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A neural network-based system for classification of industrial jobs with respect to risk of low back disorders due to workplace design

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Despite many years of research efforts, the occupational exposure limits of different risk factors for development of low back disorders (LBDs) have not yet been established. One of the main problems in setting such guidelines is the limited understanding of how different risk factors of LBDs interact in causing the injury, as the nature and mechanism of these disorders are relatively unknown phenomena. The task of an industrial ergonomist is complicated because the potential risk factors that may contribute to the onset of LBDs interact in a complex way, and require an analyst to apply elaborate data measurement and collection techniques for a realistic job analysis. This makes it difficult to discriminate well between the jobs that place workers at high or low risk of LBDs. The main objective of this study was to develop an artificial neural network-based diagnostic system which can classify industrial jobs according to the potential risk for low back disorders due to workplace design. Such a system could be useful in hazard analysis and injury prevention due to manual handling of loads in industrial environments. The results show that the developed diagnostic system can successfully classify jobs into the low and high risk categories of LBDs based on lifting task characteristics. Copyright © 1996 Elsevier Science Ltd.

Keywords: low back disorders, artificial neural network, assessment of lifting jobs

Introduction

Musculoskeletal injuries rank first among the health problems that affect quality of life of the working population (BNA, 1988; National Safety Council, 1990). These injuries include a large number of disabling injuries to the lower back due to either cumulative exposure to manual handling of loads over a long period of time, or to isolated incidents of overexertion when handling heavy objects. LBDs at work are recognized as one of the main occupational health problems in the United States (Ayoub *et al*, 1996). For example, Spengler *et al* (1986) reported that while low-back injuries comprised only 19% of all injuries incurred by the workers in one of the largest US companies, they were responsible for 41% of the total injury costs. Snook (1988) estimated the annual direct and indirect costs of back pain to be almost $16 billion.

As pointed out by the National Safety Council (1990), in 1988 overexertion injuries across all industries accounted for 28.2% of all work injuries involving disability, while approximately 25% of all worker compensation claims were related to back injuries. The highest percent of such injuries occurred in service industries (31.9%), followed by manufacturing (29.4%), transportation and public utility (28.8%), and trade (28.4%). The total time lost due to disabling work injuries was 75 million work-days, with the total work accident cost of $47.1 billion, and the average cost per disabling injury of about $16,800. The economic impact of back injuries in the US alone may be as high as $20 billion annually (BNA Report, 1988).

NIOSH (1981) cited epidemiological studies showing that frequency rates (number of injuries per man-hour on the job) and severity rates (number of hours lost due to injury per man-hour on the job) of back injuries

*Author to whom correspondence should be addressed increase significantly when: (i) heavy objects are lifted, (ii) the object is bulky, (iii) the object is lifted from the floor, (iv) objects are frequently lifted, and (v) loads are lifted asymmetrically (by one hand or at the side with the torso twisted). Despite many years of research efforts, the occupational exposure limits of different risk factors for development of LBDs have not yet been established. One of the problems in setting such guidelines is the limited understanding of how different risk factors of LBDs interact in causing the injury. Furthermore, due to their multifactorial nature and inherent complexity, the mechanisms leading to the onset of LBDs are relatively unknown phenomena (Ayoub *et al*, 1996).

Objectives

Current ergonomic techniques for controlling the risk of occupationally related LBDs consist mainly of static assessments of spine during lifting activities. However, as discussed by Marras (1992), biomechanical models and epidemiological studies suggest that the dynamic characteristics of lifting increase spine loading and the risk of occupational LBDs. Karwowski *et al* (1992) proposed that the overexertion injury due to manual load lifting should be considered as a discontinuous dynamic process, rather than static phenomena, reflecting dynamic changes in the state of the human musculoskeletal system. This study showed that the risk potential for low back injury due to manual lifting can be conceptualized in view of the mathematical elementary cusp catastrophe (Thom, 1975). Such is the case of low back injury, which may occur quite suddenly and in a non-linear fashion. In general, the nature of such changes may depend upon the combination of human strength abilities, muscular fatigue and endurance, spinal loading tolerance, as well as dynamic changes in the state of equilibrium between these variables. Modeling the mechanism of LBDs on the mathematical elementary catastrophe improved our understanding of the dynamic nature of overexertion injury phenomena.

The task of the industrial ergonomist is fairly difficult because the potential risk factors that may contribute to the onset of LBDs interact in a complex way, and require him/her to apply elaborate data measurement and collection techniques for a realistic job analysis. The main objective of this study was to develop an artificial neural network-based diagnostic system which could classify industrial jobs according to the potential risk for low back disorders (LBDs). Such a system could be very useful in hazard analysis and injury prevention due to manual handling of loads in an industrial environment.

Artificial neural networks

Artificial neural networks, or neural systems, are physical cellular networks that are able to acquire, store and utilize experiential knowledge. A neuron is a nonlinear mathematical model (*Figure 1*) that sums the product of each input and its connection weight. The neuron then acts on this summation with a nonlinear activation function. In other words, the neuron has two sections to it: a weighted-summation input and a nonlinear output activation function. In the first section, the neuron receives input signals. Each signal is multiplied by a connection weight, then summed

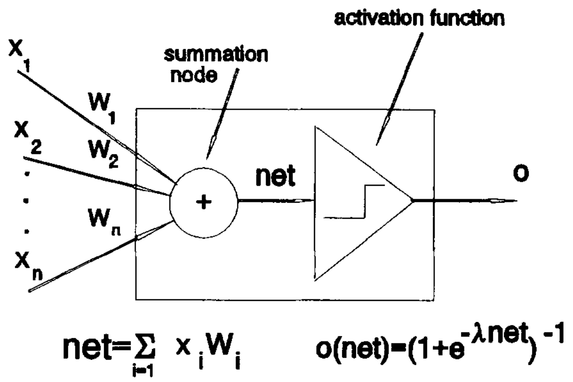

Figure 1 Model of a neuron

together. This portion essentially takes the scalar product of the input vector **x** and the connection-weight vector **W** yielding a value of net $= \Sigma \mathbf{x}_i \mathbf{W}_i$. A general nonlinear activation function such as the sigmoid function $o(\text{net}) = (1 + e^{-\lambda \text{net}})^{-1}$ (*Figure 1*) then acts upon this summation.

A single neuron by itself is of little value. Only when several neurons are used together in a layered network will they yield useful results. Therefore, neural systems are built of a dense mesh of neurons and connections which compute simultaneously on all data and inputs. Neurons perform as summing and nonlinear mapping junctions. They operate in parallel, are organized in layers and have feedback connections called weights. Neural networks are trained to achieve a specific task. Their architectures, the characteristics of the neurons, initial weights and the training modes are determined by the user. A network learns by processing a sufficient number of training patterns supplied on its input.

In this study, a feedforward neural network with error back-propagation training was implemented (Rumelhart *et al*, 1988; Zurada, 1992; Habib, 1995). During a supervised error-back propagation training, input patterns are presented sequentially to the system along with the correct response. The response is provided by the teacher and specifies the classification information for each input pattern. The network learns from experience by comparing the targeted correct response with the actual response. The network parameters (weights and thresholds) are usually adjusted after each incorrect response based on the error value generated. This process of comparison of correct and actual responses is continued for each input pattern until all examples from the training set are learned within an acceptable error. During the classification phase, the trained neural network itself operates in a feedforward manner. The input pattern is passed forward through the network one layer at a time from the input to the output, with no feedback. The network should be able to classify accurately in situations not encountered in training. More details about the error back-propagation training algorithm for a two-layer feedforward network used in this study can be found in Zurada (1992).

Neural network-based systems

Few neural-based network models were developed in the field of medical diagnosis. For example, DESKNET is a neural network-based expert system developed to instruct medical students in the diagnosis of papulosquamous skin diseases (Jones, 1991). The system has 96 input nodes (plus the bias input), one hidden layer with 20 nodes and 10 output nodes. Input data contain the results of dermatological tests, for example, the location, distribution, shape, arrangement, pattern, number of lesions, color, itching, the duration of skin lesions, etc. If the symptom is present, the input is 1, if absent, the input is 0. If specific symptoms or their parameters were not known, the input was coded as 0.5. The output neurons were indicative of 10 diseases diagnosed. The training data were comprised of 10 model diseases from 250 patients. The testing data consisted of symptom data from 99 patients not previously used in training. The skin diseases were correctly diagnosed in 80% of the cases except for psoriasis. Psoriasis patients were diagnosed correctly only in 30% of the cases because this disease often resembles other diseases within the papulosquamous group, and makes it difficult to recognize even for specialists.

Coronary occlusion is an example of another serious disease that has been difficult to diagnose accurately without the use of a neural network (Baxt, 1990). The best diagnostic approaches using conventional computer-aided diagnostic systems performed with a detection rate of 88% and a false alarm rate of 26%. Diagnoses made by physicians were reported as equal to 88% and a false alarm rate of 26%. Diagnoses made by physicians were reported as equal to 88% and 29% for detection and false alarm rates, respectively. The multilayer feedforward neural network that yielded the best results contained 20 input nodes, one output node and two hidden layers consisting of 10 neurons each. The network accepted 20 variables relevant for the diagnosis of coronary occlusion from 356 patients that were randomly divided into training and test groups. The results revealed that the network diagnosed the patients with outstanding accuracy. Among the sick patients, the disease detection ratio was 92%. However, among the healthy patients the system provided false alarms of disease in 4.3% of the cases. In spite of errors, these results outperformed the above mentioned computer-aided diagnostic systems and trained physicians (Baxt, 1990).

Like coronary occlusion, the cause of back pain is also difficult to diagnose despite being the most common problem encountered by doctors, since many of the symptoms present in patients who have a serious spinal problem may also be found in those with less severe problems. In addition, the presence of non-organic symptoms makes diagnosis difficult. Bounds *et al* (1988) developed a neural network-based system for diagnosis of low back pain. The back pain was classified in the following four classes: (1) simple low back pain, (2) root pain, (3) spinal pathology and (4) abnormal illness behaviour (back pain with psychological overlay). These classes were also used to represent the outputs of the developed neural network. The system had 50 inputs consisting of symptoms and answers to medical history questions. Most of the inputs were presented as 0 and 1, indicating the presence or absence of the symptom or yes/no answer to medical history questions. The non-binary inputs were taking values between 0 and 1. The training data were collected from 200 patients with back pain who were followed over a long period. Each category of output was trained and tested by using 50 examples, 25 for training and the remaining 25 for testing. In the comparison between the network, three groups of doctors and the fuzzy logic system, the overall performance of the network was higher than that of the doctors and slightly worse than the fuzzy logic system.

Recently, Karwowski *et al* (1994) presented a prototype of a neural network-based system for classification of industrial jobs according to the potential risk for LBDs. Although the system was trained using a limited number of data for 60 high and low risk jobs, from which 40 jobs were used for training and 20 for testing, the preliminary results showed that the developed diagnostic system could successfully classify jobs into the low and high risk categories of LBDs based on lifting task characteristics. The jobs were correctly classified into the low and high risk categories in about 80% of cases.

Methods and procedures

Experimental data for model development

The experimental data for model development were collected by Marras *et al* (1993). That study involved an industrial surveillance of the trunk motions and quantification of workplace factors in high and low risk of LBDs repetitive tasks. The data from 403 industrial lifting jobs from 48 manufacturing companies were used. These jobs were divided into two groups, high and low risk of LBDs, based upon examination of the injury and medical records. Whenever possible, company medical records were used to categorize risk. In some cases only injury logs were available. Each job was weighted proportionally to the number of person-hours from which the injury and turnover rates were derived. The odds ratio for LBDs was defined as the ratio of the probability that an LBD occurs (probability of being in the high risk LBD group) to the probability that an LBD does not occur (probability of being in the low risk LBD group).

The *low risk* of LBDs group of jobs were defined as those jobs with at least three years of records showing no injuries and no turnover. Turnover is defined as the average number of workers who left a job per year. The *high risk* group jobs were those jobs associated with at least 12 injuries per 200,000 h of exposure. The high risk group category incidence rate of LBDs corresponded to the 75th percentile value of the 403 jobs examined. Out of the 403 jobs examined, 124 of the jobs were categorized as low risk, and 111 were categorized as high risk. The remainder of the jobs (168) were categorized as medium risk and were excluded from consideration in this paper. The dependent variables in this study (Marras, 1993) consisted of workplace and trunk motion characteristics which were indicative of each job.

Marras (1992) developed a multiple logistic regression model, based on biomechanical plausibility, which indicated that a combination of five trunk motion and workplace factors allow us to distinguish between high and low risk of occupationally related low back disorders with the odds ratio of 1:10.7. These factors included (1) lifting frequency, (2) trunk twisting velocity, (3) load moment, (4) the trunk sagittal angle and (5) trunk lateral velocity. Load moment and lifting frequency are the workplace factors. Lateral trunk velocity, twisting trunk velocity and satiggal flexion angle are the trunk motion factors. As the magnitude of each of these variables increases, the risk increases. The same variables mentioned above were applied on input during network's training and testing.

The predictive power of the above described model (Marras, 1992) was found to be more than three times greater than that of the NIOSH Lifting Guide of 1981, and could be used to minimize the risk of occupationally related low back disorder. It should be pointed out here that while the 1991 NIOSH Revised Lifting Equation (Waters *et al*, 1993) abandoned the concepts of the AL and MPL, it is still comparable to the AL and MPL limits. Careful examination of these limits and the *Application Manual* (Waters *et al*, 1994) reveals that the relationship between the load lifted on the job and RWL is now defined by the lifting index (LI). The LI value at 1.0 would be equivalent to the old AI concept. According to the *Application Manual* for the Revised 1991 Equation (Waters *et al*, 1994) the LI value of 3.0 would be equivalent to the old MPL concept (MPL was three times the AL according to the 1981 NIOSH Guide). Thus, the 1981 and 1991 NIOSH Guides are conceptually comparable.

Training and test data sets

Out of the 235 industrial jobs with low and high risk values of LBDs recorded by Marras *et al* (1993), 148 jobs were randomly selected for network's training. This group of 148 jobs contained 74 low risk and 74 high risk jobs (*Tables 1* and *2*). The order of these 148 jobs in the training set was also randomized. The remaining 87 jobs were used for testing the network's performance after training. This test group consisted of 50 low risk jobs and 37 high risk jobs (*Tables 3* and *4*). The purpose of breaking the data into a training set and a test set was to provide a check on a 'real world' situation. The training set was used to train the neural network, a procedure that reduces the least mean-square error between the correct response and the actual response until all examples from the training set are learned within an acceptable overall error. New data which the system had not been exposed to were then presented to the network, and its performance on these new data patterns was evaluated.

Network input parameters

Each observation in the training data set contained the five variables which described occupational risk factors for development of LBDs. These variables were as follows: (1) lift rate in number of lifts per hour (LIFTR), (2) peak twist velocity average (PTVAVG), (3) peak moment (PMOMENT), (4) peak sagittal angle (PSUB), and (5) peak lateral velocity maximum (PLVMAX). To prevent network's saturation, these variables were normalized to values from within the interval [0, 1]. The classification variable (RISK of LBDs) takes values of 1 or 0 for *high* and *low* risk jobs, respectively. This variable was used only as teacher's response during the network's training using the error-back-propagation algorithm (Zurada, 1992).

Network architecture

Several feedforward neural networks architectures with error back-propagation have been tested. All tested networks architectures contained from eight to 20 neurons in a single hidden layer, and one or two neurons in the output layer. In all calculations the layers were fully connected. *Figure 2* shows the percentage of correct classifications versus the number of neurons in a single hidden layer. It is clear that the least number of misclassifications was obtained for the network with 10 neurons and two neurons in a single hidden layer and output layer, respectively. Therefore, this network structure was chosen for further consideration. The network accepted six inputs (five of them were mentioned above and the sixth augmented input equals -1) and two outputs trained for values (1, 0) and (0, 1) for low and high risk jobs, respectively. The weights V in the input layer and W in the hidden layer were initialized to small random values of the absolute value not exceeding 0.2.

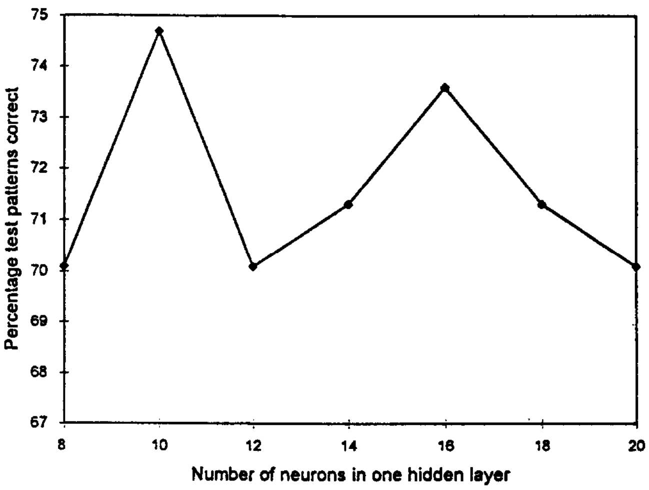

Figure 2 Test set performance of the neural network using single hidden layer with different number of neurons

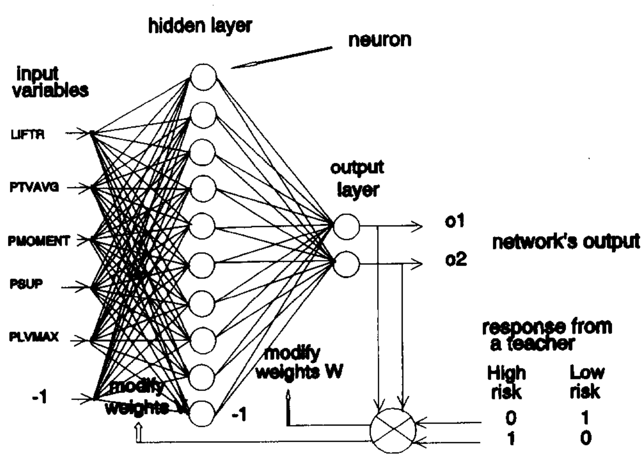

Figure 3 The architecture of the neural network used for system training purposes

Table 1 Randomly selected jobs for low risk of LBDs used for network's training

Job	Liftr (lifts/h)	Ptvavg (°/s)	Pmoment (Nm)	Psup (°)	Plvmax (°/s)	Probability of risk (%)	Class of risk
1	762.5	6.1	19.3	45.0	42.8	57.3	Low
2	31.3	6.9	63.4	8.2	38.2	33.6	Low
3	31.6	5.1	195.7	32.6	44.8	55.8	Low
4	31.3	6.0	177.6	45.0	51.3	59.7	Low
5	90.0	6.1	198.2	45.0	40.2	58.1	Low
6	150.0	6.3	13.6	12.1	44.2	32.6	Low
7	31.3	7.3	107.6	−3.3	36.0	36.8	Low
8	72.5	2.7	2.3	20.5	49.7	30.6	Low
9	75.0	2.2	7.2	40.2	35.4	29.2	Low
10	75.0	2.3	4.4	−5.6	26.8	6.3	Low
11	75.0	3.7	95.1	−1.3	14.5	23.3	Low
12	75.0	6.7	114.8	3.4	23.1	31.9	Low
13	14.5	3.3	8.7	11.5	33.3	15.6	Low
14	5.4	4.8	26.1	12.5	43.1	25.3	Low
15	99.5	9.4	20.8	0.6	47.4	28.7	Low
16	137.5	4.4	2.5	10.9	14.4	16.1	Low
17	100.0	2.9	11.9	−5.1	12.0	4.0	Low
18	43.8	9.2	3.3	22.8	70.8	51.2	Low
19	150.0	3.8	77.0	0.8	28.9	32.0	Low
20	106.3	5.9	17.7	−4.4	28.8	15.1	Low
21	200.0	15.0	14.2	29.8	39.3	60.4	Low
22	112.5	2.0	57.1	4.7	21.6	18.7	Low
23	112.5	7.6	34.9	−3.6	23.5	21.9	Low
24	50.0	15.0	81.5	−2.3	36.4	47.1	Low
25	80.0	7.7	61.8	1.1	31.5	30.1	Low
26	200.0	3.0	7.5	5.1	12.1	12.4	Low
27	87.5	4.1	88.8	2.1	28.0	29.9	Low
28	50.0	6.7	10.0	41.8	54.2	42.4	Low
29	75.0	2.9	3.9	29.2	39.7	30.9	Low
30	37.5	2.2	9.1	19.7	49.9	29.3	Low
31	50.0	4.5	1.4	25.8	27.3	28.6	Low
32	48.4	9.3	2.7	8.0	54.5	30.6	Low
33	47.3	6.5	4.0	17.3	28.0	25.8	Low
34	25.4	6.7	1.9	24.4	48.3	40.1	Low
35	76.1	5.9	6.6	8.8	38.6	20.5	Low
36	40.0	12.0	8.2	36.2	69.4	57.6	Low
37	62.5	5.6	1.1	26.1	35.7	33.4	Low
38	175.0	12.0	21.7	3.6	34.9	35.3	Low
39	56.3	11.0	99.2	−3.9	40.8	46.4	Low
40	225.0	3.1	3.6	30.7	19.6	36.0	Low
41	118.8	1.7	11.3	−3.7	22.0	8.0	Low
42	118.8	2.7	2.7	−4.8	29.2	10.5	Low
43	118.8	4.8	7.5	−0.6	60.8	25.8	Low
44	270.0	4.2	27.4	−17.4	27.1	27.3	Low
45	135.0	4.1	1.2	−2.2	36.7	17.1	Low
46	81.3	8.1	5.9	45.0	76.3	51.6	Low
47	43.8	8.7	1.3	7.1	58.0	29.8	Low
48	45.6	1.0	1.2	2.2	32.2	7.4	Low
49	86.9	3.3	0.5	−12.1	37.9	12.2	Low
50	92.5	3.6	1.0	−5.9	24.6	8.3	Low
51	91.3	4.4	20.4	8.3	29.9	15.8	Low
52	21.3	4.2	6.3	8.3	33.4	14.0	Low
53	91.3	6.1	2.3	0.7	37.2	17.5	Low
54	87.5	3.8	0.5	1.6	42.8	14.9	Low
55	125.0	2.4	0.7	16.8	18.6	19.8	Low
56	600.0	2.0	2.8	4.6	16.9	21.7	Low
57	640.0	2.4	5.4	−0.8	28.3	25.8	Low
58	390.0	8.6	0.8	−25.2	27.9	36.4	Low
59	225.0	6.2	0.7	−8.7	30.7	25.9	Low
60	84.0	9.5	11.6	4.5	43.7	25.5	Low
61	56.0	4.5	2.6	0.7	36.3	12.0	Low
62	56.0	1.3	1.0	20.3	27.0	21.6	Low
63	70.0	4.0	36.2	7.1	39.4	20.3	Low
64	45.0	2.9	17.7	15.3	30.3	17.7	Low
65	34.0	1.4	3.1	10.7	20.7	9.3	Low
66	57.0	4.6	23.6	7.3	20.8	10.6	Low
67	113.0	0.7	7.5	−14.5	28.8	10.0	Low
68	113.0	1.8	2.2	−5.4	37.3	13.1	Low
69	113.0	4.2	4.5	3.2	22.1	10.3	Low
70	225.0	2.2	10.9	−14.7	28.3	18.8	Low
71	188.0	3.0	0.2	45.0	33.0	37.7	Low
72	68.0	3.3	6.1	27.5	28.4	27.0	Low
73	105.0	4.5	5.0	−0.3	19.9	9.3	Low
74	90.0	1.9	9.1	9.3	15.9	8.1	Low

Table 2 Randomly selected jobs for high risk of LBDs used for network's training

Job	Liftr (lifts/h)	Ptvavg (°/s)	Pmoment (Nm)	Psup (°)	Plvmax (°/s)	Probability of risk (%)	Class of risk
75	200.0	18.8	169.9	31.8	88.48	91.0	High
76	900.0	34.5	198.2	15.7	101.1	91.4	High
77	225.0	15.5	152.6	45.0	63.4	90.9	High
78	120.0	21.5	158.6	−14.0	73.3	64.8	High
79	40.0	15.9	126.9	2.9	27.7	45.4	High
80	167.0	7.3	21.7	45.0	75.4	58.2	High
81	120.0	12.8	6.6	45.0	41.5	53.5	High
82	900.0	2.4	7.9	−3.2	16.5	21.5	High
83	75.0	3.0	29.4	−5.1	23.9	8.9	High
84	75.0	10.7	66.3	22.2	49.1	61.0	High
85	75.0	2.8	17.7	18.4	36.0	23.6	High
86	78.0	4.8	19.4	11.8	55.3	28.1	High
87	125.0	1.9	36.2	3.3	36.1	18.9	High
88	260.0	5.0	118.9	26.3	31.4	66.3	High
89	15.6	1.6	39.9	7.9	48.6	22.7	High
90	640.0	9.1	19.3	3.2	41.8	42.7	High
91	31.3	5.0	147.2	10.3	49.5	43.0	High
92	75.0	5.6	91.7	22.5	35.2	52.7	High
93	100.0	6.4	42.7	−8.4	20.6	19.9	High
94	25.4	10.3	42.5	−41.5	95.9	61.4	High
95	416.7	9.0	164.2	33.8	46.4	83.3	High
96	495.0	7.1	122.3	45.0	55.5	83.0	High
97	112.0	7.7	34.0	13.8	51.5	41.4	High
98	112.0	4.2	10.0	16.8	20.3	21.9	High
99	30.0	2.4	184.0	45.0	49.9	53.4	High
100	84.0	2.7	52.0	45.0	45.0	43.2	High
101	18.0	5.8	100.1	45.0	42.8	56.4	High
102	225.0	5.0	61.2	18.8	39.0	53.8	High
103	113.0	12.8	71.4	45.0	61.1	75.4	High
104	113.0	4.9	45.0	45.0	48.2	40.7	High
105	113.0	1.2	5.8	0.5	40.8	14.4	High
106	75.0	4.8	91.7	−1.40	30.9	31.3	High
107	118.0	1.9	70.8	−0.6	19.2	22.2	High
108	105.0	12.2	5.3	−6.8	43.0	31.9	High
109	283.0	5.5	54.4	39.6	26.4	58.0	High
110	120.0	20.2	203.9	17.8	29.1	63.8	High
111	65.0	7.0	12.9	10.3	40.6	23.8	High
112	114.0	18.5	95.1	24.8	45.5	75.5	High
113	206.0	7.7	8.2	45.0	96.0	61.0	High
114	120.0	12.8	73.1	2.8	62.8	57.1	High
115	250.0	3.3	94.7	20.0	46.2	63.8	High
116	500.0	18.6	47.6	47.6	65.9	87.5	High
117	176.0	2.5	167.6	−7.6	43.3	40.1	High
118	75.0	9.2	117.8	13.7	49.1	55.0	High
119	75.0	11.4	123.2	9.6	36.1	50.2	High
120	310.0	4.7	42.4	12.5	39.1	47.9	High
121	75.0	10.7	24.5	21.4	68.3	54.9	High
122	37.5	12.1	79.7	11.7	81.7	62.9	High
123	150.0	1.4	45.3	4.0	27.4	20.4	High
124	76.0	15.1	127.8	45.0	65.9	79.8	High
125	90.0	19.4	122.3	45.0	57.9	78.1	High
126	31.3	3.9	134.8	11.1	19.3	31.0	High
127	31.3	7.6	258.2	38.1	38.1	38.1	High
128	75.0	3.3	113.1	25.5	36.1	50.1	High
129	20.0	10.1	29.6	45.0	50.2	50.5	High
130	318.0	6.8	70.7	9.1	36.4	55.6	High
131	148.8	6.3	99.1	99.1	26.8	46.1	High
132	50.6	10.1	40.8	31.8	39.8	50.0	High
133	31.3	4.0	68.9	15.4	18.0	33.8	High
134	200.0	13.4	88.3	17.1	20.4	66.1	High
135	251.3	34.8	69.3	5.0	61.2	67.4	High
136	62.5	20.3	35.1	3.5	46.3	37.0	High
137	178.1	2.4	5.4	13.9	13.5	19.4	High
138	116.7	2.2	67.7	25.4	82.3	59.1	High
139	45.0	10.7	9.5	20.1	43.7	42.0	High
140	250.0	8.4	13.0	12.0	36.1	41.4	High
141	15.3	2.5	197.1	30.8	31.5	46.7	High
142	156.0	1.7	85.4	13.1	53.9	50.5	High
143	131.0	12.8	23.4	45.0	59.9	62.6	High
144	225.0	15.3	51.5	4.7	32.4	49.8	High
145	182.0	2.9	47.1	−6.5	26.7	23.5	High
146	83.0	7.3	3.4	11.1	54.2	31.5	High
147	167.3	3.5	1.2	10.6	54.5	52.8	High
148	175.0	12.2	57.1	3.9	54.5	52.8	High

Table 3 Results of the neural system-based classification of industrial jobs for low risk of LBDs

Job	Liftr (lifts/h)	Ptvavg (°/s)	Pmoment (Nm)	Psup (°)	Plvmax (°/s)	Probability of risk (%)	Class of risk	Model Prediction
1	90.9	7.7	12.6	35.0	32.4	38.4	Low	Low
2	396.0	4.4	8.2	13.5	40.7	42.1	Low	High
3	40.0	5.6	23.6	23.6	45.1	38.6	Low	Low
4	75.0	6.1	1.5	29.9	48.4	40.0	Low	Low
5	75.0	8.0	6.1	−0.5	33.7	18.3	Low	Low
6	75.0	8.4	7.9	−1.7	44.7	23.1	Low	Low
7	75.0	4.4	7.1	3.4	29.8	10.2	Low	Low
8	7.3	11.1	5.1	45.0	48.7	48.4	Low	Low
9	14.5	4.0	59.8	30.6	55.3	49.9	Low	High
10	14.5	2.5	72.5	40.5	37.2	44.8	Low	High
11	400.0	3.6	5.7	2.1	28.4	27.3	Low	High
12	34.4	7.6	15.9	−5.9	25.8	13.9	Low	Low
13	81.4	6.2	59.8	−0.8	28.6	25.8	Low	Low
14	100.0	2.9	130.5	−1.1	29.4	29.2	Low	High
15	157.5	3.5	2.7	4.2	16.2	10.3	Low	Low
16	100.0	5.4	52.3	−1.9	14.4	18.6	Low	Low
17	50.6	8.7	5.4	−0.2	41.0	21.5	Low	Low
18	50.0	2.5	9.3	15.0	62.9	29.0	Low	Low
19	37.5	5.3	15.3	1.4	18.6	7.2	Low	Low
20	37.5	1.5	16.3	18.9	37.3	23.8	Low	High
21	112.5	5.1	1.2	13.2	63.2	35.2	Low	High
22	48.1	13.8	59.9	−7.6	43.4	43.3	Low	Low
23	46.9	7.4	65.1	−0.5	30.8	29.1	Low	Low
24	95.6	7.6	7.5	13.6	28.6	26.5	Low	Low
25	95.6	7.9	8.2	−0.2	34.6	20.2	Low	Low
26	50.8	1.9	1.3	9.6	43.4	16.3	Low	Low
27	25.4	3.9	5.7	2.7	38.5	11.6	Low	Low
28	62.5	6.5	1.5	35.3	53.1	41.3	Low	Low
29	50.0	7.2	5.2	41.3	41.3	19.9	Low	Low
30	118.8	1.7	53.0	−6.8	30.5	21.2	Low	High
31	112.5	2.9	0.9	−5.1	24.4	8.6	Low	Low
32	117.2	4.2	3.3	25.3	28.0	32.5	Low	Low
33	107.5	6.0	1.2	30.2	39.6	39.2	Low	Low
34	59.1	6.7	2.9	0.5	38.8	17.0	Low	Low
35	86.9	6.4	1.3	9.0	35.5	21.3	Low	Low
36	71.9	11.8	78.8	33.0	49.4	68.1	Low	High
37	1500.0	9.0	8.2	−13.0	16.3	32.9	Low	High
38	132.0	7.4	0.9	3.6	36.2	22.8	Low	Low
39	131.0	4.8	52.6	16.2	43.5	42.3	Low	High
40	270.0	2.6	22.3	22.3	32.6	42.2	Low	Low
41	68.0	4.1	15.9	11.2	23.0	13.4	Low	Low
42	23.0	2.4	0.6	27.8	38.6	29.5	Low	Low
43	12.0	7.4	34.9	33.7	26.5	38.5	Low	Low
44	34.0	2.5	7.2	4.9	28.8	6.1	Low	Low
45	23.0	5.1	68.0	42.4	45.1	50.4	Low	High
46	113.0	0.9	2.6	−5.4	21.1	7.3	Low	Low
47	45.0	6.0	4.8	−7.0	31.5	13.0	Low	Low
48	150.0	17.4	6.8	−6.0	51.1	40.8	Low	Low
49	165.0	10.5	9.5	15.0	67.5	52.9	Low	High
50	128.0	3.5	0.2	6.6	30.3	14.8	Low	Low

Table 4 Results of the neural system-based classification of industrial jobs for high risk of LBDs

Job	Liftr (lifts/h)	Ptvavg (°/s)	Pmoment (Nm)	Psup (°)	Plvmax (°/s)	Probability of risk (%)	Class of risk	Model Prediction
51	420.0	10.5	133.4	33.6	36.0	82.4	High	High
52	480.0	9.1	70.3	−4.3	27.8	52.3	High	High
53	720.0	29.4	275.9	32.6	54.9	94.8	High	High
54	288.0	6.6	180.8	26.1	52.9	79.3	High	High
55	145.0	2.6	54.4	−5.8	26.4	22.2	High	High
56	93.8	5.5	36.2	15.8	46.2	36.5	High	High
57	75.0	4.5	8.8	31.1	62.5	42.0	High	Low
58	75.0	1.4	42.4	12.2	39.7	25.5	High	High
59	129.4	15.7	33.9	1.6	53.7	44.7	High	High
60	83.3	3.8	81.5	−3.3	36.8	30.7	High	High
61	40.0	13.7	139.5	45.0	119.9	80.2	High	High
62	66.7	6.6	158.6	38.2	54.3	62.1	High	High
63	45.0	11.3	186.9	45.0	43.2	66.6	High	High

Table 4 *Continued*

Job	Liftr (lifts/h)	Ptvavg (°/s)	Pmoment (Nm)	Psup (°)	Plvmax (°/s)	Probability of risk (%)	Class of risk	Model Prediction
64	174.0	8.4	141.6	2.3	44.9	50.8	High	High
65	56.0	2.4	4.3	1.0	53.1	14.9	High	Low
66	169.0	9.4	73.4	13.9	33.8	53.9	High	High
67	113.0	4.2	176.6	7.8	19.6	32.1	High	High
68	500.0	1.7	47.6	−0.9	16.8	30.2	High	High
69	175.0	10.5	118.4	14.0	29.6	58.9	High	High
70	840.0	18.0	22.6	−8.8	31.7	48.1	High	High
71	120.0	18.0	27.2	−0.6	36.8	35.9	High	Low
72	225.0	8.8	66.6	18.1	44.2	63.4	High	High
73	120.0	5.4	116.1	0.4	50.7	43.1	High	High
74	75.0	8.9	81.5	8.8	45.5	46.7	High	High
75	145.0	5.8	7.5	20.3	54.7	43.6	High	Low
76	37.5	1.1	10.2	23.4	49.7	33.0	High	Low
77	37.5	1.0	31.7	9.9	37.7	18.5	High	High
78	37.5	2.1	9.6	28.9	34.5	28.0	High	Low
79	62.5	2.5	0.2	−3.4	30.3	6.5	High	Low
80	37.5	7.3	57.8	24.1	53.3	54.7	High	High
81	47.5	10.8	38.5	11.2	46.7	39.8	High	High
82	126.9	13.4	31.7	21.2	96.4	66.3	High	High
83	337.5	4.5	58.0	44.5	19.8	60.8	High	High
84	87.5	11.7	14.7	11.1	47.1	37.5	High	High
85	88.1	16.5	62.0	45.0	42.5	65.3	High	High
86	28.0	5.2	19.8	38.6	59.3	41.9	High	Low
87	69.0	10.1	53.8	16.9	55.0	52.3	High	High

See text for definition of variables

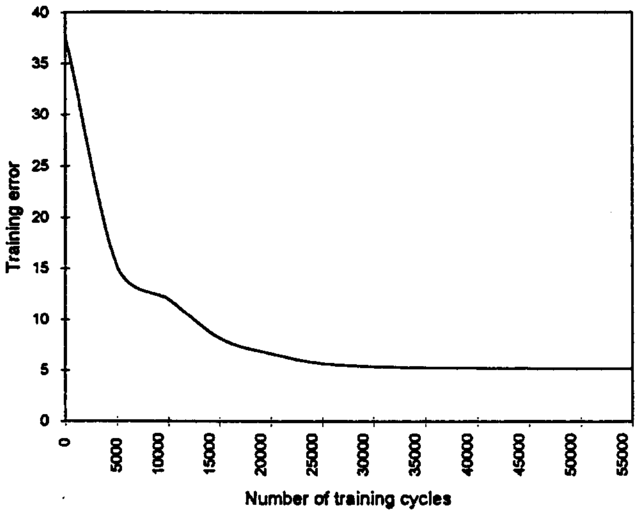

Figure 4 Training error versus number of training cycles

The final structure of the developed network contained 12 neurons, with 10 and two neurons in the hidden layer and the output layer, respectively. Each neuron used a unipolar continuous activation function $f(\text{net} = 1/(1 + \exp(-\lambda\text{net}))$, where net was defined as a scalar product of the weight and input vector. The learning coefficients and constants used in training were as follows: steepness coefficient $\lambda = 1.0$, training constant $\eta = 0.1$ and maximum allowable error value $E_{max} = 5.2$.

The classical training algorithm for feedforward multi-layer neural network with error back-propogation was used (Zurada, 1992). The architecture of the neural network used for training purposes is presented in *Figure 3*, whereas the convergence of the training process is shown in *Figure 4*. The learning process is encoded in neural network's weights.

Results and discussion

'Network performance'

After training of the network, a set with 87 remaining jobs, not used previously in training, was applied in order to test the performance of the developed lifting job classifier. There were 50 low risk and 37 high risk jobs in this set. The network based its decision on the largest of the two output values. The architecture of the neural network used for job classification is shown in *Figure 5*. It is a very similar network to the network

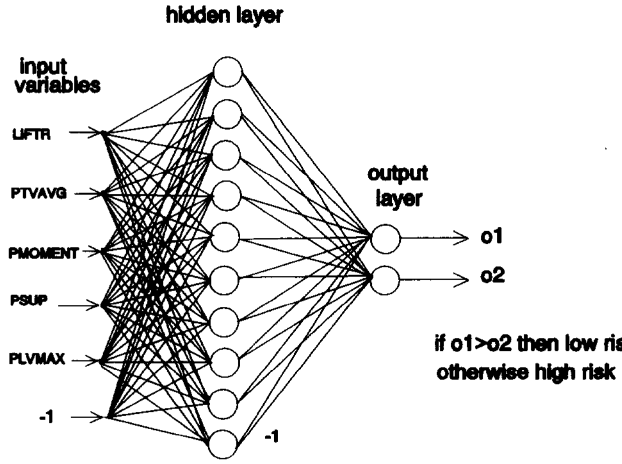

Figure 5 The architecture of the neural network used for job classification

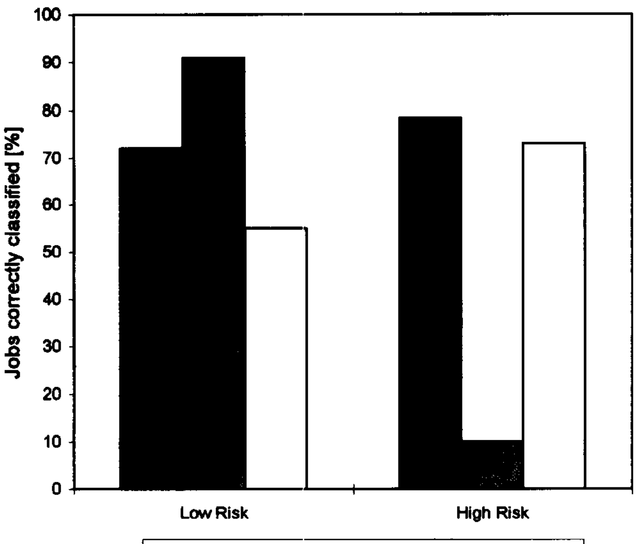

Figure 6 Comparison of job classification performance of the developed neural network system with application of the NIOSH 1981 and the 1991 Guides

depicted in *Figure 3*. The only difference is that there is no feedback from a teacher.

The developed diagnosis system classified 65 out of 87 cases correctly (74.7%). For 50 low risk jobs, only 14 jobs (28%) were incorrectly classified as high risk jobs. Out of 37 high risk jobs, eight jobs (21.6%) were incorrectly classified into low risk job category. The results are summarized in *Tables 3* and *4*, and *Figure 6*. As recently discussed by Marras *et al* (1996), the 1981 NIOSH Guide correctly classified 91% of low risk jobs, but only 10% of the high risk jobs, whereas the 1991 NIOSH Guide correctly classified 55% of the low risk jobs and 73% of the high risk jobs. It should be noted that these numbers have also been publicly reported at a DOE/OSHA hearing on the needs for an ergonomic standard in April of 1994 (Washington, D.C.). In view of the above comparison (*Figure 6*), the neural network-based system developed in this study, which allowed on average for correct classification of about 75% of the analyzed industrial jobs (with both low and high risk of LBDs), appears to be an improvement over the application of NIOSH Guides (1981 and 1991), especially with respect to identification of the high risk jobs (78.4% correct classification rate).

Quality of job classifications

There could be several reasons for the misclassifications of jobs found in this study. Some of the corresponding industrial jobs had RISK (probability) values that would classify them as high (or low) risk of LBDs, even though they were originally placed in the low (or high) risk groups, respectively. This reverse job placement could be due to the jobs with high (low) risk value assigned to the low (high) risk group based on the collected epidemiological data in the field. The data collected and reported by Marras *et al* (1993) may contain possible misclassifications because of such factors as: (1) misreporting of LBDs and corresponding jobs in the company records, (2) not enough (person-years) of exposure data to have properly estimated the classification of a job, and (3) psychosocial factors that may prevent correct recording of some of the injuries, etc.

Several studies identified a variety of psychological and psychosocial risk factors of LBDs which are related to work environment (Wickström *et al*, 1978; Damkot *et al*, 1984; Svensson and Andersson, 1989; Bongers *et al*, 1993; Ayoub *et al*, 1996). Examples of such factors are jobs satisfaction, time pressure, managerial responsibility, or the extent of social support from colleagues and supervisors. It was also reported that workers with LBDs exhibited a higher frequency of psychological symptoms than those without such disorders (Frymoyer *et al*, 1983), and that psychological symptoms were predictive of the future incidence of LBDs (Biering-Sørensen and Thomsen, 1986; Bigos *et al*, 1991). However, Riihimäki (1991) pointed out that since most of these studies (Spengler *et al*, 1986; Svensson and Andersson, 1983; Bigos *et al*, 1986) have been retrospective in nature, it is difficult to determine whether these factors are antecedents or consequences of back pain, and whether these factors play a role in the etiology of LBDs, or only affect the perception of symptoms and sickness behavior. In view of the above discussion, it should be noted that the present research project focused only on those workplace risk factors that could be controlled through engineering design changes, as suggested by the NIOSH 1981 and 1991 Lifting Guides.

As the misclassifications found in this study cannot be easily corrected, they point to limitations of the original data base used for the purpose of network training. Some of the above misclassifications could be a direct consequence of the original structure of the data reported by Marras *et al* (1993), which was used here for the purpose of model development. In Marras *et al*'s (1993) approach, the risk of LBDs was defined as the probability of being either in the high or low risk group. Therefore, a single probability value, for example 0.78, would be interpreted by the neural network as a significant probability of a given job being in the low risk group, or, alternatively, as the probability of this job being in the high risk group. This was the case because the neural network did not have any prior indication whether a particular probability values itself was originally associated with the low or with the high risk group. Only the five input (task) variables collected by Marras *et al* (1993) were indicative of LBDs risk group categorization. This problem needs to be resolved by either indexing the corresponding probability values for the low and high risk groups, or by using the normalized probabilistic sets with two separate intervals, i.e. [0, 0] and [0.5, 1.0], in order to categorize the risk probability values between the low and high risk groups, respectively.

Conclusions

The results of this study show that an artificial neural network-based diagnostic system can be used as an expert system which, when properly trained, will allow us to classify lifting jobs into two categories of associated LBDs risk, based on the available job characteristics data. The developed neural network-based classification system shows great promise because it identifies and classifies industrial jobs into the high and low risk potential for LBDs, and significantly reduces the time consuming job analysis and classification performed by traditional methods. Future work will focus on validation of the network architecture, and consider utilization of other input variables for the neural network, including individual characteristics of the workers, and the psychosocial variables, such as job satisfaction, managerial responsibility, work autonomy, time pressure, or the extent of social support.

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