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Performance of small-world feedforward neural networks for the diagnosis of diabetes

Okan Erkaymaz[a], Mahmut Ozer[b], Matjaž Perc[c,d,*]

[a] Department of Computer Engineering, Bulent Ecevit University, Zonguldak, Turkey
[b] Department of Electrical & Electronics Engineering, Bulent Ecevit University, Zonguldak, Turkey
[c] Department of Physics, Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, SI-2000 Maribor, Slovenia
[d] Center for Applied Mathematics and Theoretical Physics, University of Maribor, Mladinska 3, SI-2000 Maribor, Slovenia

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ABSTRACT

We investigate the performance of two different small-world feedforward neural networks for the diagnosis of diabetes. We use the Pima Indians Diabetic Dataset as input. We have previously shown than the Watts–Strogatz small-world feedforward neural network delivers a better classification performance than conventional feedforward neural networks. Here, we compare this performance further with the one delivered by the Newman–Watts small-world feedforward neural network, and we show that the latter is better still. Moreover, we show that Newman–Watts small-world feedforward neural networks yield the highest output correlation as well as the best output error parameters.

1. Introduction

Diabetes is a very common health problem of the modern life, spreading rapidly in the world due to the change of nutritional habits [1]. Although type-1, type-2 and gestational diabetes are all common, especially type 2 diabetes mellitus causes significant morbidity and mortality [2]. Therefore, its early detection is of vital importance. Since some forms of diabetes result in a worldwide epidemic that has made it one of the most serious health problem faced by the humankind [3], enormous efforts have been devoted to its early diagnosis and treatment.

Expert systems and artificial intelligence techniques are widely used to aid the diagnosis of diabetes. In this context, the Artificial Neural Network (ANN), originally inspired from real biological networks, has been preferred due to its high classification capability [4]. The architecture of the ANN enables users to construct different types of networks such as feedforward, recurrent and competitive [5]. Among them, a feedforward ANN (FFANN) stands out with its remarkable computational speed [4]. In this context, the FFANN has been proved to be an efficient intelligent system for the diagnosis of diabetes [6–11]. Temurtas et al. [12] used a multilayer neural network (MLNN) structure for the diagnosis of Pima Indians diabetes and found that the classification accuracy of MLNN trained by the Levenberg–Marquardt algorithm was better than that of conventional neural networks. Moreover, Wang et al. [2] have developed and evaluated an effective classification approach by means of ANN to identify those at high risk of type-2 diabetes mellitus without biochemical parameters. Soltani and Jafarian [13] used probabilistic ANN (PNN) for diagnosis of diabetes with type-2.

* Corresponding author at: Department of Physics, Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, SI-2000 Maribor, Slovenia.
E-mail addresses: matjaz.perc@uni-mb.si, matjaz.perc@gmail.com (M. Perc).

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Table 1
Features of the Pima Indians 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-h 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 Indians 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

On the other hand, new network topologies have been developed to understand the dynamics of daily life networks because both regular and random networks do not prove fully useful in striving towards the understanding of the real networks [14–18]. In this context, Watts and Strogatz [14] introduced a new network topology called as a Small-World (SW) network. The rewiring algorithm provides a range where the network behaves in a way neither regular nor random. Watts and Strogats [14] showed that some Daily life networks exhibits SW property. Latora and Marchiori [15] analyzed the real data from neural, communication and transport networks and showed that these networks also exhibits SW behavior. SW networks has been proven to be powerful tool to understand the dynamics and information processing capability of the biological neural networks [18–20]. Then, some efforts have been devoted on the application of the rewiring algorithms of the SW networks into the FFANN. Simard et al. [21] carried out a comparative study on the learning performance of regular, SW and random networks using FFANN, and showed that the performance of the SW–FFANN is better than those of regular and random ones. Li et al. [22] developed a multilayer feedforward SW neural network controller and showed that it exhibits better controller performance. We analyzed the real data for estimating the thermal performance of solar air collectors and predicting the modulus of rupture values of oriented strand boards and showed that SW–FFANN results in better accuracy than the conventional FFANN [23]. In a recent study, we compared the performance of the SW–FFANN and the conventional FFANN for diagnosis of diabetes on PIDD [24]. We showed that the SW–FFANN exhibits the highest classification performance.

Literature surveys indicate that SW–FFANNs are constructed based on the Watts and Strogatz rewiring algorithm in Watts and Strogatz [14]. On the other hand, Newman and Watts [25] proposed a different the rewiring algorithm leading to SW behavior. Newman–Watts SW networks have been also widely used to understand the dynamics of different real networks [18–20,26–28]. Therefore, our aim in this study is to extend the subject in Erkaymaz and Ozer [24], and to investigate the impact of both rewiring algorithms on the performance of SW–FFANN for diagnosis of diabetes based on PIDD.

2. Mathematical model

In order to compare the performance of the proposed model with that reported in Erkaymaz and Ozer [24], we use the same Pima Indians Diabetic Dataset (PIDD), taken from the UCI machine learning repository [29–34], which 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.

We followed the same methodology for the dataset. Therefore, since we have cleared the dataset from missing data, the new dataset has 392 samples (normal: 262, diabetic: 130). The statistical analysis of this dataset is shown in Table 2 [24].

We consider a four layered FFANN for the comparison of the proposed model with that reported in Erkaymaz and Ozer [24], involving 8 input, one output neuron and two hidden layers. We use three different network topology for the FFANN: the first one is the conventional multi-layer FFANN which has a regular topology, the second one is the Watts–Strogatz SW–FFANN and the third one is the Newman–Watts SW–FFANN. The conventional FFANN regular topology is created through

back-propagation algorithm. The Watts–Strogatz SW–FFANN is constructed by following the rewiring algorithm of Watts and Strogatz [14], where the rewiring 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 [14,15,23]. On the other hand, the Newman–Watts SW–FFANN is constructed by following the rewiring algorithm of Newman and Watts [25], where the rewiring process starts with drawing two neurons randomly. Subsequently, only if they are not already connected, a new link is added between them. This process is repeated until a total of maximum possible rewirings are added in the network [19].

In order to obtain the SW–FFANN, we follow the methodology proposed by Simard et al. [21] and use the global efficiency (D_{Global}) and the local efficiency (D_{Local}) parameters as in Erkaymaz et al. [23,24]. The global efficiency and the local efficiency are defined as follows [21,23,24]:

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

$$D_{Local} = \frac{1}{E_{Local}} \tag{2a}$$

$$E_{Local} = \frac{1}{N} \sum_{x \in N} E(G_x) \tag{2b}$$

$$E(G_x) = \frac{1}{N_x(N_x - 1)} \sum_{m \neq n \in N} \frac{1}{d_{mn}} \tag{2c}$$

where d_{ij} is the shortest path length between two nodes, and N denotes the number of nodes in the network, d_{mn} is the shortest path length between the neighboring nodes when the node x is disconnected from them. N_x is the number of neighbor nodes that are connected directly to node x. In the methodology proposed by Simard et al. [21], D_{Global} and D_{Local} correspond to L and 1/C in the SW network topology, respectively. L denotes the characteristic path length and C denotes the clustering coefficient [14]. When both D_{Local} and D_{Global} are small, the network exhibits a small-world property [15,21,23,24].

We use a bipolar-sigmoid function to activate each neuron in the layers and perform the back-propagation learning algorithm with momentum coefficient (traingdm) for training process of SW–FFANN as in Erkaymaz and Ozer [24]. This process is defined for the neuron in the output layer as follows [24]:

$$\delta_o(t) = y_o(1 - y_o)(d_o - y_o) \tag{3a}$$

$$\Delta W_{no}(t) = \alpha y_n \delta_o(x) \tag{3b}$$

$$W_{no}(t+1) = W_{no}(t) + \Delta W_{no}(t) + m\Delta W_{no}(t) \tag{3c}$$

The process is defined for the neuron in the hidden layers as follows [24]:

$$\delta_n(t) = y_n(t)(1 - y_n(t)) \sum_{o=1}^{l} \delta_o(t) w_{no}(t) \tag{3d}$$

$$\Delta w_{in}(t) = \alpha x_i(t) \delta_n(t) \tag{3e}$$

$$W_{in}(t+1) = W_{in}(t) + \Delta W_{in}(t) + m\Delta W_{in}(t) \tag{3f}$$

where y and d denote the network output and the desired output, respectively. W represents the synaptic weight and ΔW represents its change. α and m are the parameters of learning and momentum coefficients, respectively. Finally, δ is the derivative of output error.

We use the k-fold cross-validation method for training phase as in Erkaymaz and Ozer [24], which is commonly used to avoid over-fitting problem for ANN models [35]. In this method, the dataset is split into k equal-sized parts and randomly selected one part is used as the test set and the remaining k−1 parts are used as the training dataset. For each trial, we calculate the Mean Square Error (*MSE*), the Mean Absolute Error (*MAE*), and the Root Mean Square Error (*RMSE*) as follows [24]:

$$MSE = \frac{1}{SN} \sum_{i=1}^{SN} (y_i - d_i)^2 \tag{4}$$

Table 3
The confusion matrix.

		Predicted class	
		Positive	Negative
Actual class	Positive	TP	FN
	Negative	FP	TN

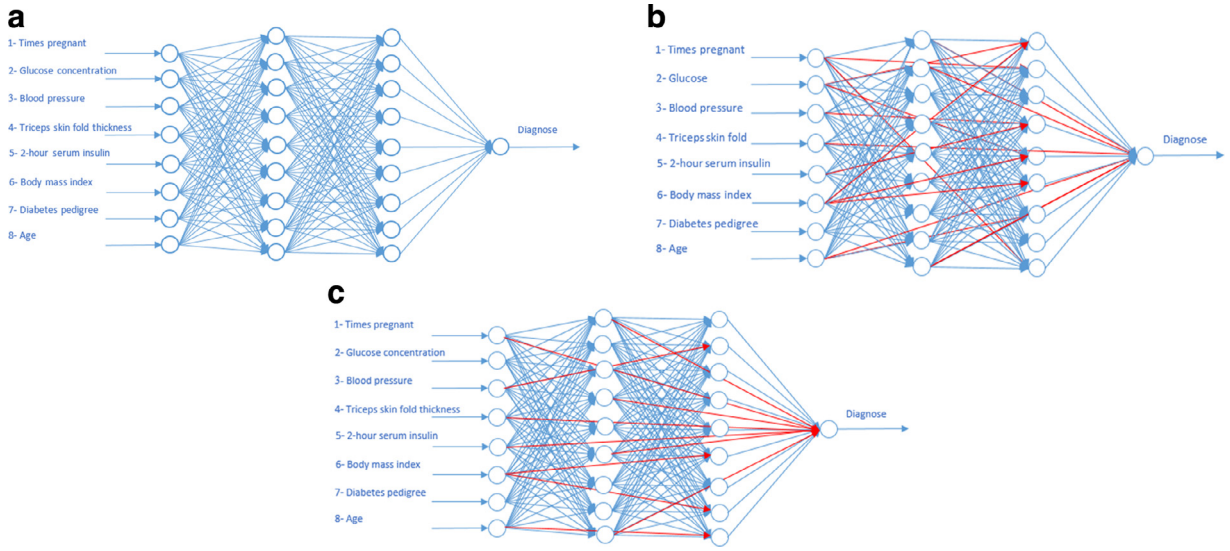

Fig. 1. The constructed networks, (a) the conventional FFANN network, (b) Watz–Strogatz SW–FFANN, and (c) Newman–Watts SW–FFANN.

$$MAE = \frac{1}{SN}\sum_{i=1}^{SN}|y_i - d_i| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{SN}\sum_{i=1}^{SN}(y_i - d_i)^2} \tag{6}$$

This process is repeated k = 10 times and the calculated values of the statistical parameters for each trial are then averaged as in Erkaymaz and Ozer [24]. Both of the MAE and RMSE must be closer to zero for reliability of the model. Since the system performance is commonly calculated based on the data in the contingency table (confusion matrix) [36], we use the confusion matrix to determine the rate of true and false predictions as in Erkaymaz and Ozer [24]. The confusion matrix with a two class classifier is shown in Table 3.

In Table 3, TP, FP, TN and FN indicate true positives, false positives and true negatives, false negatives, respectively [37]. The performance of each model is defined as follows [24]:

$$\text{Sensitivity}(\%) = 100\frac{\text{TP}}{\text{TP}+\text{FN}} \tag{7a}$$

$$\text{Specificity}(\%) = 100\frac{\text{TN}}{\text{TN}+\text{FP}} \tag{7b}$$

$$\text{Accuracy}(\%) = 100\frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{7c}$$

3. Results

In order to compare the performance of the Newman–Watts SW–FFANN with that of the Watts–Srogatz SW–FFANN for the diagnosis of diabetes based on the PIDD reported in Erkaymaz and Ozer [24], we constructed the same FFANN with four layers, involving 8 input, one output neuron and two hidden layers. Since we have already obtained the best performance of the conventional FFANN with 9 neurons in the hidden layers in [24, Fig. 2], the conventional FFANN is constructed with two hidden layers each has 9 neurons as illustrated in Fig. 1. In order to construct SW–FFANN, we need to know the number of

Table 4
The change of the performance of the network with the rewiring number (RN) for the constructed FFANN through the rewiring (a) by the Watts–Strogatz algorithm, and (b) by the Newman–Watts algorithm.

(a)				(b)			
RN	MSE	MAE	RMSE	RN	MSE	MAE	RMSE
0	0.1113	0.2172	0.3336	0	0.2502	0.1207	0.5002
5	0.1070	0.1773	0.3271	5	0.2277	0.1275	0.4772
10	0.2094	0.2628	0.4576	10	0.2125	0.1121	0.4610
15	0.1566	0.2259	0.3958	15	0.2387	0.1095	0.4886
20	0.1076	0.1797	0.3280	20	0.2430	0.1179	0.4929
25	0.1153	0.2118	0.3396	25	0.2530	0.1479	0.5030
30	0.1294	0.1662	0.3597	30	0.2279	0.1061	0.4774
35	0.1264	0.1963	0.3556	35	0.2862	0.1621	0.5350
40	0.1352	0.1673	0.3677	40	0.2307	0.1152	0.4803
45	0.1405	0.1871	0.3748	45	0.2294	0.1087	0.4789
50	0.1248	0.2251	0.3533	50	0.2264	0.1226	0.4758
55	0.2411	0.2838	0.4910	55	0.2487	0.1177	0.4987
60	0.1272	0.1710	0.3567	60	0.2400	0.1111	0.4899
65	0.1061	0.1628	0.3257	64	0.2124	0.0917	0.4608
70	0.1308	0.1928	0.3617	70	0.2362	0.1205	0.4860
75	0.1724	0.2308	0.4152	75	0.2224	0.1014	0.4716
80	0.1108	0.1760	0.3328	80	0.2238	0.1039	0.4731
85	0.1319	0.1989	0.3631	85	0.2300	0.1117	0.4795
89	0.1107	0.2244	0.3327	89	0.2287	0.0997	0.4782

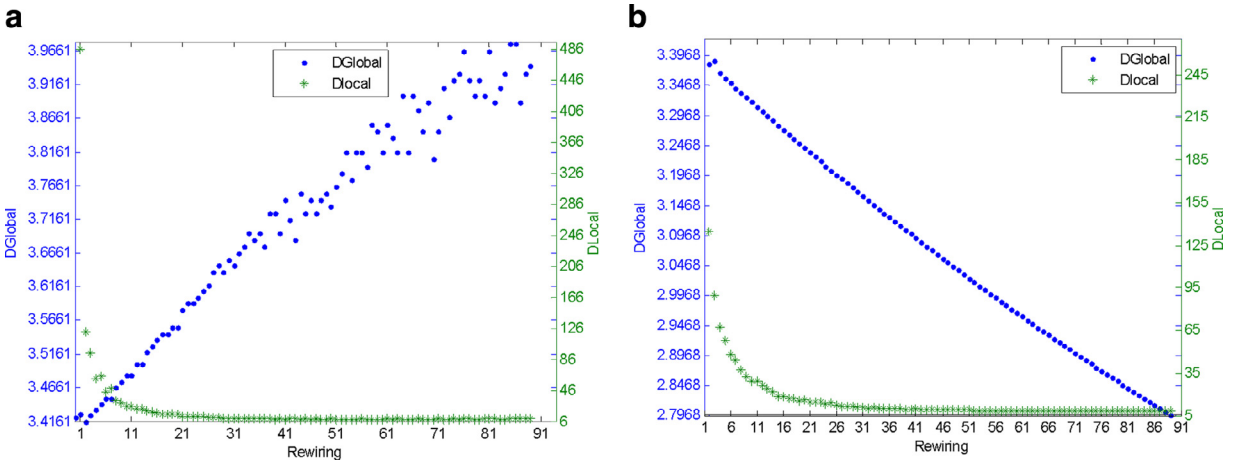

Fig. 2. The change of D_{Global} and D_{Local} with the rewiring number (RN) for the constructed FFANN through the rewirings (a) by the Watts–Strogatz algorithm, and (b) by the Newman–Watts algorithm.

maximum possible rewirings. We have also already calculated it as 89 for 9 neurons in the hidden layers in (see Table 4 in Erkaymaz and Ozer [24, Table 4]).

We first construct the Watts–Strogatz FFANN and the Newman–Watts FFANN following the algorithms described in Materials and methods section. For each rewiring step, D_{Global} and D_{Local} parameters are calculated for each type of the SW–FFANN and shown in Fig. 2. As shown in Fig. 2, as the rewiring number (RN) increases, D_{Local} decreases whereas D_{Global} increases for the Watts–Strogatz FFANN. On the other hand, both D_{Local} and D_{Global} decreases with the increasing of the rewiring number for the Newman–Watts FFANN. Since when both D_{Local} and D_{Global} are small, the network exhibits a small-world property [15,21,23,24], it is seen that the number of rewirings required to obtain a small-world property for the FFANN should be greater than 8 for the Watts–Strogatz SW–FFANN and be greater than 16 for the Newman–Watts FFANN.

Secondly, we applied the training and test processes for each FFANN following the each rewiring algorithms. We calculated the MSE, MAE and RMSE of the both network types for each rewiring number. The quantitative results repooled from simulations of 20 different realizations of the each network for any given value of RN. The obtained results are given in Table 4. We show that the rewiring numbers resulting in the best performance for both network types are within the range of the SW–FFANNs. The best performance is obtained for an optimal rewiring number of 65 for the Watts–Strogatz SW–FFANN and for an optimal rewiring number of 64 for the Newman–Watts SW–FFANN.

Then, we statistically analyzed the classification performance with RN = 65 for the Watts–Strogatz SW–FFANN and RN = 64 for the Newman–Watts SW–FFANN based on the confusion matrix as in Erkaymaz and Ozer [24]. The obtained

Table 5
Statistical performance results for three network models: the conventional FFANN network, Watz–Strogatz SW–FFANN, and Newman–Watts SW–FFANN.

Model	Sensitivity	Specificity	Accuracy (%)
Conventional FFANN	0.60	0.92	83.33
Watz–Strogatz SW–FFANN	0.80	0.96	91.66
Newman–Watts SW–FFANN	0.85	0.96	93.06

Table 6
Comparison of the classification accuracies of the Newman–Watts SW–FFANN and the existing models based on the PIDD.

Study	Method	Classification accuracy (%)
Deng and Kasabov (2001)	ESOM (10x FC)	78.40
Polat and Gunes (2007)	PCA–ANFIS (10x FC)	89.47
Polat et al. (2008)	LS-SVM (10x FC)	78.21
	GDA–LS-SVM (10x FC)	79.16
Kayaer and Yildirim (2003)	GRNN (conventional valid)	80.21
	MLNN with LM	77.08
Carpenter and Markuzon (1998)	ARTMAP-IC	81.00
Other studies reported. Detailed list can be accessible in Polat and Gunes (2007)	Various methods (3x FC. 10x FC. conventional valid)	Between 59.5 and 77.7
Temurtas et al. (2009)	MLNN with LM	82.37
	PNN	78.13
Erkaymaz and Ozer (2016)	FFANN	83.33
	Watts–Strogatz SW–FFANN	91.66
This study	Newman–Watts SW–FFANN	93.06

results are given in Table 5. We have already shown that the Watts–Strogatz SW–FFANN results in better performance on the diagnosis of diabetes with an accuracy of 91.6% than the conventional FFANN with an accuracy of 83.3% [24]. In this study, we also show that the Newman–Watts SW–FFANN improves this performance and results in an accuracy of 93.06%. It is also seen that the Newman–Watts SW–FFANN model shows robust character to detect of disease by having a sensitivity of 0.85 and a specificity of 0.96.

Finally, we compared the classification accuracy of the Newman–Watts SW–FFANN and those reported in literature based on the PIDD in Table 6 (compare it with Table 7 in [24]). As shown in Table 6, the previous classification accuracies is lower than that of the Newman–Watts SW–FFANN.

4. Discussion

In sum, we propose a new intelligent decision system for the diagnosis of diabetes based on the conventional FFANN and construct a non-conventional SW–FFANN through the rewiring algorithms of SW networks. In our previous study in Erkaymaz and Ozer [24], we obtained the Watts–Strogatz SW–FFANN through the rewiring algorithm of Watts and Strogatz [14], and showed that the Watts–Strogatz SW–FFANN warrants the best performance for the diagnosis of diabetes based on the PIDD. In this study, we revisited it and constructed the SW–FFANN based on the rewiring algorithm proposed by Newman and Watts [25]. Our results indicate that both Watts–Strogatz and Newman–Watts SW–FFANN exhibit better classification performance than the conventional FFANN. We may suggest that there is an optimal rewiring number within the SW behavior warranting the better performance. On the other hand, we also showed that the Newman–Watts SW–FFANN results in better performance than the Watts–Strogatz SW–FFANN. Since only if randomly drawn two neurons are not already connected, a new link is added between them, both D_{Local} and D_{Global} decreases with the increasing of the rewiring number for the Newman–Watts FFANN. This rewiring algorithm results in better SW behavior for the FFANNs. Therefore, we conclude that the Newman–Watts SW–FFANN model results in the best performance for the diagnosis of diabetes based on the PIDD. The proposed model suggests a clear advantage for the diagnosis of diabetes, which is crucial for our attempts at successfully mitigating the epidemics.

We hope that our study will inspire further approaches aimed at the diagnosis of disease by means of new intelligent decision-making approaches. We also hope that new applications areas, such as modeling memory in the brain [38], the use of intelligent algorithms for local search heuristic [39], or for computational intelligence in sports [40], will continue to emerge. As for the future, we plan to use the Levenberg–Marquardt algorithm for network training and compare its performance with the results presented in this study.

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