A Multilayer Perceptron Neural Network–Based Model for Predicting Subjective Health Symptoms in People Living in the Vicinity of Mobile Phone Base Stations

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Abstract

Advances in modern technologies such as telecommunication have widely expanded the applications of wireless systems. Therefore, humans are continuously exposed to electromagnetic fields (EMFs) produced by widely used devices such as mobile and cordless phones and Wi-Fi routers. According to the World Health Organization, electromagnetic hypersensitivity (EHS) is the medical term for a variety of nonspecific symptoms that afflicted subjects attribute to exposure to different sources of EMFs. About 25% of the general population reports different levels of environmental intolerance to factors such as EMFs, and studies performed in Europe show that about 75% of general practitioners had visited patients complaining of EHS. In this paper, multilayer perceptron neural network (MLPNN)–based models are proposed to predict the subjective health symptoms in inhabitants living in the vicinity of mobile phone base stations. The classifier uses several parameters such as demographic data, environmental exposure to a mobile phone station, and the health conditions of an individual as input to estimate subjective health symptoms. Out of 699 data sets recorded from 363 men and 336 women via questionnaire, 70% were used for training, 15% for validation, and the remaining 15% for testing the developed system. The performance of the developed system (sensitivity and specificity) in predicting the subjective health symptoms is as follows: headache (72%, 91%), fatigue (8%, 98%), sleep disturbance (97%, 93%), dizziness (65%, 85%), vertigo (65%, 84%). These promising results suggest that this system might be useful as a means for predicting the health symptoms in people living in the vicinity of mobile phone base stations, which ultimately enhances the quality of life of these individuals through providing appropriate medical care and introducing effective methods for reducing the effect of these exposures. Key Words: Mobile phone base stations—Electromagnetic hypersensitivity (EHS)—Artificial neural network—Radiofrequency.

1. Introduction

The past few decades have witnessed an exponential advance in modern technologies such as telecommunication and the applications of wireless systems. More than ever, now humans are continuously exposed to electromagnetic fields (EMFs) produced by different sources ranging from wireless baby monitors to Wi-Fi routers and mobile and cordless phones. The rapid growth of wireless technology has raised global concerns about how exposure to EMFs may affect human health (Abdel-Rassoul et al., 2007; Berg-Beckhoff et al., 2009; Bortkiewicz et al., 2012; Gomes

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et al., 2011; Hutter et al., 2006; Loughran et al., 2016; Safian et al., 2016; Schoeni et al., 2016; Shen et al., 2016; Son et al., 2016). According to the World Health Organization, electromagnetic hypersensitivity (EHS) is the medical term for a variety of nonspecific symptoms, which afflicted individuals attribute to exposure to EMFs. It has been reported that about 25% of the general population reports different levels of environmental intolerance to factors such as EMFs (Nordin & Nordin, 2016). Furthermore, studies performed in Europe show that about 75% of general practitioners had visited patients complaining of EHS (Slottje et al., 2016). Although the underlying mechanisms are not fully understood, now we know that the health symptoms linked to exposure to EMFs are real and cause functional impairment.

Over the past several years, several studies have been conducted to investigate the health risks of EMFs (Abdel-Rassoul et al., 2007; Ahlbom et al., 2001; Berg-Beckhoff et al., 2009; Bortkiewicz et al., 2012; Brain et al., 2003; Elliott et al., 2013; Feychting & Ahlbom, 1993, 1995; García et al., 2008; Gomes et al., 2011; Habash et al., 2003; Hutter et al., 2006; Johansen, 2004; Maslanyj et al., 2007; Meo et al., 2015; S. M. J. Mortazavi, 2013; S. M. J. Mortazavi et al., 2007, 2012, 2013). At the non-ionizing department of the Ionizing and Non-ionizing Radiation Protection Research Center (INIRPRC) at Shiraz University of Medical Sciences, we also have conducted experiments on the health effects of exposure to different sources of EMFs such as cellular phones (Mortavazi et al., 2009; S. M. J. Mortazavi et al., 2007, 2008, 2012, 2014; S. M. J. Mortazavi, Taeb & Dehghan, 2013; S. M. J. Mortazavi, Mosleh-Shirazi, et al., 2013), mobile base stations (S. A. Mortazavi et al., 2016; S. M. J. Mortazavi, 2013), mobile phone jammers (S.M.J. Mortazavi, Parsanezhad, et al., 2013), and laptop computers (S.M.J Mortazavi et al., 2010). Regarding the challenging issue of EHS, we have previously shown that when the self-reported hypersensitive participants were asked to report their perception about the real and sham exposures, only 25% could discriminate the real exposure/sham exposure phases (this simply could be due to chance). Furthermore, when all these hypersensitive participants were connected to intensive care unit monitors and the alterations in their heart rate, respiration, and blood pressure during real and sham exposure phases were recorded, no statistically significant changes between the means of these parameters were detected in real/sham exposures. At that time (this dates back to 2011), we concluded that psychological factors are possibly involved in EHS (S. M. J. Mortazavi et al., 2011). It is worth noting that this conclusion was flawed due to the limitations we had in our previous studies, and when we obtained sufficient data, we realized that EHS was not linked to psychological issues. Later, we introduced a novel multiphase method for effective screening of the patients diagnosed with EHS (Khademi et al., 2014; S. A. Mortazavi et al., 2014).

Artificial neural networks (ANNs) are gaining a great deal of interest in pattern recognition and data analysis mainly because of their flexibility and ability to adapt complicated problems. In fact, the configuration of ANNs is developed through training by cyclical processing of the training samples. In addition, recent advances in computer and software technology have led to the development of toolboxes and simulator software that make designing and developing an appropriate network relatively simple. In recent years, there has been an explosion of interest in the application of ANNs in health systems, biomedicine, and biomedical engineering. This rapid rise has led to the development of several algorithms for biomedical signal processing (Kamali et al., 2014; Parsaei & Stashuk, 2013, 2011; Parsaei et al., 2009, 2010; Rasheed, 2007; Thompson et al., 1996; Xu et al., 2001), medical image processing (Amiri et al., 2017; Bezdek et al., 1993; Withey & Koles, 2008), clinical decision support systems (Graupe et al., 1988; Güler & Koçer, 2005), and medical data analysis. In this paper, a system based on a multilayer perceptron neural network (MLPNN) is presented for predicting subjective health symptoms in people living near mobile phone base stations. The characteristics of this method, its objectives, and how it was developed and evaluated are presented in detail in this paper.

2. Methodology

The presented method is to predict the subjective health symptoms in individuals living near mobile base stations. More specifically, the main objective was to determine if these individuals may have health symptoms such as headache, fatigue, sleep disturbance, discomfort depression, loss of memory, dizziness, libido decrease, nervousness, and palpitations. As with other pattern recognition systems, the developing process consists of three main steps: data collection, data preprocessing and feature extraction, and classification. Following is a detailed description of these steps.

2.1. Data collection

Data were collected through a questionnaire-based study conducted on 699 individuals (363 men, 336 women) living in the vicinity of cellular phone base stations in Shiraz, Fars, Iran. Trained interviewers interviewed participants selected by a random sampling method at a multistage program. The first step was the selection of some mobile phone base stations out of a few hundred stations existing in Shiraz. For this purpose, we randomly selected

20% of the stations in each district of Shiraz (Shiraz was divided into 11 districts). In the second step, houses located at distances < 1000 m were selected. Then houses were divided into four different categories based on their distance from the nearest station (less than 100 m, 100–300 m, 300–600 m, and 600–1000 m). The rationale for selecting these distances was the findings of our previous study, which revealed that living at a distance < 300 m from a base station can lead to symptoms such as tiredness, headache, sleep disturbance, discomfort, irritability, depression, loss of memory, dizziness, and altered libido. In this study, people living at distances > 600 m were considered as the control group to prevent any selection bias due to potential differences in socioeconomic and lifestyle factors. All participants signed an informed consent form before answering the questionnaires prepared for this study. In total, 363 men (32 ± 13 years) and 336 women (32 ± 12 years) were examined.

2.2. Data preprocessing

In this step, the objective was to find the outliers and remove them from further analysis. This step was completed by finding inconsistent data using a graphical method such as scatterplots and box plots. Inconsistent data were those in which one of the recorded parameters was unacceptable (e.g., daily cellphone use > 24 hr).

Moreover, to reduce the dimensionally of the feature space (number of input parameters), we used sequential forward selection (SFS) technique (Duda et al., 2000). The SFS algorithms are a family of dimension reduction/feature selection methods that are used to select a subset of features that is most relevant to the problem. The SFS algorithms start with an empty set and then add one feature at a time based on the classifier accuracy until either the classifier accuracy is saturated or a feature subset of the desired size is reached. The objective of using the SFS algorithm in this work was to reduce the computational complexity of the system and the generalization error of the system by removing irrelevant features.

2.3. Classification

Classification, by definition, is the process of assigning a label to a new pattern (sample) by using a set of data that their class labels are known (i.e., training data). An algorithm that implements classification is known as a classifier. In this work, ANN-based systems have been used to predict the health status of a subject living in the vicinity of a mobile base station. Specifically, the objective was to determine if these subjects may have health symptoms such as headache, fatigue, sleep disturbance, discomfort depression, loss of memory, dizziness, libido decrease, nervousness, and palpitations.

In this work, we used an MLPNN for classification purposes. An MLPNN is a feed-forward multilayer network architecture composed of several layers of neurons, an input layer, an output layer, and several hidden layers (Haykin, 2008). For most problems, a network with one hidden layer is used, as it is shown that such a three-layer neural network can resolve complicated pattern recognition problems. An example of a three-layer neural network is shown in Fig. 1.

Designing an MLPNN-based classifier includes two main steps: (a) determining architecture and its parameters (number of layers and number of neurons in each layer) and (b) training the network. The MLPNN used in this work consists of three layers: an input layer, a hidden layer, and an output layer. The input layer consists of 11 neurons, which are equal to the number of features (parameters) used to represent living status of the subject under study. Specifically, the developed MLPNN model consists of 11 input nodes corresponding to sex, age, daily mobile phone usage (min), mobile phone usage (month), cordless phone use (month), distance from mobile base station antennae (meter), duration of exposure to the antenna (hour), duration of residence in the present house (month), daily use of video display units (VDU) (min), living in the vicinity of a power line (yes/no), using other wireless devices (yes/no).

The output was the health status of the individuals. In this work, we used one-versus-the-other strategy in designing the classifier. Therefore, the MLPNN consisted of only one node. In total, five MLPNNs were designed so that each one predicted one symptom.

The number of neurons in the hidden layer was determined experimentally using cross-validation; by setting different values for the number of neurons in the hidden layer (1–20), the network with the highest accuracy was chosen as the best system. Based on the obtained results, a hidden layer containing 10 neurons each including a sigmoid activation function provided the minimum testing error. For the output layer, two neurons were used. Training an MLPNN means estimating the value of the weights of the network using a learning algorithm such that the total error between the values estimated by the trained network and target value is minimized. Here, we used back propagation algorithm (Haykin, 2011), a widely used training algorithm, for this purpose. MATLAB software was used for all computations.

3. Results and Discussion

Considering the studied symptoms which served as the gold standard (ground truth), the performance of the developed MLPNN-based health condition prediction system was evaluated in terms of correctly predicting the type of symptom. Three performance indices

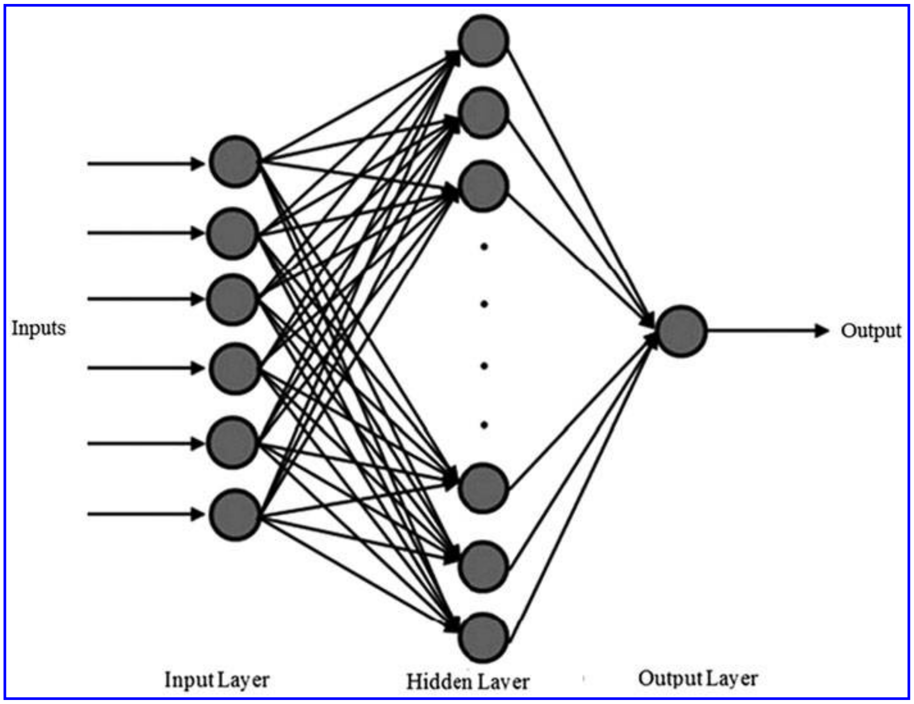

Fig. 1. A three-layer perceptron neural network (Haykin, 2011).

were used for this purpose: sensitivity, specificity, and accuracy. These three indices are given by

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

where the parameters *TP, TN, FP,* and *FN* are defined as follows.

TP = Number of subjects that correctly identified with symptom.
TN = Number of subjects that correctly identified with no symptom.
FP = Number of no-symptom individuals that incorrectly identified with symptom.
FN = Number of individuals with symptom that incorrectly identified with no symptom.

The classification performances of the developed system are summarized in Table 1. In estimating the performance of the developed MLPNN, out of 699 data sets recorded from 363 men and 336 women via questionnaire, 70% were used for training, 15% for validation, and the remaining 15% for testing. In this table, the performance indices only for testing data were reported.

As shown in Table 1, for most symptoms, the developed system could predict the subjective health symptoms with acceptable performance. However, the system was unable to predict fatigue status well. This may be due to many factors including this point that fatigue can be caused by factors other than exposure to EMFs.

For all the cases, the specificity of the system was higher than its sensitivity in predicting the subjective health symptoms. There are several reasons for this outcome. One possible reason is that the individuals with "no symptom" may answer the questions more correctly than the other subjects. In other words, the data for the no-symptom class are less noisy than for the other class. The second reason is that the number of patterns in the "no symptom" class is higher than that of the other class, which causes the MLPNN to adapt to this class and learn the patterns related to this group better than the other classes.

In terms of designing the system, as mentioned above we used one-versus-the-other strategy in designing the classifier, in which for predicting each of the discussed five symptoms (headache, sleep disturbance, dizziness, vertigo, fatigue) a single MLPNN was designed. For this five-class classification problem, a single MLPNN with 11 input nodes and 5 output nodes can be used to design the desired system. However, preliminary results showed that performance of this system is low and is not acceptable. In other words, we realized that a single model did not work in predicting all the studied symptoms. Hence, we used a separate model for each symptom.

The effect of the studied variables on each symptom considered in this work was different. Based on the results obtained by using SFS technique (discussed in subsection 2.2), the most effective variable for headache symptom is "daily mobile phone usage." There is an interaction between this variable and the two variables "duration of exposure to the antenna" and "mobile phone usage (month)." These

Table 1. Performance of the Developed MLPNN-Based System in Predicting Subjective Health Symptoms for People Living Near Mobile Phone Base Stations

SYMPTOM	SENSITIVITY (%)	SPECIFICITY (%)	ACCURACY (%)
Headache	71.8	90.9	83.8
Sleep disturbance	82.1	83.3	82.9
Dizziness	65.2	85.4	81.0
Vertigo	65.0	84.7	81.0
Fatigue	8.3	98.9	88.6

results suggest that people who "overuse" their cell phones preferably should not live near a base station. For the sleep disturbance symptom, the three most effective features were "daily mobile phone usage," "duration of exposure to the antenna," and "cordless phone use." As we can see again, overusing cell phones and cordless phones along with living near base stations may cause a sleep disturbance symptom. The same results are obtained for the dizziness symptom. For the last studied symptom, the most important parameters were "sex" and "duration of exposure to the antenna (hours/day)."

The present study was prospective and not randomized; the objective was to assess the role of MLPNN-based models in predicting the health risks of exposure to EMF sources for an individual. We used relatively simple variables as inputs. Therefore, when the model is developed (i.e., the MLPNN is trained), similar variables would be needed to provide the required information (prediction). In terms of application, this model may help physicians and scientists reduce the health risks of EMFs via predicting the subjective health symptoms for people currently living or who would like to move to houses in the vicinity of mobile phone base stations. In other words, this MLPNN-based system can be used to investigate if a person has EHS or not and ultimately can help us predict the health risks of living in the vicinity of mobile base stations. In terms of using this model, it is easy and straightforward because many software products, such as MATLAB and R, have a neural network toolbox. Therefore, users interested in using the models presented in this work can collect their data, use the parameters discussed in this paper, and put them in the toolbox.

4. Conclusions

Accurate prediction of the risk of subjective health symptoms in inhabitants living in the vicinity of mobile phone base stations can enhance the quality of their life through providing appropriate health care and suggesting effective methods for reducing the severity of these symptoms. In this paper, we proposed an MLPNN-based model for predicting the risk of several symptoms such as headache, fatigue, sleep disturbance, discomfort depression, loss of memory, dizziness, libido decrease, nervousness, and palpitations. Evaluation of the data collected in this survey that was conducted on 699 people living in the vicinity of cellular phone base stations, in Shiraz, Fars, Iran, reveals that the developed system can successfully predict the risk of subjective health symptoms (for most symptoms) with sensitivities $>65\%$ and specificities $>83\%$. We hope that the robustness and accuracy of the developed system will help scientists promote the applications of an MLPNN and pattern recognition techniques in improving the health of individuals living in the vicinity of mobile phone base stations.

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