A new mathematical model for diagnosing chronic diseases (kidney failure) using ANN

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Abstract: In this paper, we introduce a new diagnosing technique for chronic kidney disease by using Artificial Neural Network (ANN). Where, the required data for the computational health-care system is collected from various hospitals at Jazan region, Saudi Arabia. Furthermore, in order to prove the convergence of this method, a ridge function is used in the hidden layer as a basis for the neurons. The technique applied for different number of neurons, and in each case a least square error is provided for choosing the best possible approximation.

Subjects: Mathematical Modeling; Mathematics for Biology & Medicine; Mathematical Biology

Keywords: diagnosing chronic diseases; artificial neural network; least square error; ridge function

1. Introduction

In the last few decades, the advances in the computational tools and in the field of artificial intelligence have led to design expert systems which are used for making better decisions in various areas of life (Almási et al., 2016; Karlik & Olgac, 2011) And medical application is one of the fertile areas for this type of systems (Bardram, Baldus, & Favela, 2006; Canan, Oguz, & Haluk, 2011; Cosenza, 2012; Karlik & Olgac, 2011). Where multi-layer Artificial Neural Network is considered as a reliable auxiliary tool for diagnosing common diseases with better accuracy (Arista-Jalife & Arista-Viveros, 2011; Canan et al., 2011; Kabari & Bakpo, 2009; Karan, Bayraktar, Gumuskaya, & Karlik, 2012; Karlik & Öztoprak, 2007; West & West, 2000). On the other hand, the Chronic Kidney Diseases (CKD) have become a major public health problem in Saudi Arabia, and particularly in the province of Jazan due to many factors that contributed to outbreaks of this disease (Al-Sayyari & Shaheen, 2011). Therefore, the need of constructing such intelligent systems to reduce the spread of this chronic disease and propose practical solutions for early diagnosis.

ABOUT THE AUTHOR

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PUBLIC INTEREST STATEMENT

The Chronic Kidney Diseases (CKD) have become a major public health problem in Saudi Arabia, and particularly in the province of Jazan due to many factors that contributed to outbreaks of this disease. Therefore, this article proposes intelligent model developed for the early detection of chronic kidney disease based on the method of artificial neural networks that have been proven to be effective with high accuracy. The model can be used for a self-diagnosis by entering the person’s data to get the results which helps and improve the public health care.
The authors in (Arista-Jalife & Arista-Viveros, 2011) implemented multi-layer back propagation artificial neural networks coupled with self-organizing map for diagnosing some common diseases up to 96.2% of accuracy under certain conditions of truncate information input. B. Canan et al. (Canan et al., 2011) developed a client-server system to diagnose internal illnesses by using pervasive health-care computing and Artificial Neural Networks (ANNs). Next, a framework for diagnosing skin diseases using artificial neural networks presented in (Kabari & Bakpo, 2009) where the proposed system reached 90% of success. L. G. Kabari, F. S. Bakpo (Karan et al., 2012) present a novel approach for diagnosing diabetes using neural network computations to develop a mobile software service for pervasive healthcare.

In this paper, we will present a new mathematical model for diagnosing kidney failure disease by mean of artificial neural networks. The model is constructed by taking samples from Jazan hospitals (positive samples and negative samples) to train the system and then test it on different samples. Moreover, the proposed model is supported by the mathematical theory that shows the convergence of the results. It is organized as follows: In Section 2 we give an indicator of the CKD and classification. In Section 3 we present the neural network model for diagnosing kidney failure. Section 4 is devoted to data training and the numerical results. Finally, we conclude and describe future work in Section 5.

2. Indicator of the CKD and classification

According to the medical treatment of CKD, the Glomerular Filtration Rate (GFR) is the most indicator used to estimate kidney health function. Which can be computed from the patient’s blood creatinine, age, race, gender, and other factors depending on the used formulas (Chiu, Chen, Wang, Chang, & Chen, 2013; Levey, DeJong, & Coresh et al., 2011; Matsushita, Mahmoodi, & Woodward et al., 2012). However, the commonly used formula is the Modification of Diet in Renal Disease (MDRD) (Matsushita et al., 2012)

\[
GFR = \frac{186 \times (\text{create})^{-1.154} \times (\text{age})^{-0.203} \times \left( \frac{\text{ml}}{173\text{m}^2} \right)}{C_0^{0.742}}
\]  

(1)

where for a female, the result should be multiplied by a factor of 0.742.

Moreover, the classification of CKD defined by the foundation's Kidney Disease Outcomes Quality Initiative (KDOQI) (National Kidney Foundation (NKF), 2002), is shown in Table 1.

3. Neural Network model for diagnosing kidney failure

The artificial neural network (ANN) is a mathematical computational method that is used in different areas of science such as: approximation of functions, numerical solutions for PDEs and ODEs, speech recognition, videos games, medical diagnosis, and in many other domains (Almarashi, 2012; Almarashi & Al-Wagih, 2007; Almarashi, Mechai, & Alghamedi, 2015). In the literature, there are many different types of neural network models, however, in this paper, the study is limited to the Back-Propagation Neural Network (BPNN) method with Ridge basis functions as illustrated in Figures 1 and 2.

| Table 1. Classification of CKD defined by KDOQI |
|-----------------------------------------------|
| Stage | State of kidney function | Classification by severity by GFR |
|-------|--------------------------|-----------------------------------|
| 1     | Kidney damage with normal or increasing in GFR | GFR ≥ 90 |
| 2     | Kidney damage with mild decreasing in GFR | GFR of 60 – 89 |
| 3     | Moderate with decreasing in GFR | GFR of 30 – 59 |
| 4     | Severe with decreasing in GFR | GFR of 15 – 29 |
| 5     | Kidney failure | GFR<15 (or dialysis) |
The following theorem gives the sufficient conditions for the convergence of the Neural network method (Almarashi et al., 2015).

**Theorem 1.** Let \( \phi(x) \) be a ridge basis function, nonconstant, bounded, and monotone increasing continuous function. Let \( K \) be a compact subset on \( \mathbb{R}^n \), and \( f(x_1, \ldots, x_n) \) a real value continuous function on \( K \). Then for any arbitrary \( \varepsilon > 0 \), there exist integer \( N \) and real constants \( v_j, \theta_j, w_{ij} \) for \( i = 1, \ldots, n \) and \( j = 1, \ldots, m \) such that

\[
\hat{f}(x_1, \ldots, x_n) = \sum_{j=1}^{m} v_j \phi_j \left( \sum_{i=1}^{n} w_{ij} x_i + \theta_j \right) + d,
\]

satisfies

\[
\max_{x \in K} |\hat{f}(X) - f(X)| < \varepsilon.
\]

In other words, for any arbitrary \( \varepsilon > 0 \) there exists a three-layer network: where the hidden layer represented by the ridge basis function \( \phi(x) \), which has an input-output function \( \hat{f}(x_1, \ldots, x_n) \) such that

\[
\max_{x \in K} |\hat{f}(X) - f(X)| < \varepsilon.
\]
4. Training data for kidney failure

The proposed model for diagnosing kidney failure consists of using one input layer, one hidden layer, and one output layer as presented in Figure 3. Where the input vector has dimension 11 and the output vector has dimension 2. Furthermore, the input data names and their units are shown in Table 2, Table 3, Table 4 and the outputs will be NORMAL and ABNORMAL. The input data set was collected from different government and private hospitals in Jazan region KSA, and 1150 patients’ cases were used for the training data selected from 1576 observations. The first 520 samples are negative, while 630 are positive (see Table 5).

First, the system was trained for positive and negative samples with different numbers of neurons in the hidden layers (2, 5, 10, 20, 30, 50, 100), to choose the optimal number of iterations and the best weights $v_j, w_{ij}, \theta$ and $d$ in Equation (2), where the results are presented in Figure 4. The training least-squares error indicates that, increasing the number of neurons leads to better accuracy with less iterations see Figure 4(a–e). However, after having more than 50 neurons in the hidden layers the (BPNN) model gives almost the same results and therefore the proposed model is convergent and stable.

Next, the system was tested using the best weights obtained in the training phase for each fixed neurons in the hidden layers and the results shown in Table 6. In the case of two neurons, the least-square error for the testing data is 0.4367. And increasing the number of neurons leads to better neural network approximation until reached 50 neurons, where the
least-square error for the testing data is 0.0012. Similarly as in the training case, the system converges and stable after taking more than 50 neurons in the hidden layers.

5. Conclusion
We investigated in the present work a new diagnosing technique for chronic kidney disease by using Artificial Neural Network (ANN). And the needed positive and negative samples, for the model are collected from the Jazan hospitals region. Where we used the ridge function in
the hidden layer as a basis for the neurons. The obtained numerical results show that the proposed model can be used to make a precise diagnosis of the CKD. As a future work, we propose to implement the model in smart devices and make it available for public health-care users for early diagnoses of the CKD which leads to better treatment and reduces the outbreaks of this disease.
Table 6. Training and testing data least-squares error for the (BPNN) model

| No. of neurons in hiding layers | Epochs | Training Least-squares error | Testing data Least-squares error |
|--------------------------------|--------|-------------------------------|----------------------------------|
| 2                              | 5000   | $10^{-4}$                     | 0.4367                           |
| 5                              | 2009   | $10^{-2}$                     | 0.1739                           |
| 10                             | 405    | $10^{-11}$                    | 0.0832                           |
| 20                             | 15     | $10^{-15}$                    | 0.0164                           |
| 30                             | 82     | $10^{-20}$                    | 0.0085                           |
| 50                             | 7      | $10^{-25}$                    | 0.0012                           |
| 100                            | 6      | $10^{-21}$                    | 0.0012                           |

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