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The Diagnosis of Iron-Deficiency Anemia using Feedforward Backpropagation Neural Network

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Abstract

Iron-deficiency anemia results from insufficient dietary intake and absorption of iron or iron loss from bleeding. The cause of chronic blood loss may be related with the patient's gender, age, and history. Iron-deficiency anemia is the most common anemia disease in the world. The diagnosis of iron-deficiency anemia requires blood tests and physicians' decision. This decision process can be estimated using neural networks by referencing previously taken sample object data. In this paper, at first 1441 iron-deficiency anemia samples trained using feed-forward neural network. A gradient descent with momentum back-propagation used as train technique. After this stage, implemented network tested with another 359 samples within 1800 samples. Experiments demonstrate that an approximately 99.53% success rate is reached, and the relative false detection rate is very low.

Keywords: *Feedforward Backpropagation Neural Network, The Diagnosis Of Iron-Deficiency Anemia*

1. Introduction

Iron-deficiency anemia is the most common anemia disease in the world. It is caused by insufficient dietary intake and absorption of iron or iron loss from bleeding (Brady, 2012). A moderate degree of iron-deficiency anemia affects about 610 million people. This rate is 8.8% of world population. Iron-deficiency anemia is more common in female (9.9%) than males (7.8%). A mild of iron-deficiency anemia affects another 375 million people. This rate is about 5.41% (Vos, 2012).

Table 1. The lowest hemoglobin concentration rate by age (Blanc, 1968)

Description	Value
Children aged 6 months to 6 years	11
Children aged 6-14 years	12
Adult males	13
Adult females, nonpregnant	12
Adult females, pregnant	11

According to World Health Organization the diagnosis of iron-deficiency anemia disease requires subject's hemoglobin concentration and hematocrit rate. Hemoglobin concentration should not be below specific range depending on gender. Also hematocrit rate should not be below specific range depending on hemoglobin concentration. Hematocrit rate is 39% for women, 36% for men. Hemoglobin concentration limit is 13%, 12% for men and women respectively. If blood test results are lower than specific range, it is sign of iron-deficiency anemia (Blanc, 1968).

Table 2. The lowest hemoglobin concentration rate by gender as assessed by various sources

Source	Women (g/dL)	Men (g/dL)
(Blanc, 1968)	12	13
(Rapaport, 1987)	12	14
(Tietz, 1995)	11.7	13.2
(Jandl, 1996)	12.2	14.2
(Goyette, 1997)	11.7	13.2
(Lee, 1998)	11.6	13.2
(Beutler, 2001)	12.3	14.0
(Hoffman, 2004)	12.0	13.5

In diagnosis of iron-deficiency anemia, a physician analyzes subject's complete blood test. In the implemented network model was automated for the detection of iron-deficiency anemia disease by using feedforward backpropagation neural network.

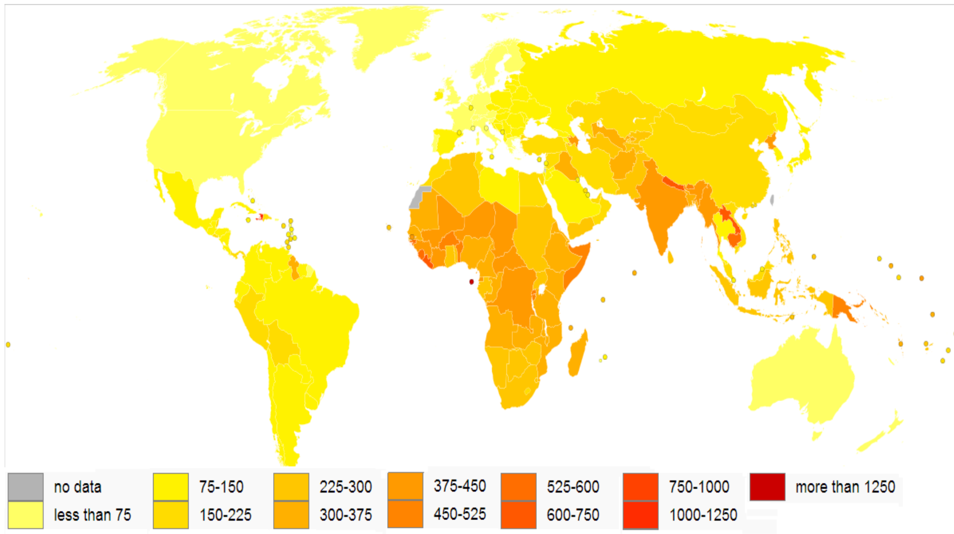

Figure 2. Age-standardised disability-adjusted life year rates from iron-deficiency anemia by country (per 100,000 inhabitants) (Mathers, 2003).

Different classification problems can be handled effectively by soft computing techniques. Some statistical techniques are neural networks, fuzzy logic, support vector machine, k-means classification, genetic algorithms and some others, which will lead to an intelligent, high-speed and low cost solution than traditional techniques. Artificial Neural Network (ANN) is one of the most used statistical method for pattern recognition. The applications of neural networks are almost limitless. They can be classified into six main categories like a taxonomy of digital signal processing (DSP), linear transformations, pattern classification, detection, time series modeling, system identification (Hu, 2002). Feedforward networks are the most well-known and widely-used class of neural network. The most common learning algorithm is called backpropagation (BP) for feedforward neural networks. Some examples of the application of neural networks are diagnosing cancer disease (Ganesan, 2010), pattern recognition (Ebrahimzadeh, 2010; Ou, 2007), printed character optical recognition (Namane, 2014), performance prediction of a solar thermal energy system (Yaïci, 2014) and others. Many researchers have compared artificial neural netwoks (ANNs) and other statistical models. The comparison of statistical methods is shown that neural networks are able to make a better generalization over the traditional statistical methods. (Chen, 2012; Nedic, 2014; Kiang, 2003).

In this study, subject's disease condition was decided by using RBC, HGB, HCT, MCV, MCH, MCHC values of subjects' complete blood test on Octave. 359 subjects' data were used for test within 1800 iron-deficiency anemia samples. Experiments demonstrate that an approximately 99.53% success rate is reached.

Table 3. Complete blood test elements' full name and ranges (Yılmaz, 2012)

Description	Values Min – Max
Red Blood Cell (RBC)	4.5 - 6
Hemoglobin (HGB)	12 – 16
Hematocrit (HCT)	36 – 48
Mean Corpuscular Volume (MCV)	80 – 100
Mean Corpuscular Hemoglobin (MCH)	27 - 34
Mean Corpuscular Hemoglobin Concentration (MCHC)	31 - 37

2. Materials and Methods

2.1. Dataset

In this study, 1441 subjects' data were used for neural network training from 1800 iron-deficiency anemia samples. After this stage, 359 subjects' data were used for test.

2.2. Artificial Neural Networks (ANN)

Artificial neural networks are computational models inspired by the human's central nervous systems which are generally presented as systems of interconnected "neurons" (Zupan, 2003). A neural network is a system of programs and data structures that approximates the operation of the human brain which can be performed with hardware and software (Öztemel, 2003).

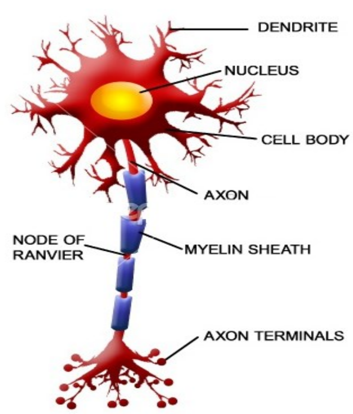

Figure 3. A structure of neural cell (Khalid, 2013)

ANN learning methods can be classified into three major types supervised, unsupervised and reinforcement learning (Sathya, 2013).

In supervised learning model, each sample is a pair consisting of an input object (vector) and a target output value (also known as the supervisory signal). In unsupervised learning model, each sample hasn't any target output value. It identifies the pattern class information heuristically. Reinforcement learning model is inspired by behaviorist psychology. Reinforcement model networks learn through test and error interactions with its environment.

Patient code	MEDICAL DATA					DIAGNOSIS
1	$data_{1,1}$	…	$data_{1,i}$	…	$data_{1,m}$	POSITIVE
2	$data_{2,1}$	…	$data_{2,i}$	…	$data_{2,m}$	POSITIVE
3	$data_{3,1}$	…	$data_{3,i}$	…	$data_{3,m}$	POSITIVE
…	…	…	…	…	…	…
k	$data_{k,1}$	…	$data_{k,i}$	…	$data_{k,m}$	NEGATIVE
k+1	$data_{k+1,1}$	…	$data_{k+1,i}$	…	$data_{k+1,m}$	NEGATIVE
…	…	…	…	…	…	…
n	$data_{n,1}$	…	$data_{n,i}$	…	$data_{n,m}$	NEGATIVE

Figure 4. Example of training dataset structure. Each row in table represents a set of subject's data with a numerical code. Each column in table represents sets of blood test elements (Amato, 2013).

Principles of training multilayer neural network include following eight steps:

- Sample collection
- The neural network's topology design
- The neural network's learning parameters assign
- The neural network's initial weights assign
- Select the samples from the learning dataset and train neural network
- Forward calculation during training
- Comparison target to expected value
- The neural network's weights update

2.3. Feedforward Neural Networks (FNN)

A feedforward neural network is an artificial neural network where the topology graph does not contain any directed cycles. It is different from recurrent neural networks. The feedforward neural network is the first and simplest type of artificial neural network designed. In this type of network, the information moves forward direction, from the input layer, through the hidden layer and to the output layer. There are no cycles or loops between layers in the network.

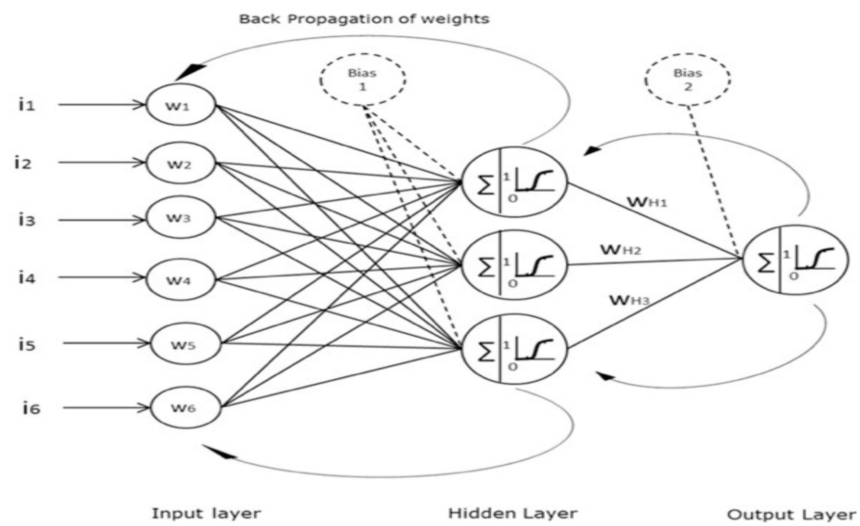

Figure 5. A model of multilayer feedforward backpropagation neural network (Kafetzopoulou, 2013)

Feedforward neural network is one of the multilayer neural network. Feedforward neural networks includes following two steps for calculation:

- Forward calculation
- Backward calculation

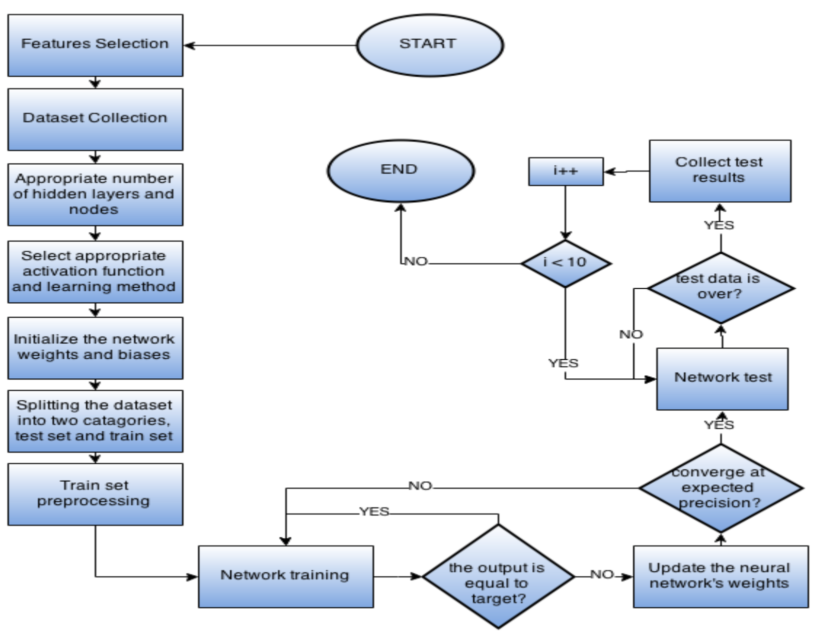

Figure 6. Diagram of implemented network for detection of anemia

The designed neural network model includes six neurons in input layer, 13 neurons in hidden layer, one neuron in output layer. The network's activation function is sigmoid activation function. The network's learning function is the gradient descent with momentum weight and bias learning function. The network was trained with 6000 iterations. The network's normalization function is min-max normalization function. Learning rate was chosen 0.4 and momentum constant was chosen 0.8. Min-max normalization function is calculated by formula 1. This formula is applied each of input data.

$$y = \frac{(y\max - y\min) * (x - x\min)}{(x\max - x\min)} + y\min \tag{1}$$

3. Discussion and Experimental Results

In this study, 14 number neurons of hidden layer was produced the lowest testing accuracy (98.33), sensitivity (98.02) and specificity (98.45).

Finally the best network model obtained consists of six input neurons, one hidden layer with 13 hidden neurons and one output unit in Octave neural network tools which were used for the diagnosis of iron-deficiency anemia (Eaton, 2008; Schmid, 2009). In Octave neural network tools, 1441 subjects' data were used for feedforward backpropagation neural network training from 1800 subjects' data. 359 subjects' data were tested successfully by the trained neural network. In test, 103 subjects were detected as iron deficiency anemia patient and 256 subjects were detected as non-patient. ROC analyze was used for neural network's performance analyze. ROC parameters' explanations are shown in Table 4.

Table 4. The ROC parameters

Abbreviation	Definition
TP: True Positive	The number of positive test results in subjects known to have iron-deficiency anemia
TN: True Negative	The number of negative test results in subjects known to healthy
FP: False Positive	The number of positive test results in subjects known to healthy
FN: False Negative	The number of negative test results in subjects known to have iron-deficiency anemia

As a best result of test processes of feedforward backpropagation neural network, 103 TP, 256 TN, 0 FP, 0 FN with 100% sensitivity and 100% accuracy was achieved in first test. Detailed test results are shown in Table 5 and graphical test results are shown in Figure 7.

Table 5. Detailed test results

Test Number	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
1	103	256	0	0	100%	100%	100%
2	102	256	0	1	99.72%	99.03%	100%
3	100	256	0	3	99.16%	97.09%	100%
4	103	255	1	0	99.72%	100%	99.61%
5	102	255	1	1	99.44%	99.03%	99.61%
6	102	254	2	1	99.16%	99.03%	99.22%
7	101	256	0	2	99.44%	98.06%	100%
8	102	255	1	1	99.44%	99.03%	99.61%
9	101	256	0	2	99.44%	98.06%	100%
10	103	255	1	0	99.72%	100%	99.61%

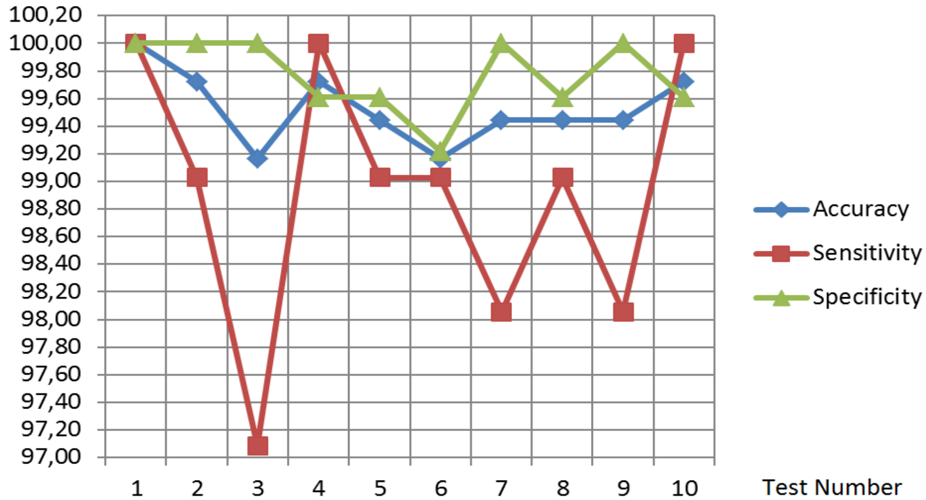

Figure 7. Graphical analysis of test results

Sensitivity, accuracy and specificity are calculated by formula 2, formula 3 and formula 4. Average test results are shown in Table 6. Experiments demonstrate that an approximately 99.53% accuracy rate, 98.93 % sensitivity rate and 99.77% specificity rate are reached.

Table 6. Average test result

TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
101.9	255.4	0.6	1.1	99.53%	98.93%	99.77%

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (3)$$

$$Specificity = \frac{(TN)}{(FP + TN)} \quad (4)$$

4. Conclusions and Future Works

In this paper, feedforward backpropagation neural network was trained by 1441 iron-deficiency subjects' data. After training, the network was tested with 359 subjects' data. The network was trained by using gradient descent with momentum backpropagation method. As the rounded average result of neural network test, 101 TP, 255 TN, 0 FP, 1 FN with 99.53% accuracy, 98.93% sensitivity and 99.77% was achieved. The experimental results proved that feedforward neural network technique provides convincing results for classification.

In future work, different classifier algorithms can use for the detection of iron-deficiency anemia and can compare these current classifier, feedforward backpropagation and statistical classification methods like support vector machine (SVM), regression trees, naive Bayes classifier, k-means clustering.

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