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Original

Risk Factors of Low Back Pain Using Adaptive Neuro-Fuzzy

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Abstract

Background: Musculoskeletal disorders are one of the most common factors that lead to occupational injuries among hospital staff. Considering the key role of hospital staffs in providing health services to patients, this study was conducted to assess risk factors that are effective on low back pain and the use of adaptive neuro-fuzzy inference system (ANFIS) model to predict it. **Methods:** This cross-sectional study was conducted in 90 nurses of the Isfahan hospitals in 2018. First, the risk factors that affect pain in the lumbar region was assessed, then a model with the precision of 0.91% to predict low back pain was developed using the ANFIS by the MATLAB2016a software. **Results:** First, linear regression model showed four risk factors repetitive movements, long-standing, bending of the back, and carrying heavy objects were the most significant ones compared to other risk factors associated with musculoskeletal disorders. After a study of these risk factors in the ANFIS, various tests were conducted and the best model with a confidence level of 91% was selected as the model. **Conclusion:** The ANFIS can be used as an appropriate tool to predict lower back pain.

Keyword: Musculoskeletal disorders; Nursing; Neuro-fuzzy system; Low back pain; Prediction

Introduction

Literature Review

Nurses play an important role in any health institution and include the largest workforce in each health care institution. These people act as direct caregivers who go to the hospital 24 hours a day and seven days a week.[1] Considering that nurses spend a significant part of their life in a work environment under different conditions, they are more exposed to occupational problems and this has a profound effect on the health and quality of nursing care provided.[2] Nurses are affected by many factors that can affect their job well-being. Nurses are involved with several problems, such as musculoskeletal disorders, digestive problems, fatigue, and stress.[3]

Work-related musculoskeletal disorders (WMSDs) are considered as one of the most important occupational problems in nurses.[4,5] Musculoskeletal disorders among health care workers are a common concern, with nurses' populations representing about 33% of the population of the hospital staff at high risk.[6] During daily work, nurses do a lot of physical activity, including displacing and lifting patients and bending forward repeatedly.[7] Musculoskeletal disorders have been reported to have a profound impact on the quality of life, resulting in loss of working time or absenteeism and increased work restrictions.[6] The most problems of

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musculoskeletal disorders in nurses were related to the lower back followed by pain in the neck, shoulder, and knee. In studies, the prevalence of musculoskeletal disorders in nursing has been reported to be between 70% and 90%.[7] It is very important that we reduce the complaints of nurses due to physical problems, and symptoms in the lumbar region can lead to symptoms in other parts of the body.[8]

The idea of combining fuzzy logic and the neural network for modeling was first used by Athanassopoulos and Curram for classification and prediction.[9,10] The ability of fuzzy systems is also confirmed in solving complex problems of modeling and prediction, control and artificial intelligence.[11-13] But due to the complementary (rather than competitive) capabilities of the two solutions, they can be combined to use their advantages simultaneously. Development of neuro-fuzzy systems is a procedure that two methods are combined to use learning and parallel processing of artificial neural networks and fuzzy, and it is a smart system that in dealing with a system, without having the governing differential equations and by using the least possible features (e.g., approximate descriptive and linguistic descriptions, or certain values of a variable) is able to equip, analyze, and the compatibility of that problem, help us face with changing systems. Regarding the key role of hospitals staff in providing health services to patients, this study was conducted to evaluate the risk factors affecting lower back pain and using a high-performance model called ANFIS to predict pain in the lower back of the nurses.

Structure and algorithm

ANFIS is a multilayer feeder network that uses nerve network learning algorithms and fuzzy logic to draw an input space into an output space. ANFIS, with the ability to combine a fuzzy system's verbal power with a comparative network's nervous system, has been shown to be very powerful in modeling numerical tasks, including river flow prediction.[14,15] In order to simplify, it is assumed that the inductive system of interest has two inputs x and y and one z output. For a Takagi-Sugeno model, first, one can set a set of sample rules with two if-then fuzzy expressions as follows:

Rule 1: If x is equal to A1 and y is B1, then z1 = p1x + q1y + r1

Rule 2: If x is equal to A2 and y is equal to B2, then z2 = p2x + q2y + r2

Where pi, qi, and ri (i = 1,2) are linear parameters in the consecutive section of first-order Takagi-Sugeno models. The ANFIS structure consists of 5 layers. Figure 1 and a summary of the model are shown below.

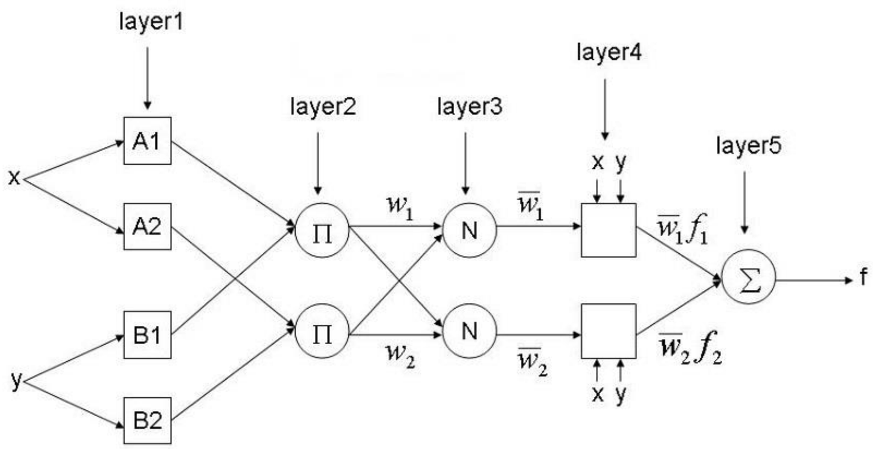

Figure 1. An example of the structure of the ANFIS model

$$R^2 = \left(\frac{\sum(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum(O_i - \bar{O})^2 \times \sum(S_i - \bar{S})^2}}\right)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|S_i - O_i| \quad (3)$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{S}| + |O_i - \bar{O}|)^2} \quad (4)$$

$$MSE = \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{n} \quad (5)$$

$$NMSE = \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (6)$$

ANFIS's distinctive feature is providing an associative learning algorithm, gradient method and least squares method to modify the parameters. The gradient method is used to set up the nonlinear preliminary parameters (ai, bi, ci), while the least squares method is used to determine the linear parameters of the consecutive section. As shown in Fig. 1, circular nodes are fixed (not adaptive) nodes without variable parameters, and square nodes have variable parameters (parameters change over the course of the experiment). In order to evaluate the model, R2, RMSE, mean absolute error (MAE), mean squared error (MSE), normalized mean standard error (NMSE) and Willmott's index of agreement (d) are used, shown in relations (1-6)

In the above relations, Si is the computational data of the inductive neuro-fuzzy system, S is the mean of computational data, Oi is the observational data, Δ is the mean value of observational data and n is the number of observations. The variation range of the Wilmont index of the agreement is from ∞ 1, where the value of 1 shows the complete agreement between observational and computational data. The low RMSE and the high R2 coefficient indicate the model's acceptable accuracy and superiority to the other model. MAE, MSE, and NMSE each show a discrepancy between observational and computational data, the lower the amount, the more resultant work.

Methods

This descriptive-analytic study was performed on 90 nurses working in Isfahan hospitals in 1397. Before distributing the questionnaire between individuals while observing the ethical principles adopted by the Medical Ethics Committee of the university, general explanations of the research objectives, how to fill out the questionnaire and the confidentiality of the information were given to all individuals. Reliability and validity of the questionnaire have been approved by other researchers. In this study, the Cornell Musculoskeletal Discomfort Questionnaires (CMDQ) was used for pain scoring in different areas. To fill out the questionnaire easily, a 10-point Likert Scale was used.

Finally, to perform statistical analyses, it was changed to the baseline, also the postures adopted by the staff were also observed and recorded. A questionnaire including demographic data and information on the posture and severity of pain in different areas of the body were used to collect information. The demographic section included questions regarding age, gender, height, weight, working hours and resting hours per day, hours of exercise per week, and smoking. In the second part, the questionnaire was used to examine the predominant posture adopted by the nurses. Examples of postures include: carrying heavy objects, back bending and curvature, repeated movements, hands extension, long sitting or standing, and neck posture. Another part of the questionnaire addressed pain in various areas of the body.

All questions in this questionnaire were rated on a 3-point scale which was converted to 10-point to achieve convenience, finally returned to the baseline state to perform statistical analysis. In this questionnaire, the demographic information of people, including age, gender and working hours, was also addressed. The data obtained from this questionnaire were collected by the SPSS for the correlation between variables through a linear regression test. Also, in order to prevent the influence of the age parameter on the results of the study, the effort was made to select people with approximately the same age.

After the linear regression test, the risk factors associated with pain in the lower back region were selected and investigated as the input of the neuro-fuzzy system. In the neuro-fuzzy system, the default parameters that define membership function were determined using the gradient method and the resulting parameters were determined using the least squares method. Input data were studied and tested based on the parameters of interest, and then used to predict pain in the lower back region. After training and testing, the error reached a stable state and the predicted values were recorded using MATLAB 2016a software, and compared with experimental values. In order to evaluate the models, R2, Root Mean Square Mean Error (RMSE), Mea Total Error (MAE), Mean Standard Error Square (MSE), Mean Standard Normalized Error Mean (NMSE) and Willmott's index of agreement (d) have been used. The low RMSE value and the high R2 coefficient indicate the acceptable accuracy of the model and its superiority to the other model.[16] MAE, MSE, and NMSE differently show a discrepancy between observational and computational data, with the lower the amount, the more fruitful the work.

Results

A total of 90 nurses participated in this study, with an average age of men and women were 33.3 (2.3) and 35.98 (3.5), respectively. Table 1 summarizes the supplementary information of the subjects studied.

Regarding the primary analysis performed by regression test, it was found that 4 parameters repeated movements, long-standing, bending of the back and carrying and displacement of the load were the most significant factors associated with pain in the low back than other risk factors associated with musculoskeletal disorders Table 2.

Table 1. Participant's individual characteristics

Individual characteristics		Number (percentage)
Gender	Male	35 (38/80)
	Female	55 (61/20)
Working hours per day	Less than or equal to 8 h	43(47/80)
	Over 8 h	47 (52/20)
Resting hours per day	Less than or equal to 8 h	(93/30) 84
	Over 8 h	6 (6/70)
Exercise hours per week	Less than 3 h	74 (82/20)
	3 h and over	16 (17/80)

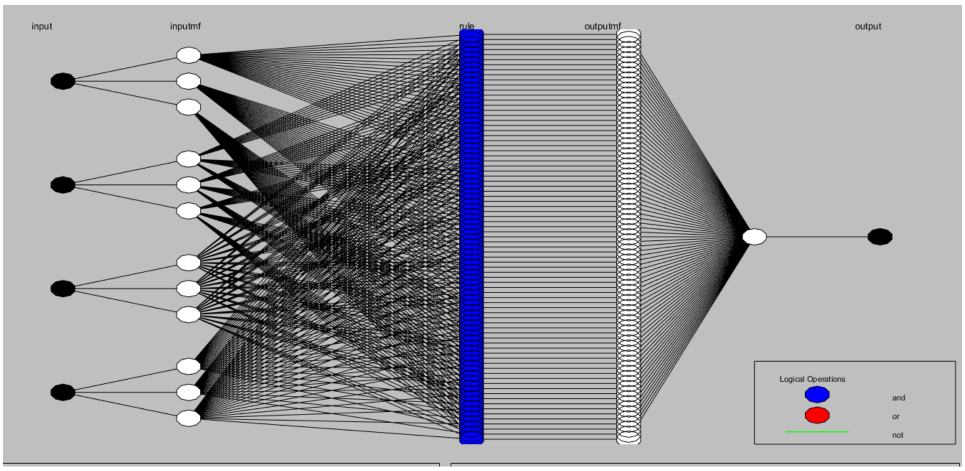

Figure 2. The structure of the ANFIS model used in this study

Table 2. The results of the linear regression test between posterior posture and pain in the lower back region

Posture	*P*- value
Repeated movements	0.03
Long-standing	0.03
Hands extension	0.07
Load carrying and displacement	0.02
Back rotation	0.06
Neck posture	0.74
Back bending	0.00

Table 3. Different structures of input into the ANFIS

Model	Model input	(R^2)
ANFIS	$A_{(1)}, A_{(2)}, A_{(3)}, A_{(4)}$	0.9117

Table 4. Statistical Parameters of the accuracy of the ANFIS model in predicting pain in the lower extremity

RMSE	MAE	d	MSE	NMSE	R2	Model
0.9257	0.40	0.9762	0.8568	0.0884	0.9117	1

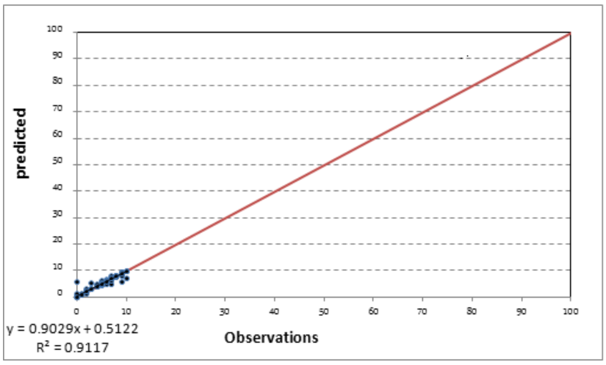

Figure 3. Distribution of observational data and predicted data

Also, the structure of the ANFIS model used in this study is shown in Figure 2 to examine the effect of the mentioned factors on pain in the lower back region.

In Table 3, different input structures include significant variables that include repeated movements, long-standing, bending of the back, and carrying and displacing loads, and are shown as inputs to the ANFIS model.

A1 :Repeated movements

A2: Long-standing

A3 :Back bending

A4 :Load carrying and displacement

The results of various input structures into the ANFIS model have been evaluated by statistical parameters in Table 4. These parameters include R2, RMSE, MAE, MSE, NMSE and Willmott's index of agreement (d).

Drawing the figure for distribution of observational data against the predicted data is very important in order to make a better comparison of the modeling. Fig. 4 shows the distribution pattern of observational data and predicted data for the entire data using the neuro-fuzzy model. In these Figures, the fitted regression line is shown between the data with the solid line and the equation for the regression line is also shown in each of the graphs.

Discussion and conclusion

The created neuro-fuzzy model indicates that it is important to predict pain in the lower back as a valid and appropriate approach to predicting and preventing musculoskeletal disorders. In addition, in interpreting this model and the obtained algorithm, it can be argued that based on this analytical model, by having scores related to repeated movements, long-standing, bending of the back and carrying and displacing the load, lower back pain can be predicted in the staff of hospitals and health centers. Nurses have a lot of physical activity, including displacing and lifting patients, frequent bending forward and long-standing during the work shifts.

Musculoskeletal disorders have been reported to have a profound impact on the quality of life, as well as signs in the lumbar region can lead to symptoms in other parts of the body, so reducing symptoms and physical problems is a very important issue in this regard. Regarding the key role of hospitals staff in providing health services to patients, this study was conducted to evaluate the risk factors affecting lower back pain and using a highly innovative model, namely, ANFIS, to predict pain in the lower back region among the nurses.

First, a study of the association between all recorded postures and pain in the lower back region was performed by linear regression test. Among these parameters, four posture repeated movements, long-standing, bending of the back, and carrying and displacing loads were the most significant factors compared to other risk factors are related to musculoskeletal disorders, so these four parameters were selected as inputs of the model and analyzed by the neuro-fuzzy system. In this study, different models were tested in order to achieve an appropriate level of reliability and low error rate, and the best model with the highest confidence level (0.91) and the lowest error rate (0.9257) was selected.

The results show that the prediction model has a confidence level of 0.91 which has a relatively high accuracy, which can be used to predict pain in the lower back region. In a study using the neuro-fuzzy system for pain relief in the back region, it was shown that this system can be used with high accuracy and reliability .[17] In a study (2013), it was observed that the use of the neuro-fuzzy system could be used to better understand the pain in the lower lumbar region with high precision.[18] In another study, in order to compare two neural network systems and a neuro-fuzzy system to predict pain in the lumbar region, it was found that the use of the neuro-fuzzy combination system has a higher precision in predicting the back pain in the lumbar region.[19] In the study of ADEYEMI, a fuzzy logic system was used to predict and reduce pain in the lower back region, in which three parameters were investigated and it was observed that the model has high accuracy in prediction.[20]

In a search in literature, the ANFIS was found to be used to predict and model in different fields, including prediction and diagnosis of cardiovascular disease, diabetes, multiple sclerosis, kidney disease, and diagnosis.[21-24] Various models, including regression model, have been used for predicting lower back pain and musculoskeletal disorders. In this study, for the first time, the pain in the lower back region was examined and predicted by the ANFIS. And it was found that using the four parameters examined, this model can have high efficacy in predicting pain in the lower lumbar region.

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