Prediction Effects of Personal, Psychosocial, and Occupational Risk Factors on Low Back Pain Severity Using Artificial Neural Networks Approach in Industrial Workers

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Abstract

Objectives: This study aimed to provide an empirical model of predicting low back pain (LBP) by considering the occupational, personal, and psychological risk factor interactions in workers population employed in industrial units using an artificial neural networks approach.

Methods: A total of 92 workers with LBP as the case group and 68 healthy workers as a control group were selected in various industrial units with similar occupational conditions. The demographic information and personal, occupational, and psychosocial factors of the participants were collected via interview, related questionnaires, consultation with occupational medicine, and also the Rapid Entire Body Assessment worksheet and National Aeronautics and Space Administration Task Load Index software. Then, 16 risk factors for LBP were used as input variables to develop the prediction model. Networks with various multilayered structures were developed using MATLAB.

Results: The developed neural networks with 1 hidden layer and 26 neurons had the least error of classification in both training and testing phases. The mean of classification accuracy of the developed neural networks for the testing and training phase data were about 88% and 96%, respectively. In addition, the mean of classification accuracy of both training and testing data was 92%, indicating much better results compared with other methods.

Conclusion: It appears that the prediction model using the neural network approach is more accurate compared with other applied methods. Because occupational LBP is usually untreatable, the results of prediction may be suitable for developing preventive strategies and corrective interventions. (J Manipulative Physiol Ther 2017;xx:1-8)

Key Indexing Terms: *Prediction; Risk Factors; Low Back Pain; Artificial Neural Networks Approach; Workers*

Introduction

The musculoskeletal disorders are defined as injuries and complications in muscles, nerves, tendons, ligaments, joints, cartilage, and the spinal column.[1] Occupational low back pain is the most prevalent work-related musculoskeletal disorder and has been considered a significant health problem in recent years.[2] Absence from work, treatment costs and the related medical compensation, and considerable socioeconomic effects are the most important and problematic consequences of LBP today.[2,3] Total compensation costs have been estimated at US$100 billion per year. About US$20 billion have been devoted to the musculoskeletal disorders, and a major part has been spent on LBP. It is also known that 5% of worker absenteeism of at least a day per year is due to LBP.[3,4] It is generally believed that occupational LBP is caused by factors related to work.[5] However, it has been noted that LBP reporting has not decreased, despite significant changes and corrective intervention in occupational design (eg, reducing heavy tasks and manual material handling).[6] Therefore, previous studies identified 3 risk factor categories for LBP: personal characteristics (eg, age, gender, etc), occupational factors and workplace parameters (eg, force, working posture, noise, vibration, etc), and psychosocial factors (eg, overtime, stress, etc).[7] Research on each of these risk factors has identified degrees of correlation with LBP.[8] This correlation is most

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likely multidimensional, complex, and interactive. Many of the identified risk factors across categories are not mutually exclusive. Consequently, the study of the risk factors' interaction in the incidence of LBP is obviously essential.[9-11] Further, regression methods, fuzzy approaches, and even the neural network have been used predict LBP.[12] Furthermore, Marras et al.[13] have designed a conceptual model for interaction among of various risk factors of LBP. In spite of the extensive use of the aforementioned techniques in prediction of LBP, previous studies have not simultaneously investigated all 3 broad categories of risk factors.[13] For example, Sari investigated only occupational factors,[14] and other researchers have studied just 1 of these 3 factors alone.[9-11] Moreover, the studies that have investigated nearly all risk factors have used the classical approaches for prediction.[15-17] Hence, one of the most important issues is assigning more accurate and more powerful models that are able to predict the complex relationships among different risk factors. These models can combine a large number of risk factors, and therefore a more realistic prediction could be made of LBP. The artificial neural networks (ANNs) are widely used in basic sciences, medicine, and engineering as an alternative statistical method to predict complicated phenomena.[18,19] Presently this method has been recognized as an innovative and accurate method for modeling in various sciences. The ANN, as one of the most important artificial intelligence techniques, can be called an electronic model of the human brain. It has the intrinsic capability to store and apply empirical data.[20] Its known features are the ability to determine the complex relations among different variables and the capacity of using multiple learning algorithms. Actually, ANNs are powerful methods for fitting a mathematical model into a pattern for a set of observed data and can be used for classification and estimation problems. They can be used in problems where analyses based on discriminant analysis or logistic regression are standard statistical techniques and are capable of learning complex, nonlinear correlations between inputs and outputs.[20] The structure of ANNs is similar to the structure of biological neural networks in the brain and is trained for a specific processing task by applying large amounts of data. ANNs modify their structure by changing the weights between neurons (processing units) to improve their performance on the training data. After training, the neural network can extrapolate to provide solutions to novel input patterns, provided the training data were adequate.[21] In recent years, successful applications of ANN to medical outcomes, especially for LBP, have been reported in many studies. Nonetheless, a few studies have applied them to predict of occupational diseases such as LBP considering all 3 broad categories of risk factors simultaneously. Therefore, this study aimed to present an artificial neural network model, considering the interactive effects of personal, occupational, and psychosocial factors, for prediction of LBP in industrial workers.

Methods

Study Design and Participants

This study was a case-control study that was carried out in different factories located in the west of Iran. Data were collected in September 2015. A total of 160 (114 men, 46 women) participants were employed voluntarily as the study population. A total of 92 participants who were patients, already suffering from LBP as a result of their work, were selected as the case group. In the case group, eligibility criteria were age older than 18 years, participation in manual labor (such as lifting, lowering, pushing, and pulling), prolonged sitting/standing during work, and suffering from LBP. Eligibility also required that occupational medicine confirm LBP of case group participants. Also, 68 participants who did not have LBP were selected as the control group. In the control group, eligibility criteria were age older than 18 years, participation in manual labor (such as lifting, lowering, pushing, and pulling), prolonged sitting/standing during work, and not suffering LBP. All participants were selected from among workers in different parts of heavy industries, including maintenance, blast furnaces, and manual material handling parts of the steelmaking and rubber production factory. The participants signed an informed written consent before participation. This study was approved by the scientific and ethical review committees of the Kurdistan University of Medical Sciences Institutional Review Board.

Description of Model Variables

To process and select the final variables of the model for LBP prediction, the following sequence of steps was performed. A questionnaire was completed mainly by interview and study of workers' periodic medical examinations records to obtain personal and demographic information, identify the occupational risk factors (including application of force, working posture, work duration, repeated task, vibration, etc) and know the pattern of behaviors, including smoking, alcoholism, exercise, and social relations. Also, a questionnaire was used to identify psychosocial risk factors, including job satisfaction, job security, and social relations. A job stress questionnaire from the National Institute of Mental Health was used to assess job stress.[22] The subjective mental workload (SMWL) at work was assessed using a National Aeronautics and Space Administration Task Load Index (NASA-TLX).[23] The Rapid Entire Body Assessment worksheet also was used to identify and assess the occupational risk factors, including force, posture, repetition, and vibration exposures at work. Three general risk factor categories for LBP—personal, psychosocial and occupational—are presented in Table 1.

Body mass index generally was denoted in 3 categories: ideal, overweight, and obese. Family history of LBP, smoking and alcohol consumption, lob satisfaction, and job security were denoted with a "yes" or a "no." Social

Table 1. *Potential Risk Factors for LBP*

Classification	Risk Factors					
Personal	Age	Gender BMI	Smoking	Family history	Alcohol	Physical activity
Psychosocial	Job stress	Job satisfaction	Job security		Social relations	SMWL
Occupational	Force	Repetition	Vibration	Posture (bending, twisting and lifting)	Career length	

BMI, body mass index; *LBP,* low back pain; *SMWL,* subjective mental workload.

relations were defined in 3 levels (low, moderate, and good). Repetition and exposure to vibration at work were converted into "yes" or "no" categories indicating presence or absence. Force was scored based on the weight of the load lifted (low and high). Scores of SMWL were determined by NASA-TLX software in 6 dimensions and scores ranged from 1 to 100. Posture was converted to "close to neutral" and "non-neutral" categories. The dependent variable in this study was LBP. LBP is a nominal variable. This variable was assigned a binary code (0 for persons without LBP and 1 for persons with LBP). Finally, 16 features—age, gender, body mass index, smoking status, alcohol status, family history, family history, SMWL, job stress, job satisfaction, job security, social relations, force, repetition, posture, and career length—were identified as the input variables to develop the prediction model.

Structure of Neural Network Model

The neural networks as a data-based procedure without considering the assumptions in model-oriented methods are innovative methods for classifying complex categories. In this study a neural network was developed to classify the present data into 2 classes of "healthy individuals" and "individuals with LBP." Multilayer Perceptron, Hopfield Network, and Kohonen are 3 types of neural network structures.[24] The intrastructure relations are of the progressive type and the type of training is back propagation with supervisor.[20] Training on the basis of "learning by supervisor with back propagation algorithm" is the dominant method in training models. The optimal selection of various parameters like network size, rate of learning, number of learning periods, and acceptable error occurs in this phase.[25] In method of "learning by supervisor" a set of data pairs called learning data are given to the learning algorithm and then the learning error is calculated. This error is subsequently used to adjust the network parameters (weights) so that if the same data input is given to the network in the next phase, the network output approaches the goal output.[26] The number of training cycles of the network required for appropriate generalization is determined on the basis of trial and error. The real output depends on the specific activating function that is selected, and it should meet the intended criteria of the problem for which the neuron has been used. Among the various activating functions, the sigmoid function is usually used, which is defined according to Equation 1.[20]

$$F(z) = \frac{1}{1 + e^{-\mu z}} \in (0, 1) \quad for \quad \mu > 0 \tag{1}$$

The main reason for using this function is that it is linear, ascending, and differentiable, and it can also be displayed in the closed form. It is easy to be differentiated and compresses the input range of $-\infty$to $+\infty$ into the [0, 1] output. The number of neurons of the input layers is determined by the problem description considered, and the number of neurons of the output layer is 1. For most problems, the use of 1 to 4 latent layers for the middle layers would suffice. There is also no scientific method for estimating the number of neurons in the hidden layers. To determine the number of neurons in each layer here, all possible states from 1 to 4 hidden layers have been tested. The number of neurons in each hidden layer is determined to be 1 to 2 times greater than the tested input variables and the optimized number. To do so, a neural network with 1 to 4 hidden layers and 1 to 30 neurons each with 10 performances were tested. Moreover, 80% of the data was randomly selected for training and 20% for testing. The neural network with a hidden layer and 26 neurons had the least classification error in both training and testing phases.[26,27] The results are presented in Figures 1 and 2. To obtain the classification error, Equation (2) was used.

$$\begin{aligned} &Classification\ \ Error \\ &= Number\ \ of\ \ Misclassified\ \ Data / Total\ \ Number\ \ of\ \ Data \end{aligned} \tag{2}$$

To assess the performance of neural networks, the classification accuracy standard is used. To obtain the classification accuracy, Equation (3) was used.

$$\begin{aligned} &Accuracy \\ &= Number\ \ of\ \ Correctly \\ &\quad Classified\ \ Data / Total\ \ Number\ \ of\ \ Data \end{aligned} \tag{3}$$

In this study, 80% of the data was randomly used for training the network and 20% for testing the network. Training the network continued until a certain number of training cycles, or epochs, were completed (1000 episodes) or until the time when changes in prediction errors of the network either became stable over a specific period or

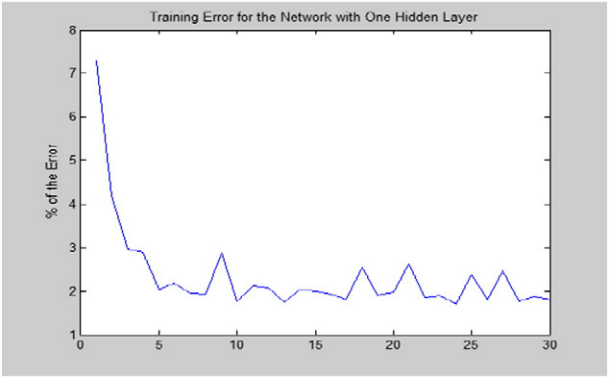


Fig 1. *Classification error chart of training phase for a network with 1 hidden layer and the number of 1 to 30 neurons.*

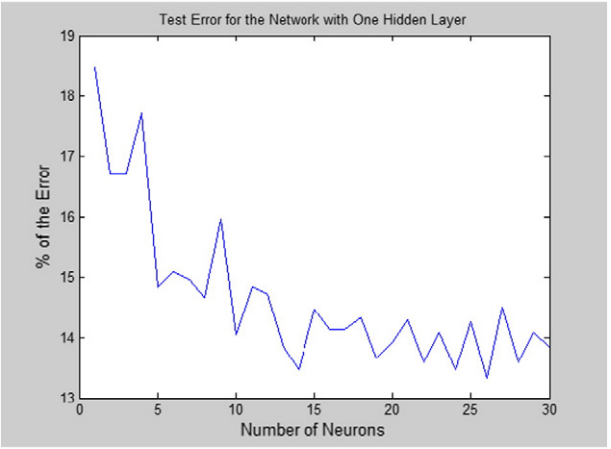


Fig 2. *Classification error chart of testing phase for a network with 1 hidden layer and the number of 1 to 30 neurons.*

reduced to the least acceptable limit. The learning algorithm of the neural network randomly determines the primary values of the weights first. Then it estimates the sum of the values of connection weights leading to the least error using gradient descent. Next, the network characteristics are selected. Their properties are given in Table 4 and Figure 3.

Bias

To address potential sources of bias, the participants (both the case and control group) were selected from among individuals who had exposure to each of the 3 broad categories of risk factors simultaneously. Also, identification of the case group (with LBP) and the control group (healthy subjects) was confirmed by occupational medicine practitioners. Furthermore, job conditions, psychosocial, and personal characteristics of the participants were investigated 2 months before the beginning of the study. Then the required instructions regarding the method and processes of the study and the method of completing the questionnaires and using the NASA-TLX software were given to participants.

Quantitative Variables

In this study, 4 features as quantitative variables, age, career length, job stress, and subjective mental workload were determined for development of the prediction model. Age and career length were analyzed based on year. Job stress was calculated based on the average scores on the questionnaire. Subjective mental workload was analyzed based on 6 subscales, including mental demand, physical demand, temporal demand, and effort, performance, and frustration level using NASA-TLX software.

Statistical Methods

The data collected, including all 3 broad categories of risk factors for LBP along with demographic information, were analyzed with SPSS Version 19 (IBM Corp., Armonk, NY) using logistic regression and the k-nearest neighbor (k-NN) algorithm, which is one of the simplest methods for classification and prediction.

Results

Participants and Descriptive Data

Descriptive statistics of the considered variables of the participants for developing the prediction model are shown in Tables 2 and 3.

The descriptive results indicated that the mean of age and work experience of the workers participating in this study were almost at the same level and there was no significant difference in these variables. Also, the results indicated that job stress and the result of the 6 subscales of SMWL were higher in the participants who were patients. The data that resulted from assessment of the 6 subscales of SMWL using NASA-TLX software indicated that the participants had determined the Effort scale as the highest and Performance and Efficiency scales as the lowest scores among the 6 subscales of SMWL.

The descriptive results of qualitative variables indicated that 56% of male workers, 60% of female workers, 66% of workers who smoked, and 74% of workers who drank had low back pain. Generally, Tables 3 and 4 indicate the percentage of participants who suffered from low back pain based on the studied variables.

Results of Neural Network Performance for Classification of Low Back Pain Data

In this study, 837 930 neural networks with different numbers of layers (ranging from 1-4 layers) and different numbers of neurons (ranging from 1-30 neurons) were run in MATLAB software. Then neural networks were assessed with the test data. The best neural network was selected from among the networks with 1 to 4 layers (Fig 3).

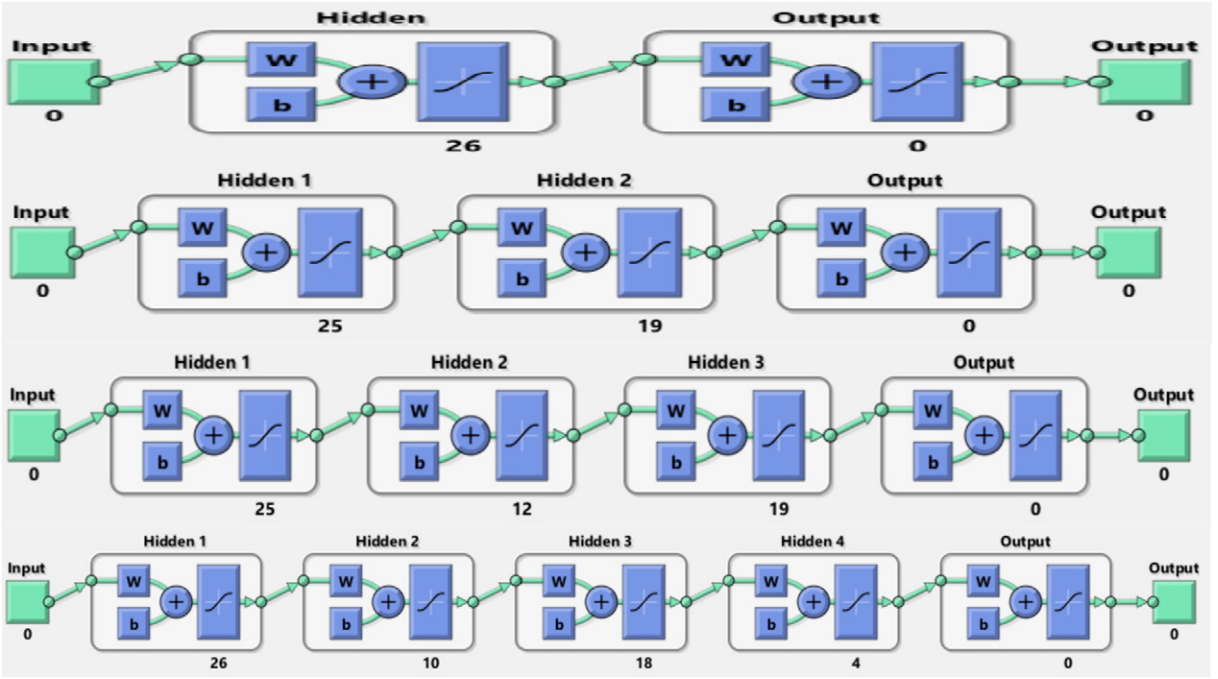


Fig 3. *Neural networks used for data classification with 1, 2, 3, and 4 hidden layers.*

Table 2. *Descriptive Statistics of Quantitative Variables for Development of Prediction Model*

			With LBP (n = 92)	Without LBP (n = 68)
Quantitative Variables		Unit	Mean (SD)	
Age		Year	39.94 ± 10.45	37.19 ± 8.50
Career length		Year	10.90 ± 5.92	9.22 ± 4.24
Job stress		Point	144.34 ± 28.30	109.31 ± 25.50
SMWL	Mental demand	Point	67.12 ± 26.5	61.12 ± 17.32
	Physical demand	Point	41.28 ± 27.97	38.18 ± 22.72
	Performance	Point	36.0 ± 22.63	35.2 ± 22.63
	Temporal demand	Point	60.8 ± 24.66	76.8 ± 12.2
	Effort	Point	62.8 ± 25.27	45.8 ± 14.12
	Frustration level	Point	47.5 ± 28.6	36.5 ± 14.6
	Overall	Point	69.28 ± 21.11	44.63 ± 14.02

LBP, low back pain; *SD,* standard deviation; *SMWL,* subjective mental workload.

The results of comparison of structures of these 4 neural networks with the best results obtained in the training and testing phases are displayed in Table 4.

To arrive at the assessment results, each of the designed networks were performed 50 times, and the training and testing data were selected randomly each time. The mean of classification accuracy, standard deviation, and the best result of the 50 performances for training, testing state, and total are presented in Table 5. Our findings revealed that the mean of classification accuracy of the structures of all the developed neural networks was nearly 96% for the set of training data. Also, the mean of classification accuracy of the testing data was about 87%, which indicates the results are acceptable. As can be seen from Table 5, the results are very close together and a single hidden layer sufficed for solving this problem.

Other Analyses

To assess the obtained results, the results of neural network classification accuracy were compared with the results of the 2 classification methods. The present data were classified using logistic regression and also k-NN with k values of 1, 3, and 5. The results of classification accuracy are given in Table 6.

As shown in Table 6, the neural network model has highest level of accuracy compared with the logistic regression and k-NN methods. Also, the neural network model can classify the data into healthy and LBP individuals with greater accuracy. The mean of classification accuracy resulting from 50 performances for the testing data is about 88%, which is better compared with other methods. In addition, the mean of classification accuracy of both training and testing data was 92%, indicating much better results compared with other methods.

Table 3. *Descriptive Statistics of Qualitative Variables for the Development of Prediction Model*

Quantitative Variables	Category	Number (N = 160)	Low back pain (%) Number
Genders	Male	114	(69.5%) 64
	Female	46	(30.5%) 28
BMI	Ideal (<25)	113	(64%) 59
	Overweight (25-30)	35	(27%) 25
	Obese (>30)	13	(8.7%) 8
Physical activity	No to Low	106	(88%) 81
	Moderate to high	54	(12%) 11
Family history	Yes	24	(19.5%) 18
	No	136	(80.5%) 74
Smoking status	Nonsmoker	77	(40.2%) 37
	Smoker	83	(59.8%) 55
Alcohol status	Yes	39	(32%) 29
	No	121	(68%) 63
Job satisfaction	Yes	59	(30.4%) 28
	No	101	(69.6%) 64
Job security	Yes	71	(44.5%) 41
	No	89	(55.5%) 51
Social relations	Low	89	(38%) 35
	Moderate	58	(52%) 48
	Good	13	(10%) 9
Force	Low	78	(34.8%) 32
	High	82	(65.2%) 60
Repetition	Yes	103	(52%) 48
	No	57	(48%) 44
Posture	Close to neutral	60	(30%) 28
	Not neutral	100	(70%) 64
Vibration	Yes	100	(51%) 47
	No	60	(49%) 45

BMI, body mass index.

Table 4. *Structural Characteristics of the Neural Network Model for Data Classification*

Row	Characteristics of Neural Networks	Type or Amount
1	Type of network	Multilayer Perceptron
2	No. of neurons in the input layer	15
3	No. of hidden layers	1 to 4
4	No. of hidden layer neurons	1 to 30
5	No. of neurons in the output layer	1
6	Activation function	Sigmoid
7	Type of network training	Algorithm of Error Back Propagation
8	No. of repetitions	1000

Discussion

According to previous studies, personal, occupational, and psychosocial factors certainly contribute to LBP severity and incidence.[2,4,7] But few studies have investigated the impact of risk factors and their interactions on LBP severity and incidence. Hence, the assessment of risk factors and prediction of LBP are considered valuable assessments of the human factors in workplaces. One of the most accurate approaches in assessment of interactions between risk factors is the neural network approach, which can be used as an alternative statistical technique for the prediction of complex phenomena such as LBP. Analysis of the results indicated that the applied neural network can accurately predict the rate of LBP in the presence of effective main variables. Although previous research has indicated that statistical methods such as multiple regression do not present reasonable prediction accuracy,[27] Govindu et al[2] surveyed the effects of personal, occupational, and psychosocial factors on LBP severity in 60 LBP patients using multiple regression models. They highlighted that for prediction of LBP researchers should consider each of the 3 broad categories of risk factors simultaneously. However, their final model consisted of both main effects and interaction terms between risk factor categories and had an adjusted R^2 value of 0.85.[2] On the other hand, in other studies, Parsaeian et al[12] and Aliabadi et al[27] reported that the empirical prediction model based on artificial neural networks can provide a more accurate prediction of LBP and hearing loss compared with multiple regression. A few studies have used the neural network model for the prediction of occupational LBP, but they still have not considered all 3 broad categories of studied risk factors simultaneously.[11,13-17] Hasenbring and Hallner investigated just the psychosocial risk factors as the input variables of the neural network with 83% accuracy to predict LBP.[15] Mendelek et al[11] also investigated only the quantitative relation between personal and occupational risk factors with incidence of LBP using the phase model. Moreover, Zurada[28] just studied the factors related to manual material handling and Gulbandilar et al[17] only measured 2 factors, skin resistance and visual analog scale scores, as input variables for the developed fuzzy logic algorithm for discovering intensity level of LBP. Therefore, our study presented a method of classifying individuals affected with LBP and healthy individuals considering 3 general risk factor categories (personal, occupational, and psychosocial) including 17 input variables for LBP. The neural network was used for classification, and using the training and testing data, a large number of neural networks with various parameters were performed. The neural network models possess high flexibility and fewer parameters compared with parametric models. In this study, many neural networks were created to model the classification. They included hidden layers ranging from 1 to 4 with different numbers of neurons ranging from 1 to 30. The test results indicated that there was no significant correlation among the created network with various hidden layers, and the network with just 1 hidden layer and 26 neurons produced better results compared with other networks. This finding illustrates that increasing the number of hidden layers does not improve the network accuracy and that the parameters do not have complicated interrelations. Each parameter has an independent effect on the results of classification and decision making. The results obtained from the developed model considering studied risk factors of LBP indicate that this method presents a reasonable prediction accuracy using

Table 5. *Prediction Performance of the Developed Neural Network Models in the Training, Testing, and Overall Phases*

Modeling Phase		Training			Testing			Overall		
Evaluation Criteria		Accuracy (%)			Accuracy (%)			Accuracy (%)		
Neural Network Type	**No. of Neurons**	**Mean**	**Std**	**Max**	**Mean**	**Std**	**Max**	**Mean**	**Std**	**Max**
1 hidden layer	26	96.2	1.6	99.8	87.8	4.2	96.9	92	2.9	98.4
2 hidden layers	19-25	96	1.1	99.4	86.5	4.1	96.9	91.6	2.6	98.2
3 hidden layers	19-12-25	96.5	1.3	99.4	86.9	4.1	96.9	91.7	2.7	98.2
4 hidden layers	4-18-10-26	96.5	1.4	99.4	86.5	4.1	96.9	91.5	2.8	98.2

Max, maximum; *Std,* standard.

Table 6. *Compare Data Classification Accuracy With Developed Methods for Prediction of LBP*

Category Methods	Accuracy %
Logistic regression	82.5
k-NN-3	78.8
k-NN-5	80.3
k-NN-1	83.3
Neural networks	92

k-NN-1, k nearest neighbor algorithm with k = 1; *k-NN-3,* k nearest neighbor algorithm with k = 3; *k-NN-5,* k nearest neighbor algorithm with k = 5; *LBP,* low back pain.

the features measured for the healthy individual. The mean accuracy of the neural network model in training and testing phases was about 92%, which was the highest level of accuracy compared with logistic regression and k-NN methods. Therefore, this method was significantly different from other methods regarding classification and diagnostic accuracy. In other words, this method was more accurate than the previous models, in spite of many more variables embedded in its prediction model. To sum up, the results indicated that the selected input variables had significant correlation with LBP severity and incidence as the output feature. Also, the prediction model based on artificial neural networks to classify individuals into 2 classes of healthy and LBP individuals is acceptable and accurate.[29] It can be used as a method for diagnosing individuals with LBP. Future studies may combine artificial intelligence methods and use phase methods to increase the diagnostic accuracy.

Limitations and Future Studies

The present study identified an ability to detect all possible interactions between studied variables. It may be there are many other variables that can influence LBP in real situations; however, it is impossible for all of them to be incorporated in the model. Therefore, it may be a source of bias for the results of this study. Thus, this concern should clearly be addressed in future studies.

Another limitation is the neural network model that was used. Empirical nature, greater computational burden, and proneness to over fitting were identified as limitations of the neural network model. Moreover, performance of the prediction model depends on both the quality and quantity of the dataset, and also there are not clear rules for optimal structure design. Therefore, in future studies, this concern should clearly be addressed.

Conclusions

Prediction of work-related low back pain, especially in the initial phase of development, is important in workplaces. In this study, the neural network prediction model was more accurate compared with the regression method. It seems that the empirical prediction model based on artificial neural networks along with considering all 3 broad categories of risk factors could accurately predict the LBP of workers. Because LBP is usually not curable, the results of prediction can help experts to modify and improve preventive and intervention strategies. Because the model used in this study investigated each of the 3 categories of variables contributing to low back pain simultaneously and comprehensively, the obtained results may provide us with a more accurate prediction of occupational low back pain.

Funding Sources and Conflicts of Interest

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Contributorship Information

Concept development (provided idea for the research): E.D.
Design (planned the methods to generate the results): A.M.
Supervision (provided oversight, responsible for organization and implementation, writing of the manuscript): E.D.
Data collection/processing (responsible for experiments, patient management, organization, or reporting data): E.D.

Analysis/interpretation (responsible for statistical analysis, evaluation, and presentation of the results): S.S.
Literature search (performed the literature search): E.D.
Writing (responsible for writing a substantive part of the manuscript): O.G.
Critical review (revised manuscript for intellectual content, this does not relate to spelling and grammar checking): E.D.

Practical Applications

- This study found that all three categories of risk factors (personal, psycho-social and occupational) simultaneously increased the risk of occupational LBP in the workplace.
- These findings suggest that artificial neural networks could provide more accurate predictions of LBP considering all three risk factors, than other applied methods such as multiple regressions.
- This study found that the developed neural networks with one hidden layer and 26 neurons accurately predicted LBP.

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