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ORIGINAL ARTICLE

A prediction model based on artificial neural networks for the diagnosis of obstructive sleep apnea

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Abstract
Background Recently, artificial neural networks (ANNs) have been widely applied in science, engineering, and medicine. In the present study, we evaluated the ability of artificial neural networks to be used as a computer program and assistant tool in the diagnosis of obstructive sleep apnea (OSA). Our hypothesis was that ANNs could use clinical information to precisely predict cases of OSA.
Method The study population in this clinical trial consisted of 201 patients with suspected OSA (140 with a positive diagnosis of OSA and 61 with a negative diagnosis of OSA). The artificial neural network was trained by assessing five clinical variables from 201 patients; efficiency was then estimated in this group of 201 patients. The patients were classified using a five-element input vector. ANN classifiers were assessed with the multilayer perceptron (MLP) networks.
Results Use of the MLP classifiers resulted in a diagnostic accuracy of 86.6 %, which in clinical practice is high enough to reduce the number of patients evaluated by polysomnography (PSG), an expensive and limited diagnostic resource.
Conclusions By establishing a pattern that allows the recognition of OSA, ANNs can be used to identify patients requiring PSG.

Keywords Obstructive sleep apnea · Artificial neural networks · Polysomnography · Diagnostic accuracy

This research has not been presented at a conference.

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Introduction

Obstructive sleep apnea (OSA) is diagnosed based on the results of an overnight sleep test known as polysomnography (PSG). However, the availability of PSG is limited such that evaluations are mostly restricted to large medical centers in urban areas. Furthermore, the exam is time consuming, uncomfortable for the patient, expensive, and requires a patient-specialized protocol. At Mevlana University Hospital in Konya, Turkey, patients typically wait several months to 1 year for a PSG evaluation. However, increasing awareness of the adverse effects of OSA on health and the importance of the timely initiation of therapy have increased the demand for PSG. Consequently, prediction procedures have become important for screening patients who are likely to have sleep apnea.

Prior attempts to improve clinical screening or to develop case-finding methods to allow the improved detection of OSA have suffered from inadequate sensitivity or specificity [1]. Even experienced sleep physicians using subjective criteria accurately diagnose OSA only in approximately 50 % of patients [2]. Portable home sleep monitoring is an inexpensive procedure that, in individuals with suspected OSA, has the advantage of being performed in their habitual environment. The disadvantages include the difficulties inherent in unaccompanied monitoring and the need for a technician to instruct the patient in the home use of the device. Furthermore, the great majority of home monitoring systems have not been sufficiently validated. Thus, in OSA, simplified and accurate diagnostic techniques are still needed.

The diagnosis of OSA relies on the collection of the appropriate data and their accurate analysis. Data processing by physicians is typically based on statistical techniques aimed towards facilitating decision-making. However, the complexity of the data and current requirements regarding their storage and accessibility necessitate the use of computers and sophisticated software. In the field of medical research, this has led to the implementation of bioinformatics [3] which is well suited to medical diagnostics, as demonstrated by the study described in this report.

Artificial neural networks (ANNs) are computer programs modeled after the biological nervous system. They are used in the design of complicated, data-dependent models in which experience, as a source of learning, is advantageous. ANNs also allow adaptation and generalization of knowledge in solving unfamiliar problems and can be executed as a software program. ANNs make use of data mining and can manage enormous amounts of information, while very quickly finding the optimal solution. In fact, artificial intelligence has already been successfully used in daily medical practice, by predicting the likelihood of acute myocardial infarction in patients presenting in the emergency room [4], by recognizing the occurrence of a pulmonary embolism [5], lung cancer classification [6], detection of abnormal shadows from X-ray images of lungs [7], automatic epileptic seizure detection [8], and automated medical diagnosis [9].

The present study focuses on OSA, a condition that is recognized and diagnosed mainly on its clinical characteristics, which can also serve as ANN inputs [10–12]. Therefore, we propose an ANN-based method for the diagnosis of OSA, based on easily acquired patient demographic data (sex, age, body mass index (BMI), and snoring status).

Method

Patients

The clinical data were gathered together from a retrospective review of randomly selected patients who presented to the Mevlana University Sleep Center Clinic for assessment of probable OSA and who went on to have PSG. Reasons for not going on to PSG included a clinical diagnosis other than OSA (e.g., insomnia) and patient refusal. Excluded from the observation were patients, 16 years of age, patients with an inappropriate study (e.g., complete sleep time, 2 h), and patients applied for split-night studies.

Overnight PSG

PSG was performed in one night on whole patients. The sleep study montage contained EEG (C3/A2, C4/A1, O2/A1), electro-oculogram, submental electromyogram, right and left anterior tibialis electromyogram, thoracic-abdominal motion, ECG, oro-nasal airflow (expired CO_2), and arterial oxygen saturation with pulse oximetry using a finger probe sensor. Recordings from PSG were analyzed according to the system proposed by Rechtschaffen and Kales for the purpose of obtaining a final diagnosis. Apnea was described as a cessation of airflow for 10 s or longer. Hypopnea was described by a decreasing, absence of complete cessation, of airflow of at least 50 %, associated by a decline of greater than 4 % in the saturation of hemoglobin. The apnea-hypopnea index (AHI) was the average determined from the total of apneic events detected in PSG and the total time, in hours, of sleep. At last, a threshold of AHI≥10 events/h was accepted to decide the subjects influenced by OSAS.

ANN in the diagnosis of OSA

A program used in the diagnosis of OSA served as the basis for the ANNs. A review of the OSA literature identified sex, age, BMI, and snoring status as the determinant diagnostic factors. These four independent parameters were therefore used as network inputs. The network output vectors were the following:

(1) Healthy
(2) OSA patient

Patient data obtained from the Mevlana Sleep Disorder Center were used to create a dataset comprising data input from 201 patients with confirmed OSA. Data on sex, age, BMI, and snoring status provided input data for each input setting. These data were used to train the ANNs. Then, ANNs were tested with data from 15 individuals, with and without OSA (Table 1).

It is important to note that the success of the multilayer perceptron (MLP) networks changes depending on the amount of data used for training and testing. The MATLAB program package was used in the development of the neural networks. The feed-forward net order, a command for solving a particular situation that requires a solution, was used to create the MLP networks. The ANNs created in this study with the feed-forward net command consisted of an input layer with 4 neurons, an intermediate layer with 20 neurons, and one output layer (Fig. 1).

The network training function was applied to use the Bayesian regularization method [9] as the feed-forward-net command training method for ANN training. The Bayesian regularization method reduces errors and the number of considered weights to precisely predict those combinations needed for network creation. It updates weight and bias parameters according to the Levenberg Marquardt optimization method. Regularization techniques force networks to consider a smaller number of weight values.

Table 1 Training test's data

Gender (1 male, 2 female)	Age	BMI	Snoring (1 present, 2 absent)	Patient status (1 healthy, 2 OSA)
2	48	32	1	1
1	55	30.9	1	2
1	32	24.6	1	2
2	41	25	2	2
1	37	28.4	1	2
2	20	21.2	1	1
2	60	28.4	1	1
1	28	34.5	2	1
1	56	29.1	2	2
1	47	25.3	1	2
1	44	40.4	2	2
2	57	40.8	2	2
2	63	39.1	2	2
1	62	24.2	2	2
1	38	32.6	2	2

To develop our artificial neural-network-based method, the initial patient population was randomly divided into training and test sets. However, males are more likely to have OSA than females, and patients with OSA tend to be older and have a higher BMI than patients without OSA (Table 2).

This study was approved by the Mevlana Medical University Hospital (Konya, Turkey). Initial values were selected randomly by the MATLAB command, resulting in different error rates during the training phase. Two different simulation results were obtained in this study, as described in the following section.

Simulation results

The simulation of the training performance obtained using the multilayer feed-forward neural networks is shown in Fig. 2. The mean minimum error was obtained at epoch 624. The epoch date in this study is also reported in Fig. 3.

The mean square error of the ANNs is shown in Fig. 3. The square of the mean of the minimum training error (0.12804) was reached at epoch 438. The time needed for training ANNs was 2 min and 16 s. The ANN test results obtained after

Table 2 Data of patient demographics

Characteristics	Data (n=201)
Age	49.1±12.7
Male/female (%)	58.4/41.6
BMI >25 patient number	84 %
Snoring (%)	72.3 %

network training and based on the data of the 15 individuals with and without OSA are reported in Table 1. The network results and actual results are compared in Table 3. The error rate was 0.13333.

Training, validation, and testing of artificial neural networks were done using data of Mevlana Medical Center. But after training artificial neural networks, by entering the input data of the desired person, anybody may find whether that person is sick or not by the proposed ANN software

Discussion

In the present retrospective study, we developed a novel ANN-based technique to support the accurate diagnosis of OSA based on the age, sex, BMI, and snoring status of the patient. The results showed that artificial neural networks are effective tools for modeling the complexity of the diagnosis of OSA.

OSA is an appropriate choice for the development and testing of screening or case-finding methods. It is a chronic condition that is highly widespread in the general population, with a prevalence of 2–8 % in the USA [13]. In Asia, the prevalence is 4.1 and 2.4 % in males and females, respectively [14]. These figures translate into a large number of patients who require diagnosis and treatment. Moreover, OSA patients frequently require medical interventions, most commonly continuous positive airway pressure, but in some cases corrective surgery.

The most accurate diagnostic test for OSA is PSG, but it is costly, time consuming, and not readily available. In Turkey, where there are only a few sleep-medicine centers in rural areas, the waiting period for a PSG test is 1–6 months, with a cost of approximately US$400. Therefore, a preliminary

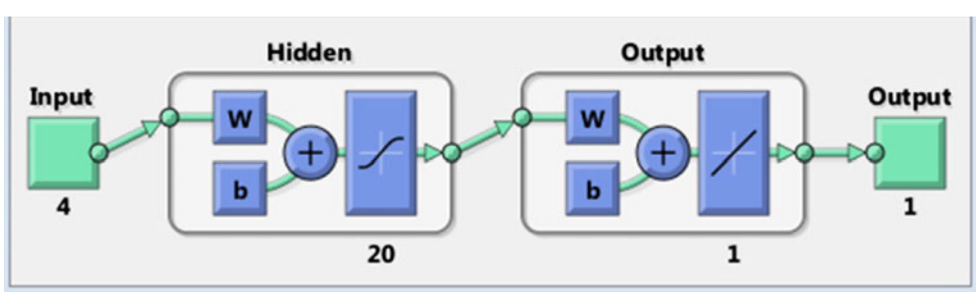

Fig. 1 Feed-forward neural network model

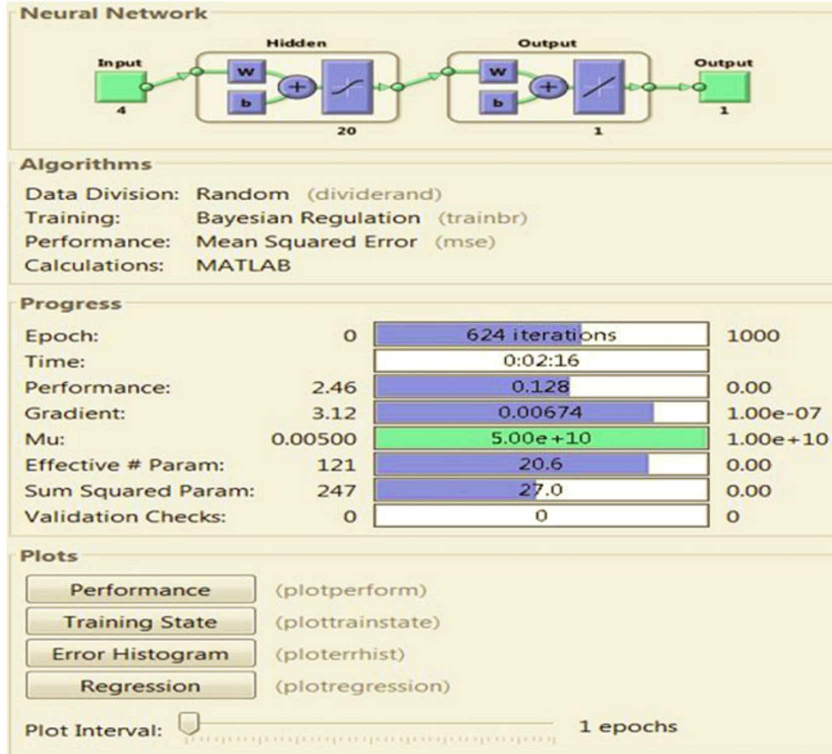

Fig. 2 Simulation of multilayer feed-forward neural network training performance

screening method would be beneficial in terms of time and money.

MLP networks are extensively used as neural classifiers [15]. The input data of these ANN systems are obtained from data mining, allowing the creation of models from existing information. The efficiency of ANNs in problem solving within a large investigative space explains the success of this approach compared to other techniques. This method was applied in our study with the aim of developing an algorithm for the diagnosis of OSA. Specifically, we entered all well-established OSA risk factors as input data. Our experimental results had 80 % accuracy. Moreover, once the data were entered, only a few seconds were needed for the system to recognize patients who were very likely to suffer from OSA. Confirmation of the accuracy of this ANN in further studies would allow its use as a relatively simple clinical filtering tool to discriminate between those patients who would benefit from PSG and those who would not because a diagnosis of OSA is unlikely.

The majority of clinical screening studies have been aimed towards the detection of OSA with a high degree of sensitivity. In the study by Hoffstein and Szalai [2] on 594 patients

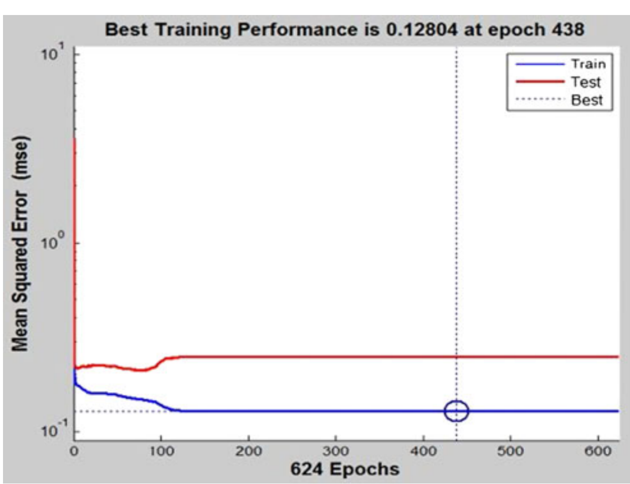

Fig. 3 ANNs mean square error (MSE)

Table 3 Comparison of the values with real results

Real result (1 healthy, 2 OSA)	ANN test (results after round) (y)	Error (e=test target$-y$)
1	1	0
2	2	0
2	2	0
2	1	1
2	2	0
1	1	0
1	1	0
1	2	−1
2	2	0
2	2	0
2	2	0
2	2	0

referred for probable OSA, data on age, sex, BMI, witnessed apneas, and pharyngeal examination, as predictors of OSA, were recorded from the history and physical examination. Nevertheless, the subjective impression of the physician was just as accurate in recognizing 51 % of the patients with OSA and the 71 % of those without OSA (specificity, 65 %; sensitivity, 60 %). Based on these results, the number of requests for PSG studies decreased by one third. Oximetry also has a high sensitivity for the diagnosis of OSA, and in one study reduced the number of PSG studies performed by nearly 25 % [16]. However, as an at-home study, oximetry can be difficult to coordinate and interpret.

In contrast, a neural network such as the one developed in this study allows accurate clinical prediction in the office setting. Our ANN had better sensitivity for the diagnosis of OSA and better specificities than the above-described methods and did not miss cases of significant OSA, suggesting the ability of this approach to reduce the need for PSG. Other studies have also used neural networks in the diagnosis of OSA. Kirby et al. [12] reported the 98.9 % sensitivity and 80 % specificity of a method based on a generalized regression neural network and 23 clinical variables. Using feed-forward neural networks together with clinical and anthropomorphic information to predict OSA, El-Solh et al. [11] achieved a sensitivity of 94.9 % and a specificity of 64.7 %. However, unlike in this study, neither of those groups included a validation stage to determine network architecture.

To the best of our knowledge, this is the first study in which a neural network used data on only four variables, sex, age, BMI, and snoring status, to accurately diagnose OSA. ANNs are a valuable means to simultaneously process data to optimize diagnostic performance in OSA. The most important feature of ANNs as a screening technique is their high sensitivity and low false-negative rate. Thus, our neural network is unlikely to miss severe cases of OSA, even if it does make a diagnostic error.

Optimization of the ANN with respect to the diagnosis of OSA would eliminate the use of PSG in the diagnostic assessment of non-OSA patients. PSG would thus be reserved for patients with a serious sleep-related breathing disorder who are most likely to benefit from this type of study. For example, some patients with suspected OSA may be good candidates for a therapeutic (continuous positive airway pressure trial) rather than a diagnostic PSG study. In centers with long waiting lists for PSG, this would reduce waiting times for analysis and allow earlier therapeutic intervention in patients with confirmed OSA.

Our study had several limitations, including the retrospective nature of the data review and the lack of prospective validation. In addition, the precision of our ANN must be tested using a larger dataset. However, in general, the performance of neural networks improves as the size of the dataset increases. Thus, with a larger population as the training set, the ANN would produce a better model with a higher discrimination capacity. Low-age patients (under 16 years of age), low-BMI patients (under BMI<21), or without snoring OSA patients were not assessed in our study. Of course, this limitation prevented the recognition of younger, low BMI, or without snoring OSA patients. In addition, a bigger even multinational study could be planned for another research population.

Conclusions

The ANN approach based on the patient's sex, age, BMI, and snoring status can be used to accurately diagnose OSA. The neural MLP networks classifier resulted in 86.6 % accuracy in patient classification and thus may contribute to reducing the need for PSG in patients with suspected OSA. This study confirms the good performance of artificial neural networks when applied for the diagnosis of obstructive sleep apnea.

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Conflict of interest The authors declare that they have no conflict of interests regarding the publication of this paper.

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