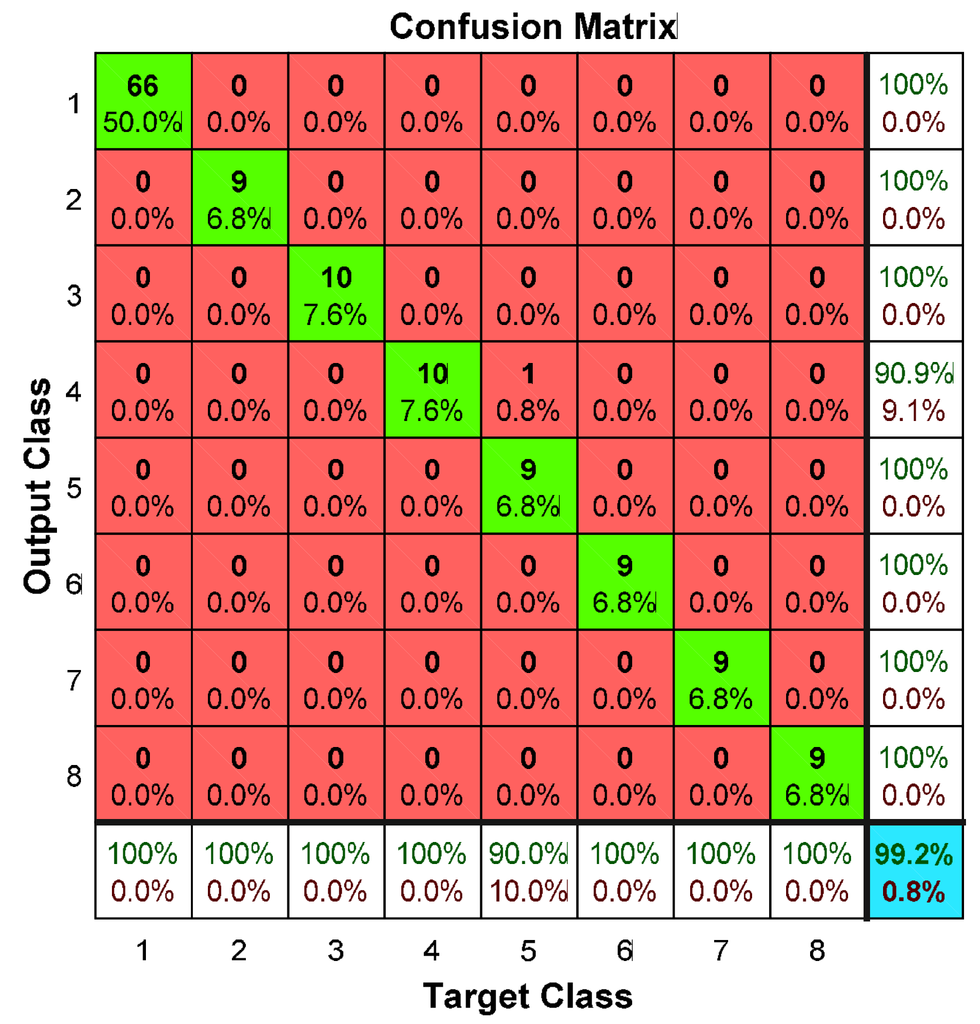


Figure 5: Classification rate of trained ANNs

Number of neurons in the hidden layer should be as smallest as possible to reduce the complexity of ANN which leads to decrease the response time of ANN. As a result, the lowest number of neurons that provides the highest maximum classification rate is selected in the proposed system. In this case, 5 neurons are chosen to be in the hidden layer. Hence, architecture of the designed ANN will be 3-5-8. Among 10000 trained ANNs, the one that provides the maximum classification rate is chosen in the final system for thyroid diagnosis.

To clarify the performance of final selected ANN, the confusion matrix is illustrated in **Figure 6** to show the classification rate of the network by using 131 test samples (20% of total samples in the data set) which are not used in the training process. The green diagonal cells of the matrix demonstrate the number of samples that are correctly classified by ANN and their percentages. On the other hand, the red off-diagonal cells show the number of samples that are misclassified by ANN. The white cells of last row demonstrate the percentage of correct classified samples and percentage of misclassified samples in each target case type, while the white cells of last column demonstrate the corresponding percentages in each actual output case type of ANN. The blue cell indicates the total percentages of correct classified samples and misclassified samples. It can be shown that classification rate of designed ANN is 99.2% which is considered very high as compared to results of previous works (Gharehchopogh *et.al.,* 2013; Temurtas, 2009; Aziz, 2011; Isa *et.al.,* 2010; Shukla *et.al.,* 2009). Only one of the 131 test samples is misclassified. This implies that ANN is almost successfully able to classify samples into eight thyroid cases.



1	Euthyroidism (normal)	**5**	T3 thyrotoxicosis hyperthyroidism
2	Primary hyperthyroidism	**6**	Primary hypothyroidism
3	Secondary hyperthyroidism	**7**	Secondary hypothyroidism
4	Subclinical hyperthyroidism	**8**	Subclinical hypothyroidism

Figure 6: Confusion matrix of the designed ANN

To simplify dealing with the designed ANN system by general users, a graphical user interface (GUI) is made. After laboratory blood tests for TSH, T4, and T3 are done for a specific patient, resulting values of the tests are easily entered into corresponding fields of GUI by a user. Then, the user presses OK bottom to see type of thyroid case for the patient. This will assist the medical staff to detect thyroid disease and distinguish its type without need for a specialist doctor in thyroid disease. As a result, the medical staff can quickly do necessary treatments to the patient, and prevent dangerous side effects of thyroid disease. **Figure 7** shows examples of using GUI for three different real patients.

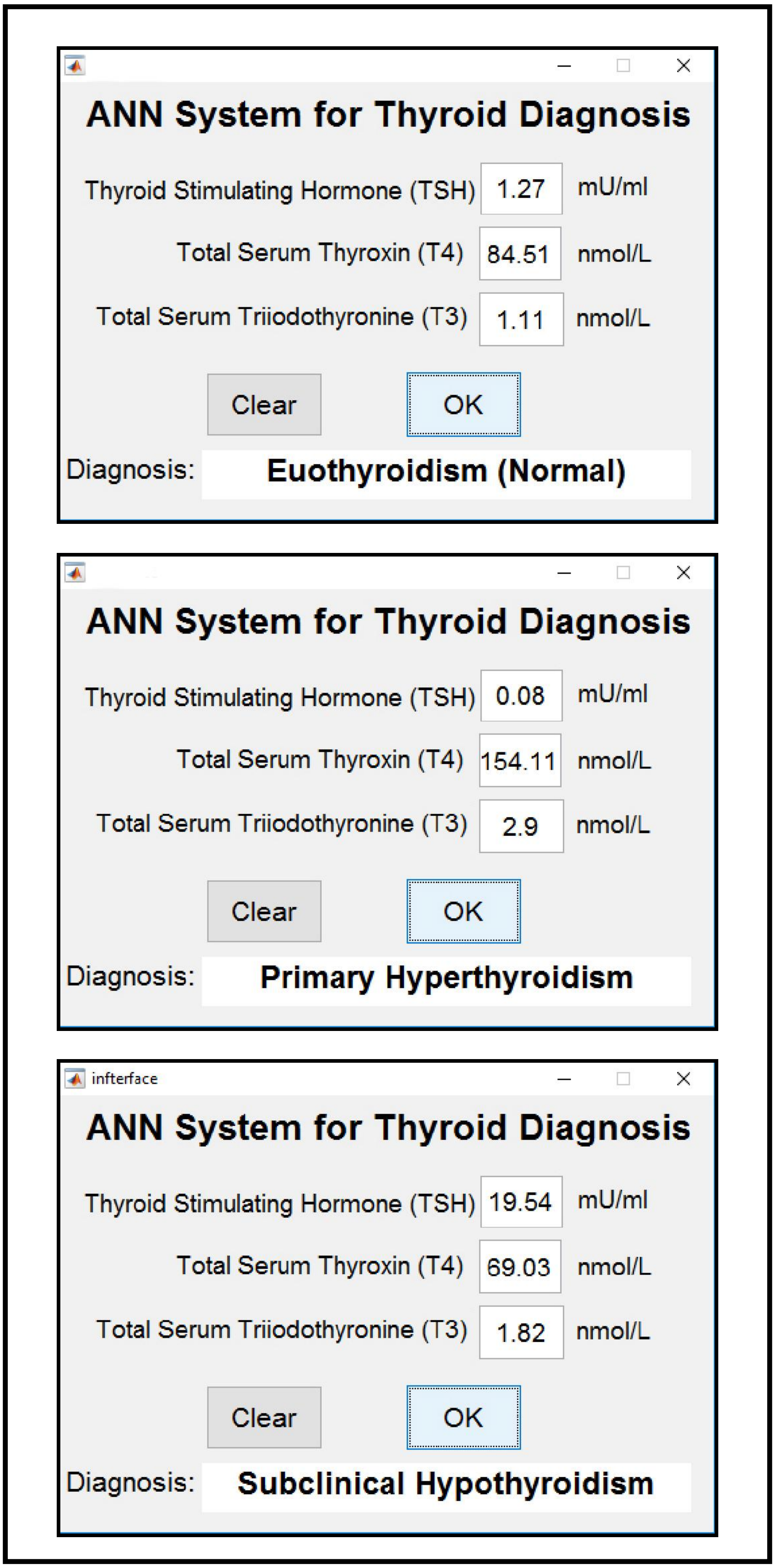


Figure 7: Examples of using GUI for the ANN system

6. Conclusion

In this work, diagnosis of thyroid disease is modeled by neural network techniques. A multilayer feedforward is selected as ANN architecture, and back propagation is used as training algorithm. The results of this work show that classification rate of ANN and number of neurons in the hidden layer are directly proportional. After extensive search for best network, the one with only one hidden layer that has 5 neurons is chosen to perform thyroid diagnosis system. The selected ANN has high classification rate which is about 99.2%. As a result, the proposed structure of ANN can effectively categorize the type of thyroid cases.

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