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Impact of small-world network topology on the conventional artificial neural network for the diagnosis of diabetes

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ABSTRACT

Artificial intelligent systems have been widely used for diagnosis of diseases. Due to their importance, new approaches are attempted consistently to increase the performance of these systems. In this study, we introduce a new approach for diagnosis of diabetes based on the Small-World Feed Forward Artificial Neural Network (SW- FFANN). We construct the small-world network by following the Watts–Strogatz approach, and use this architecture for classifying the diabetes, and compare its performance with that of the regular or the conventional FFANN. We show that the classification performance of the SW-FFANN is better than that of the conventional FFANN. The SW-FFANN approach also results in both the highest output correlation and the best output error parameters. We also perform the accuracy analysis and show that SW-FFANN approach exhibits the highest classifier performance.

1. Introduction

Diabetes is an important and very common healthy problem. The clinical studies show that diabetes may cause some problems in human body such as kidney, nervous and heart diseases [1]. There are three common types of diabetes: type-1, type-2 and gestational. Type 1 diabetes depends on the beta-cells of the body whose destroying in the pancreas causes lack of insulin production [2,3]. Thus, the concentration of the glucose is reduced. Type 2 is a metabolic disease where the body does not use the insulin appropriately, which is also known as insulin resistance (hyperglycemia) [2,3]. The gestational diabetes has been found in women having high blood glucose levels during pregnancy. According to The World Development Indicators (WDI), diabetes spreads rapidly in the world due to the change of nutritional habits [4]. Therefore, early diagnosis of diabetes has become crucial in medical science.

During the last several decades, computer-aided clinical intelligent systems have been suggested to diagnose the diseases accurately and fastly. Conventional clinical intelligent systems are generally based on machine learning methods such as Artificial Neural Network (ANN) [5,6], Bayesian networks [7], support vector machines [8], regression, classification and regression trees [8]. Among them, ANN has become prominent due to its high generalization and classification capability [6]. An ANN, is a computational paradigm, originally inspired from real biological networks, that uses a layered structure composed of interconnected process units (neurons). Interconnection strengths or "synaptic weights" between units determine the performance of an ANN on various tasks such as prediction, classification or decision. Another key factor that effects these cognitive functions of an ANN is its structural architecture determining the network type such as feed forward, recurrent and competitive artificial neural networks [5]. A Feed Forward ANN (FFANN) stands out from others with its remarkable computation speed characterizing the efficiency of an intelligent system [6].

The FFANN has been proposed as a powerful tool for diagnosis of diabetes [9–14]. For instance, Wyk et al. [15] used

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the particle swarm optimization (PSO) algorithm instead of the bounded activation function in a FFANN for the diagnosis of diabetes, and obtained that PSO removes the need for scaling the inputs as required by a bounded activation function of fixed domain. Karan et al. [16] proposed a client/server software architecture based on the FFANN for mobile devices to be used in diagnosis of diabetes. They obtained the optimum learning parameters of the model. Temurtas et al. [17] suggested two models, FFANN with Levenberg–Marquardt (LM) learning algorithm and Probabilistic Neural Network (PNN) to classify the Pima Indian diabetes. They showed that their proposed model, FFANN with LM, outperforms than PNN and the models reported in the previous studies. Kazemnejad et al. [18] reported that there is no performance difference between logistic regression model and FFANN model for the diagnosis of diabetic patients.

On the other hand, the FFANN is known to have a regular network topology due to the highly ordered structure. However, regular networks do not stand for the structure and functions of complex brain networks [19–22]. In order to increase this similarity between the network topologies of the brain and artificial networks, Watts and Strogatz proposed a new network topology, being neither regular nor random, called Small-World (SW) network [23,24]. SW network topology has been widely used to understand how the brain functions [19,20,23,24]. In the literature, there are limited number of studies presenting the effects of SW topology on the performance of FFANNs. In this context, Simard et al. [25] compared learning performance of SW, regular and random FFANNs by using back-propagation algorithm. They showed that SW-FFANN learning performance is better than the other topologies. Recently, we showed that there is an optimal rewiring number within the SW topology warranting the best performance for real life problems considered [26]. Li et al. [27] designed a new neural network controller with a SW-FFANN to control linear and nonlinear systems. They compared performance of small-world FFANN and regular neural network, and showed that SW-FFANN exhibits better controller performance.

The literature surveys leaves us with the impression that there is no any attempt to investigate the performance of the SW topology for the FFANN for the diagnosis of diabetes. Therefore, in this study, we attempt to show the performance of SW-FFANN model in diagnosis of diabetes. We construct a SW-FFANN based on the algorithm proposed in [25,26], and comparatively investigate the classification performances of regular FFANN with standard gradient descent algorithm and SW-FFANN. We also examine the statistical performance of both models based on the confusion matrix.

2. Materials and methods

In order to measure accurately the performance of the proposed model, we use very commonly used the Pima Indian diabetic dataset (PIDD), taken from the UCI machine learning respiratory [28–32]. The observed dataset includes 768 samples and two classes (normal: 500, diabetic: 268). Each samples have eighth features and one response. These features are shown in Table 1.

Since some attributes of the PIDD have zero values encoded missing data, we have cleared dataset from missing data. New dataset has 392 samples (normal: 262, diabetic: 130). Statistical analysis of this dataset has been shown in Table 2.

Table 1
Features of the Pima Indian diabetic dataset.

Features	Diagnosis	Unit
1	Number of times pregnant	–
2	Plasma glucose concentration	Mg/dl
3	Diastolic blood pressure	mmHg
4	Triceps skin fold thickness	Mm
5	2-hour serum insulin	mu U/ml
6	Body mass index	kg/m^2
7	Diabetes pedigree function	–
8	Age	Year
9	Result	–

Table 2
Brief statistical analysis of Pima Indian diabetic dataset.

Features	Mean	Deviation	Min	Max
1	3.301	3.211	0	17
2	122.628	30.861	56	198
3	70.663	12.496	24	110
4	29.145	10.516	7	63
5	156.056	118.842	14	846
6	33.086	7.028	18.2	67.1
7	0.523	0.345	0.085	2.42
8	30.865	10.201	21	81
9	0.471	0.332	0	1

We consider a four layered FFANN for the investigation. The network has 8 input, one output neuron and two hidden layers. We use to two different network topology for the FFANN: the first one is the conventional multi-layer FFANN which has a regular topology; and the other is the SW-FFANN. While regular topology is created through back-propagation algorithm, SW topology is constructed by the rewiring algorithm of Watts and Strogatz [19]. The construction process starts with disconnecting a randomly selected link from its end point and rewiring it to a randomly selected neuron in the network. Notably, if the new connection already exists between 2 nodes, we cancel this rewiring and select a new node randomly. This process is continued for up to the number of maximum possible rewirings [19,20,26]. A schematic illustration of the rewiring process is shown in Fig. 1.

The SW network is characterized by two structural parameters, namely the clustering coefficient (C) and the characteristic path length (L). The characteristic path length is defined as the average number of edges in the shortest path between any two nodes or simply as the average node-to-node distance, while the clustering coefficient measures to what extent local interactions are intact or broken [19]. For a regular FFANN topology, these two parameters C and L cannot be calculated due to having non-connected neurons within the same layer. Thus, we use the global efficiency (D_{Global}) and the local efficiency (D_{Local}) parameters which were proposed by Latora et.al [20]. The global efficiency is defined as follows [26]:

$$D_{Global} = \frac{1}{\frac{1}{N(N-1)} \sum_{i \neq j \in N} \frac{1}{d_{ij}}} \quad (1)$$