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# An application of multilayer neural network on hepatitis disease diagnosis using approximations of sigmoid activation function

## *Sigmoid aktivasyon fonksiyonu kestirimi kullanılarak karaciğer hastalığı tanısında çok katmanlı sinir ağı uygulaması*

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**ABSTRACT**

**Objective:** Implementation of multilayer neural network (MLNN) with sigmoid activation function for the diagnosis of hepatitis disease.

**Methods:** Artificial neural networks (ANNs) are efficient tools currently in common use for medical diagnosis. In hardware based architectures activation functions play an important role in ANN behavior. Sigmoid function is the most frequently used activation function because of its smooth response. Thus, sigmoid function and its close approximations were implemented as activation function. The dataset is taken from the UCI machine learning database.

**Results:** For the diagnosis of hepatitis disease, MLNN structure was implemented and Levenberg Morquardt (LM) algorithm was used for learning. Our method of classifying hepatitis disease produced an accuracy of 91.9% to 93.8% via 10 fold cross validation.

**Conclusion:** When compared to previous work that diagnosed hepatitis disease using artificial neural networks and the identical data set, our results are promising in order to reduce the size and cost of neural network based hardware. Thus, hardware based diagnosis systems can be developed effectively by using approximations of sigmoid function.

**Key words:** Hepatitis disease diagnosis, multilayer neural network, 10-fold cross validation, approximations of sigmoid activation function

**ÖZET**

**Amaç:** Hepatit hastalığının teşhisi için çok katmanlı sinir ağı (MLNN) ve sigmoid aktivasyon fonksiyonu uygulanmıştır.

**Yöntemler:** Yapay sinir ağları (YSA) tıbbi tanı için halen yaygın olarak kullanılan etkili araçlardır. Donanım tabanlı mimarilerde aktivasyon fonksiyonları YSA davranışında önemli rol oynamaktadır. Sigmoid fonksiyonu yumuşak tepkisi nedeniyle en sık kullanılan aktivasyon fonksiyonudur. Bu nedenle, sigmoid fonksiyonu ve yaklaşımları aktivasyon fonksiyonu olarak uygulanmıştır. Veri kümesi UCI makine öğrenme veri tabanından alınmıştır.

**Bulgular:** Hepatit hastalığının tanısı için, MLNN yapısı hayata geçirilmiş ve Levenberg Morquardt (LM) algoritması öğrenme için kullanılmıştır. Hepatit hastalığını sınıflandıran yöntemimiz 10-kat çapraz doğrulama yoluyla 91.9%'den 93.8%'e doğruluklar sağlamıştır.

**Sonuç:** Yapay sinir ağları ve aynı veri setini kullanarak hepatit hastalığını teşhis eden önceki çalışma ile karşılaştırıldığında, bizim sonuçlarımız sinir ağı tabanlı donanımın boyutunu ve maliyetini azaltması bakımından umut vericidir. Böylece, donanım tabanlı tanı sistemleri sigmoid fonksiyonu yaklaşımları kullanılarak etkili bir şekilde geliştirilebilir.

**Anahtar kelimeler:** Hepatit hastalığı tanısı, çok katmanlı sinir ağı, 10-kat çapraz doğrulama, sigmoid aktivasyon fonksiyonu yaklaşımları

## INTRODUCTION

Liver is the largest organ which is responsible for carrying out the most important functions within the body [1]. Hepatitis is characterized by soreness of the liver. Bacterial infections, viruses, drugs or toxins can cause Hepatitis Disease [2].

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Medical diagnosis of the diseases is one of the main problems in medicine. Artificial neural networks (ANNs) are efficient tools currently in common use for this purpose [2]. Many techniques for classification of hepatitis disease diagnosis presented in the literature [1-16]. Chen et al. proposed a hybrid system named LFDA-SVM which consists of two integrated methods; a feature extraction method (Local Fisher Discriminant Analysis-LFDA) and a classification algorithm (Supporting Vector Machine-SVM), and an accuracy of 96.8% was obtained [1]. Polat and Gunes used a medical diagnosis method which involves three stages; feature selection program, fuzzy weighted pre-processing and Artificial Immune Recognition System (AIRS) and obtained 94.1% classification accuracy in test phase [3]. Dogantekin et al. proposed a hepatitis disease diagnosis system based on LDA and Adaptive Network based on Fuzzy Inference System (ANFIS). The classification accuracy of LDA-ANFIS system was obtained 94.1% [4]. Calisir and Dogantekin have obtained 95.0% classification accuracy using a method based on Principle Component Analysis (PCA) and Least Square Support Vector Machine (LSSVM) classifier (PCA LSSVM) [5]. Sartakhti et al. used a method (SVM-SA) which hybridizes SVM and Simulated Annealing (SA) techniques and obtained 96.2% classification accuracy [6].

In the techniques above, hybrid systems were proposed which involves feature extraction methods and classification algorithms. The hardware implementations of hybrid systems require large scale multipliers and chip resources. For the disease diagnosis systems, multilayer neural networks (MLNNs) have been the most commonly used tools [17]. Different types of learning algorithms can be used to train MLNN [18,22]. Levenberg Morquardt (LM) algorithm, which regarded as one of the most efficient algorithms, is a second order algorithm and converges much faster than first order algorithms. In this study, we used LM algorithm, uses Hessian matrix in order to perform better estimations and improve convergence, to determine the weights of the connections [22,29].

Our aim here is to diagnose hepatitis disease using MLNN through the sigmoid activation function and its approximations. Activation function plays an important role to determine the outputs. The sigmoid activation function contains the exponential expression ex, so it's difficult to perform for hardware based architectures and requires large chip resources [30]. In this study, the approximations of sigmoid function were used in order to improve the calculation speed of activation function and reduce the size of the hardware. We took the dataset from University of California at Irvine (UCI) machine learning repository [31]. 10 fold cross validation, a widely used performance technique, was used to obtain the classification accuracy [9].

## METHODS

### Hepatitis disease dataset

Hepatitis disease dataset taken from the UCI machine learning repository was used to compare the performance of our classification system with previous studies which used same dataset [31]. This dataset which was donated by Jozef Stefan Institute, Yugoslavia, is commonly used to check the performance of the networks [1,8]. The dataset comprises of two classes including 155 samples: Class 1 - death cases (32) and Class 2 - alive cases (123). 19 attributes were included in all samples, which are shown in Table 1.

**Table 1.** Hepatitis disease dataset

| Number | Attribute | Value/Range |
|---|---|---|
| 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 | A. Phosphatase | 33, 80, 120, 160, 200, 250 |
| 16 | SGOT | 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 |

**Multilayer neural network**

Nowadays, ANNs are efficient applications currently in common use for medical diagnosis [2]. For the diagnosis of hepatitis disease the MLNN was used consisted of an input layer, two hidden layers and an output layer. The structure of MLNN is shown in Figure 1.

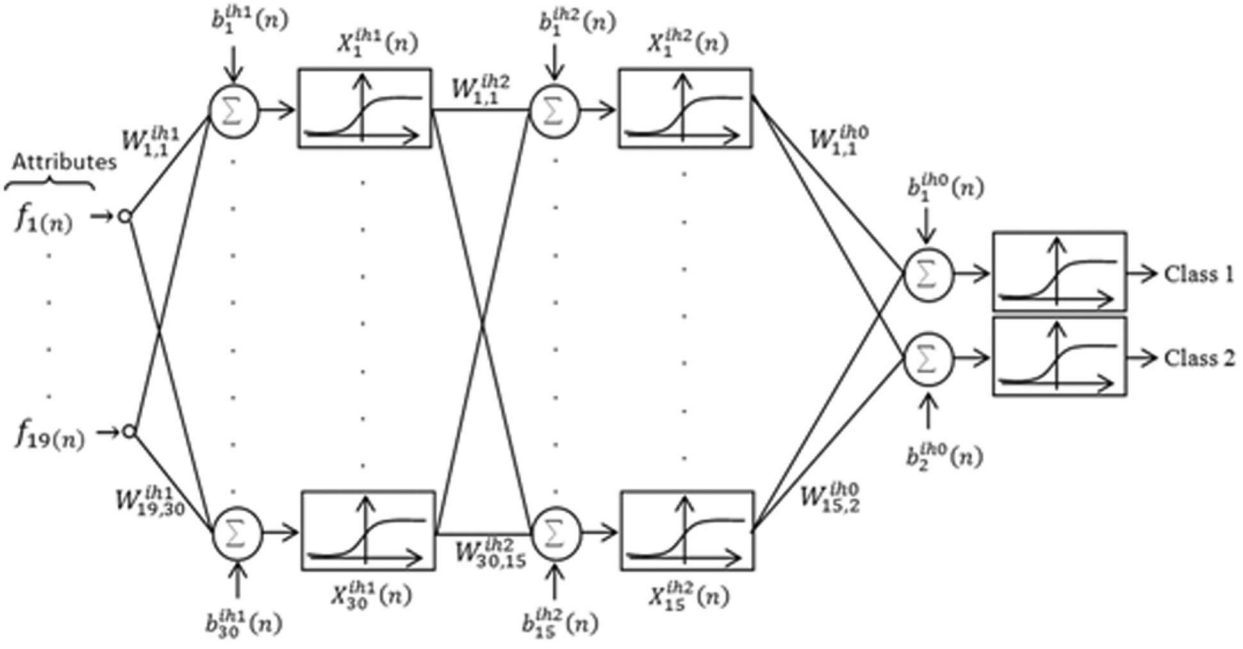


**Figure 1.** Multilayer neural network architecture

The output layer had 2 neurons and the hidden layers had 30 and 15 neurons respectively. All neurons in the MLNN architecture used sigmoid function or its approximations. In this study, we used Levenberg Morquardt (LM) learning algorithm to determine the weights of the connections. The LM algorithm, which is a second order algorithm and an approximation of Newton method, uses Hessian matrix in order to perform better estimations and improve convergence. The sum of the mean squared error is calculated by [29,32]:

$$E(\vec{w}) = \frac{1}{2PN}\sum_{t=1}^{P}\sum_{m=1}^{N}\left(l_{tm}\right)^2 \quad (1)$$

where l is the difference between actual value and desired value, is the mean squared error function, P is the number of training pattern and N is the number of output. The weights are updated by;

$$\vec{w}(k) = \vec{w}(k-1) - (\vec{H}(k) + \lambda\vec{I})^{-1}\vec{g}(k) \quad (2)$$

$$\vec{g}(k) = \frac{\partial E(\vec{w}(k))}{\partial \vec{w}(k)} \quad (3)$$

$$\vec{H}(k) = \frac{\partial^2 E(\vec{w}(k))}{\partial \vec{w}(k)^2} \quad (4)$$

where is the gradient of the mean squared error, is the Hessian, is an unit matrix, k is the iteration number, λ is a scalar value, is the weight vector and is the weight vector in the preceding iteration. The applications of LM learning algorithm for MLNN can be found in [29, 31].

10-fold cross validation was used to obtain the classification accuracy. The dataset is randomly partitioned into k subsets, and the process is repeated k times in k-fold cross validation, which is a commonly used performance method [9]. Every time, for testing the model a single subset is used and for training the remaining k-1 subsets are used.

To produce a single estimation the k results from the folds then can be averaged (or otherwise combined). All data points are used for both training and validation which is the advantage of this method. For classification accuracy, we used the following equations [9,21,33]:

$$classification\ accuracy(N) = \frac{\sum_{i=1}^{|N|} asses(n_i)}{|N|}, n_i \in N \quad (5)$$

$$asses(n) = \begin{cases} 1, & if\ classify(n) = nc \\ 0, & otherwise \end{cases} \quad (6)$$

where N is the set of data items to be classified (the test set), n ϵ N, nc is the class of the item n, and classify (n) returns the classification of n by neural networks.

## Sigmoid activation function

Neural networks require the use of an activation function at the output of each neuron [34].

The most frequently used activation function, the sigmoid function, can be formulized by:

$$y = \frac{1}{1+e^{-x}} \quad (7)$$

where *x* defines the number of artificial neurons in the network and *y* represents the artificial neuron output. The sigmoid function is shown in Figure 2.

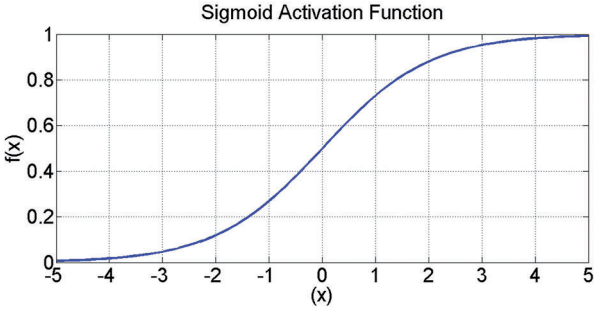


**Figure 2.** Sigmoid activation function

Sigmoid activation function is difficult to perform for digital implementation because it consists of an infinite exponential series but there are different ways to implement sigmoid function or its close approximations.

## Dataflow implementation of sigmoid function

The sigmoid activation function contains the exponential expression ex, which is difficult to calculate. For this reason, dataflow approximation can be used instead of sigmoid function. This function is a simple polynomial that does not involve any transcendentals, and can be formulized by [35]:

$$y = \frac{1}{2}\left(\frac{x}{1+|x|}+1\right) \quad (8)$$

The sigmoid function and dataflow approximation are shown in Figure 3.

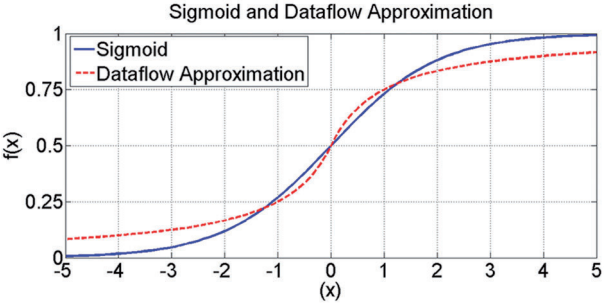


**Figure 3.** Sigmoid function and dataflow approximation

## Piecewise linear approximation

Various approximations of the sigmoid activation function for MLNNs are discussed in the literature [36]. The piecewise linear approximation, proposed here and plotted in.

The piecewise linear technique, which gives a close approximation to the sigmoid function, is presented in Table 2. Detailed computational issues about the piecewise linear approximation of sigmoid function can be found in [37,38]. Figure 4.

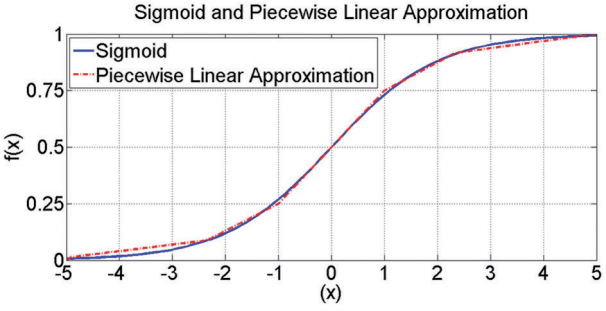


**Figure 4.** Sigmoid function and piecewise linear approximation

### Taylor series expansion

A Taylor series is a way of approximating an analytic function around a single point using only the derivatives of the function at that point. It is a suitable method which used for approximating functions. The sigmoid function has also been generated by Taylor series expansion. This implementation used 3 intervals to generate sigmoid function and formulized by [39]:

$$y = \begin{cases} 0.571859 + (0.392773)x + (0.108706)x^2 + \\ (0.014222)x^3 + (0.000734)x^4 & -\infty < x \le -1.5 \\ \frac{1}{2} + \frac{1}{4}x - \frac{1}{48}x^3 + \frac{1}{480}x^5 & -1.5 < x < 1.5 \\ 0.428141 + (0.392773)x - (0.108706)x^2 + \\ (0.014222)x^3 - (0.000734)x^4 & 1.5 \le x < \infty \end{cases} \quad (9)$$

Taylor series expansion gives the closest approximation to the sigmoid function and provides much higher accuracy than previous approximations. The approximated function is shown in Figure 5.

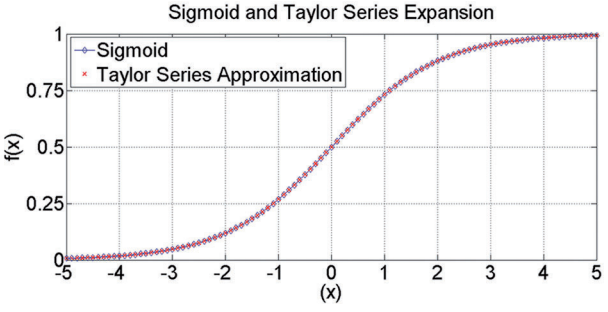


**Figure 5.** Sigmoid function and Taylor series approximation

**Table 2.** Equations of piecewise linear approximation

| Operation | Condition |
|---|---|
| Y = 1 | \|X\| ≥ 5 |
| Y = 0.03125 · \|X\| + 0.84375 | 2.375 ≤ \|X\| < 5 |
| Y = 0.125 · \|X\| + 0.625 | 1 ≤ \|X\| < 2.375 |
| Y = 0.25 · \|X\| + 0.5 | 0 ≤ \|X\| < 1 |
| Y = 1 - Y | \|X\| < 0 |

**Table 3.** Classification accuracies for activation functions

| Activation function | Classification accuracy (%) |
|---|---|
| Sigmoid function | 93.7 |
| Dataflow implementation | 91.8 |
| Piecewise linear approximation | 92.5 |
| Taylor series expansion | 93.1 |

## RESULTS

In this paper a number of approaches of sigmoid function for hepatitis disease diagnosis were presented. For this purpose, MLNN structure was implemented and LM algorithm was used for learning. 10-fold cross validation was used to obtain the classification accuracy.

Sigmoid function and its approximations were applied respectively as activation function to obtain classification results. These activation functions are; sigmoid function, dataflow implementation of sigmoid function, piecewise linear approximation and Taylor series expansion approximation. The classification accuracies obtained by mentioned approximations were presented in Table 3. It is clear that the Taylor series expansion gives the closest approximation to the sigmoid function.

The classification accuracies of this study were also compared with the previous studies results on the diagnosis of hepatitis disease which used the same dataset. The comparison of the previous studies and our study are given in Table 4.

**Table 4.** Classification accuracies for the diagnosis of hepatitis disease

| Author | Method | Accuracy (%) |
|---|---|---|
| Chen, et al. | LFDA-SVM | 96.8 |
| Ansari, et al. | FFNN | 91.3 |
| Ansari, et al. | GRNN | 92.0 |
| Ansari, et al. | SOM | Not able to diagnose |
| Ozyilmaz and Yildirim | CSFNN | 90.0 |
| Ozyilmaz and Yildirim | MLP (5xFC) | 81.3 |
| Ozyilmaz and Yildirim | RBF (5xFC) | 85.0 |
| Grudziński | Weighted 9-NN (10xFC) | 92.9 |
| Grudziński | 18-NN, stand. Manhattan | 90.2 |
| Grudziński | 15-NN, stand. Euclidean | 89.0 |
| Adamczak | FSM with rotations | 89.7 |
| Adamczak | FSM without rotations | 88.4 |
| Adamczak | RBF (Tooldiag) | 79.0 |
| Adamczak | MLP+BP (Tooldiag) | 77.4 |
| Stern and Dobnikar | LDA, linear discriminant analysis (10xFC) | 86.4 |
| Stern and Dobnikar | Naive Bayes and Semi-NB (10xFC) | 86.3 |
| Stern and Dobnikar | QDA, quadratic discriminant analysis | 85.8 |
| Stern and Dobnikar | ASR (10xFC) | 85.0 |
| Stern and Dobnikar | Fisher discriminant analysis (10xFC) | 84.5 |
| Stern and Dobnikar | LVQ (10xFC) | 83.2 |
| Stern and Dobnikar | CART (decision tree) (10xFC) | 82.7 |
| Stern and Dobnikar | MLP with BP (10xFC) | 82.1 |
| Stern and Dobnikar | ASI (10xFC) | 82.0 |
| Stern and Dobnikar | LFC (10xFC) | 81.9 |
| Jankowski | IncNet (10xFC) | 86.0 |
| Polat and Gunes | FS-AIRS with fuzzy res. (10xFC) | 92.5 |
| Polat and Gunes | FS-Fuzzy-AIRS (50-50%) | 81.8 |
| Polat and Gunes | FS-Fuzzy-AIRS (10xFC) | 94.1 |
| Bascil and Temurtas | MLNN (MLP) + LM (10xFC) | 91.9 |
| Dogantekin, et al. | LDA-ANFIS (10xFC) | 94.1 |
| Tan, et al. | GA-SVM | 89.6 |
| Calisir and Dogantekin | PCA-LSSVM | 95.0 |
| Sartakhti, et al. | SVM-SA | 96.2 |
| Bascil and Oztekin | PNN | 91.2 |
| Our study | MLNN (with sigmoid function) | 93.7 |
| | MLNN (with dataflow implementation) | 91.8 |
| | MLNN (with piecewise linear approx.) | 92.5 |
| | MLNN (with Taylor series expansion) | 93.1 |

In this study, we used LM algorithm, uses Hessian matrix in order to perform better estimations and improve convergence, to obtain promising results. According to Table 4, the classification accuracies of MLNN, implemented in this study provide better results than the accuracies of the other MLNN (MLP) structures. This can be because of that, LM algorithm converges much faster than first order algorithms but it can cause the memorization effect when the over-training occurs. So, an over-trained MLNN with LM algorithm can impact performance negatively. The accuracy values can be checked during the training process to prevent the memorization effect [40]. On the other hand, Bascil and Temurtas reported 91.9% classification accuracy using MLNN with LM. This result is quite similar to the results obtained by our study. But we used the approximations of sigmoid activation function that do not involve any transcendentals. The approximations of sigmoid function can easily be performed and our results are promising in order to reduce the size and cost of neural network based hardware. One can see that the FS-Fuzzy-AIRS, LDA-ANFIS, PCA-LSSVM and SVM-SA classification accuracies which use hybrid methods are better than the results of this study. However, the mentioned methods which are specific for classification, provide better classification accuracies; these methods are too complex for digital implementations.

## DISCUSSION

In this study sigmoid function and its close approximations were implemented for digital applications. In hardware based architectures activation functions play an important role in ANN behavior. The sigmoid function and its approximations are suitable for training because of their smooth response. These approximations, mentioned above, can be used to develop learning strategies for implementation of ANNs on adaptive hardware. Additionally, approximations of sigmoid function can be used instead of sigmoid function. Because, it is hard to perform sigmoid function on adaptive hardware. The results showed that the approximations of the sigmoid function can easily be performed for hardware based architectures. Having compared obtained results, Table 3 shows that approximated functions perform classification accuracy as good as sigmoid function. When compared to previous work that diagnosed hepatitis disease using artificial neural networks and the identical data set, it was observed that hybrid methods achieved the best classification accuracies. On the other hand, the hardware implementations of hybrid systems require large scale multipliers and chip resources.

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