Predicting Pneumoconiosis Risk in Coal Workers using Artificial Neural Networks

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Objectives: This study aimed to create a model to predict pneumoconiosis risk in coal workers using artificial neural networks (ANNs).

Methods: An ANN-based model was developed using the health records of a population of coal workers (all men). Input neurons comprised current age, year the worker began his employment, occupational category, the number of days spent working underground, the total days spent working, the duration of employment in working underground (i.e., in a so-called group 1 job), and smoking status. Output neurons comprised the states of having pneumoconiosis and being free of pneumoconiosis.

Results: The study found that an ANN model incorporating the variables age, the duration of employment in a group 1 job, the number of days spent working underground, year the worker began his employment, the total days spent working, smoking status, and occupational category can be used to estimate pneumoconiosis risk. The model's success rate was 95.3%; sensitivity was 90.3%, and specificity was 96.5%. The most influential input variable for pneumoconiosis was age, followed by the duration of employment in a group 1 job.

Conclusion: Predicting pneumoconiosis risk in coal workers provides great advantages for strategically monitoring miners and developing preventive health programs. Artificial neural network models should be developed, integrated into occupational medicine practice, and used to evaluate workers' health status.

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Key words: Occupational health, Coal worker, Occupational disease, Pneumoconiosis, Artificial neural network

Pneumoconiosis is one of the most significant occupational diseases worldwide, and there is no drug to cure it. It is very important to be able to accurately estimate the risk of disease development and design effective prevention and control strategies (1, 2). Studies have found that economically significant gains could be achieved by the implementation of effective preventive measures for workers who are at risk for developing pneumoconiosis (3- 5).

Prediction models can estimate lung-disease development risk without the need for invasive and expensive reference testing. Diagnostic models help in the decision-making process and, with routine use, may reduce costs (6, 7). Currently, artificial neural networks (ANNs) are one of the new analytical methods used to predict the risk of developing coal workers' pneumoconiosis (2). Artificial neural networks are computational systems that learn the relationships between events from previous examples, similar to the biological learning function of the human brain, and then use this information to make decisions about cases that they have not encountered before (8). Owing to their strong learning and generalization ability, ANNs are widely used for data correlation, data filtering, image processing, diagnosis, prognosis, classification, prediction, interpretation, and survival analysis in the industrial, financial, military and defense, and healthcare fields (8- 10). There are few studies in the literature that predict the risk of developing pneumoconiosis using ANN (1, 3, 11). However, in Turkey, where coal mining is an important industry and pneumoconiosis is frequently observed in coal workers, no study has yet used ANN to model the risk of developing pneumoconiosis, a lack the study described here in attempted to rectify.

Materials and Methods

This was a methodological research study that aimed to develop an ANN-based model that could predict the risk of developing pneumoconiosis. The research was conducted using the health records of the workers, all men, employed in the locations owned by the Turkish Coal Enterprises. On March 15, 2020, we had accessed the health records of 7897 workers employed by the corporation. We excluded 9 workers missing data from their records and 271 workers with suspected pneumoconiosis, though without a definitive diagnosis. A total of 7617 workers were included in the study.

Of the 7617 workers, 144 had a diagnosis of pneumoconiosis. Samples were selected from the 7473 workers without pneumoconiosis using systematic stratified sampling at a ratio of 1:4. The data of 720 subjects, 144 with and 576 without pneumoconiosis, were used in the study to create an ANN model. After reviewing the literature, data collection forms were prepared by the researchers to compile datas that may be associated with the risk of developing pneumoconiosis. These variables included

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the workers' sociodemographic characteristics, any chronic diseases they may have had prior to or been experiencing at the time of data collection, their smoking status, age at which the worker began his employment, year the worker began his employment, the duration of their employment, number of days spent working underground, number of days spent working above the ground, previous occupations, and their departments within the corporation. The information for the forms was extracted from the workers' health records.

Health related data are regularly kept for each worker at Turkish Coal Enterprises. Each worker undergoes a yearly examination, the results of which are recorded in that worker's digital file. We received special permission from the institution to access the data. Most of workers had worked in different groups of jobs, both underground and aboveground, on a rotational basis at different periods of their working lives. The number of days of underground and aboveground work were calculated by authors for all the workers in the sample. Branches of activity were divided into 4 groups based on levels of dust exposure and risk of coal workers' pneumoconiosis, with input of 2 occupational physicians and 2 public health professors. In the subsequent classification, group 1 jobs were underground activities with heavy dust exposure that involve a high risk for pneumoconiosis, group 2 jobs were underground activities with a moderate risk for pneumoconiosis (e.g., dredging, dismantling, drilling), group 3 jobs included underground activities with a low risk for pneumoconiosis (e.g., electrical work, underground electromechanical supervision, well maintenance), and group 4 jobs were aboveground activities. Next, based on these job groups, 5 different occupational categories were created—production, combined, auxiliary, aboveground, and short-term workers.

Production Group: Those who had worked in any of the group 1 jobs for 3 years or more.

Combined Group: Workers who had a total working period of 1 year or more, but had worked in group 1 jobs for less than 3 years, or who work only in group 2 jobs, or who work in group 3 or 4 jobs together with group 2, are included in combined group.

Support Group: Those who had worked only in group 3 jobs for 1 year or more or those who had worked in group 4 job in addition to group 3 job.

Aboveground Group: Those who had worked only in aboveground jobs (group 4) for 1 year or more.

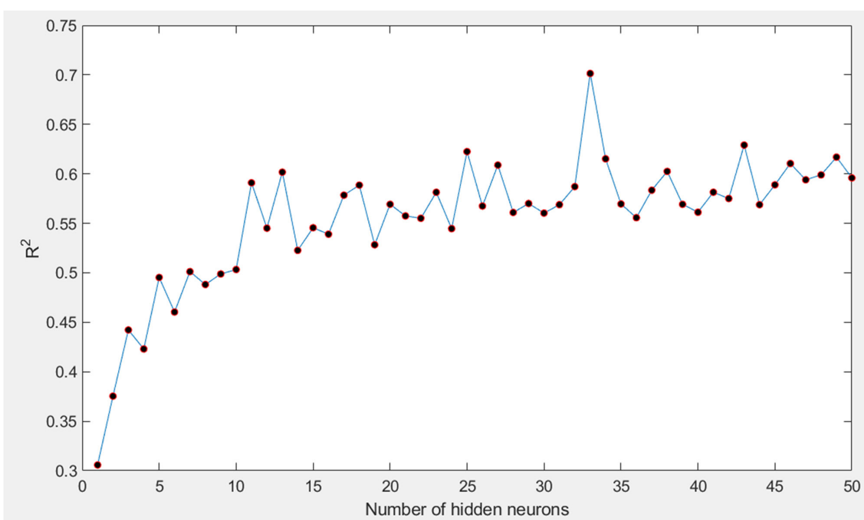
Short-Term Workers: Those who had worked in any job for less than 1 year in total.

In the neural network analysis, 80% of the dataset (consisting of 720 workers) was randomly assigned for training, 10% was assigned for validation, and 10% was assigned for testing. In the data space, the training set consisted of 576 samples, the validation set consisted of 72 samples, and the test set consisted of 72 samples. The experiments resulted in the creation of a 3-layer ANN model—an input layer with 7 neurons, an intermediate layer, and an output layer with 2 neurons.

Using a methodology informed by the literature, the input layer neurons were initially analyzed with 13 variables derived from worker health records. These variables included age, year the worker began his employment, occupational category, number of days worked underground, total number of days worked, duration of employment in group 1 jobs and smoking status, the duration of employment in the corporation, age at first dust exposure, educational level, marital status, and the presence of chronic diseases and respiratory system diseases. Each parameter was removed individually and the analysis repeated. The inputs with the highest success rates were retained in the model. Variables such as the duration of employment in the corporation, age at first dust exposure, educational level, marital status, the presence of chronic diseases and respiratory system diseases were not included because they reduced the performance of the model. Finally, the input layer in the model was determined to consist of 7 neurons, which include age, year the worker began his employment, occupational category, number of days worked underground, total number of days worked, hours worked in group 1 jobs and smoking status. Finally, the output layer of the model was determined to consist of 2 neurons, representing the categories of being a pneumoconiosis patient and being free of pneumoconiosis.

The coefficient of determination (R^2) was used as the evaluation criterion to determine the optimal number of interlayer neurons for the ANN design. In this process, the number of interlayer neurons was increased from 1 to 50, and after 100 trials had been performed for each of the obtained network structures, it was found that the network design with 33 interlayer neurons obtained the best classification performance. Figure 1 shows the performance of the network structures resulting from the interlayer simulations.

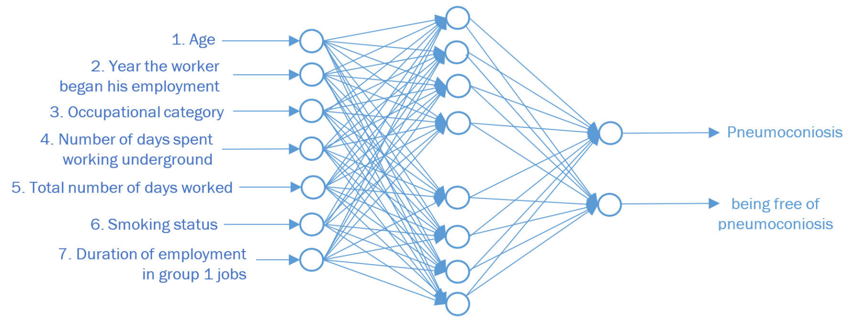
Figure 1. Change in the performance of the artificial neural network according to the number of interlayer neurons



*Coefficient of determination (R^2)

As a result of the simulations, the network model was determined to have a 7-33-2 architecture. The designed network architecture was tested by conducting 1000 trials, and the model with the best performance was selected. The neuron architecture of the observed optimal network model is shown in Figure 2. The performance of the selected model was statistically evaluated using a confusion matrix. Neural network analysis was performed using the R2018b version of the MATLAB software.

Figure 2. Artificial neural network architecture



Statistical analysis was performed using SPSS 19.0 (IBM Corp. Released 2010. IBM SPSS Statistics for Windows, Version 19.0. Armonk, NY: IBM Corp.). The conformity of numerical variables to a normal distribution was examined using the Kolmogorov Smirnov test. The distributions were non-normal. Descriptive statistics were expressed as arithmetic means (±standard deviations) for numerical variables, and as numbers and percentages for categorical variables. Between-group differences among categorical variables were examined using the chi-square test. The Mann–Whitney U test and the Kruskal–Wallis analysis of variance were used to compare numerical variables of the groups, and the level of significance was set at $P < .05$.

The study received the approval of the Bülent Ecevit University Faculty of Medicine Clinical Research Ethics Committee (approval number: 33479383/46; date: October 21, 2019). In addition, the workers' identifying data were not collected during the research.

Results

This study included a total of 720 coal workers, of whom, 20% (n = 144) had coal workers' pneumoconiosis. The mean age of the workers was 37.1 (±6.9) years. The mean age at first dust exposure was 25.9 (±3.8) years. Furthermore, 12.6% of the workers had a chronic disease. In 1.3% of them, a respiratory disease other than pneumoconiosis was present. The average number of days spent working underground was 2959.7 (±2196.5). The average duration of employment was 3850.5 (±2489.3) days, and 68.1% (n = 490) of the workers had smoked before their participation or were current smokers. With regard to the occupational categories, 63.1% (n = 454) of the workers were in the production group, 5.6% (n = 40) in the combined group, 10% (n = 72) in the auxiliary group, and 6.9% (n = 50) in the aboveground group. Additionally, 14.4% (n = 104) had been working for less than 1 year, and 81.3% (n = 585) of the workers had group 1 jobs. The average duration of employment in the group 1 jobs was 5.5 (±4.9) years (0–22 years).

There were significant differences between those with and those without pneumoconiosis in terms of age, number of days spent working underground, total number of days worked, occupational category, duration of employment in group 1 jobs, educational level, and marital status (P<.001); smoking status (P=.028); and having an occupational background in group 1 jobs (P=.002). There was no significant difference between those with and those without pneumoconiosis in terms of age at first dust exposure and the presence of a chronic or respiratory disease (P>.05). Table 1 presents a comparison of the subjects with and without pneumoconiosis based on their sociodemographic characteristics and occupational background, and Table 2 presents a comparison of the subjects based on age and occupational background.

The 7-33-2 network architecture was tested by conducting 1000 trials to determine the model with the best performance. The performance of the optimal network was 95.3% (CI: 94.0%-96.6%) for classification, 90.3% (CI: 85.4%-95.1%) for sensitivity, 96.5% (CI: 95.0%-98.0%) for specificity, 86.7% (CI: 81.2%-92.1%) for positive predictive value, and 97.5% (CI: 96.2%-98.8%) for negative predictive value.

The confusion matrix of the optimal network model is presented in Figure 3A and the receiver operating characteristic (ROC) curve in Figure 3B. The success rate was 95.1% in the training set, 100% in the test set, and 91.7% in the validation set.

To determine the importance of the inputs on determining risk of pneumoconiosis, the absolute values of the weights connecting the input neurons to the interlayer neurons were summed for each input. The input with the highest total value was determined to have the greatest effect on pneumoconiosis. Table 3 shows the levels of importance based on the sum of the absolute values of the weights of the inputs. According to this analysis, age seems to be the most influential input variable of pneumoconiosis. Other significant inputs are, by order of importance, duration of employment in group 1 jobs, number of days spent working underground, year the worker began his employment, total number of days worked, smoking status, and occupational category.

Discussion

Artificial neural networks are increasingly being used for the prediction of diseases in the field of medicine. In the literature, few studies have used ANN to predict the risk of the the developing of coal workers' pneumoconiosis. It is known that workers with different occupational backgrounds have different risk factors in terms of developing coal workers' pneumoconiosis. In our study, a 3-layer ANN model was created based on the medical histories of the workers in order to predict the risks of pneumoconiosis. The study found the classification performance of the optimal network to be 95.3%.

Table 1. Comparison of workers with and without pneumoconiosis in terms of sociodemographic characteristics and occupational background

		With pneumoconiosis (n= 144)		Without pneumoconiosis (n = 576)		Total (n = 720)	
		n	%	n	%	n	%
Educational level*	Primary school	62	43.1	204	35.4	266	36.9
	Secondary school	36	25.0	71	12.3	107	14.9
	High school	43	29.9	249	43.2	292	40.6
	Associate degree	2	1.4	39	6.8	41	5.7
	Undergraduate/ postgraduate degree	1	0.7	13	2.3	14	1.9
Marital status*	Married	132	91.7	434	75.3	566	78.6
	Single	12	8.3	137	23.8	149	20.7
Chronic disease**	Yes	25	17.4	66	11.5	91	12.6
	No	119	82.6	510	88.5	629	87.4
Respiratory disease**	Yes	4	2.8	5	0.9	9	1.3
	No	140	97.2	571	99.1	711	98.7
Smoking***	Current smoker or smoked before	109	75.7	381	66.1	490	68.1
	Non-smoker	35	24.3	195	33.9	230	31.9
Occupational category*	Production group	126	87.5	328	56.9	454	63.1
	Combined group	9	6.3	31	5.4	40	5.6
	Auxiliary group	9	6.3	63	10.9	72	10.0
	Aboveground group	0	0.0	50	8.7	50	6.9
	Short-term workers	0	0.0	104	18.1	104	14.4
Group1 jobs*	Yes	131	91.0	454	78.8	585	81.3
	No	13	9.0	122	21.2	135	18.7

*P<.001 , **P>.05, ***P =.028

A study by Liu et al. aimed to predict coal workers' pneumoconiosis using ANN; the rates under the ROC curve in the training, validation, and test sets were 0.98, 0.97, and 0.99, respectively (11). Another study, this one conducted by Shen et al. in China, aimed to predict coal workers' pneumoconiosis risk, using the input layer variables occupational category, year of first dust exposure, duration of dust exposure, and cumulative dust exposure; the accuracy of the model was 91.8%; its sensitivity was 81.4%, and its specificity was 92.3 (1). Zang et al. used an artificial intelligence based model to screen for pneumoconiosis using radiographs and found the accuracy to be 0.973; sensitivity and specificity were greater than 0.97 for the test set (12).

Although there are many studies that have attempted to predict the risk of different diseases using ANN, there are few studies that have attempted to predict the risk of pneumoconiosis using ANN. In a study by Baxt and Skora, the sensitivity and specificity of ANN for diagnosing myocardial infarction was 96% (13). In a series of studies conducted by Astion and Wilding, the success rate of ANN for diagnosing malignant breast masses was 78% and 88% for benign conditions (14). In a study led by Er that used ANNs with a radial basis for the diagnosis of chronic obstructive pulmonary disease, the accuracy was found to be 90%. In another study from the same author, but using multilayer ANNs, the accuracy was found to be 95.4% (15, 16). Golub et al. used ANN for the prediction of bile duct stones and found the average accuracy of 10 randomly derived networks to be 91% (17).

Artificial neural networks lend themselves to this area owing to the ability to enter a large number of variables into the model, the ability of the model to run despite missing data, and fault tolerance (18). However, although ANN has been demonstrated to have advantages in the prediction of disease in many studies, its use remains difficult due to the skills that users must possess, the length of time required to develop the model, and the need to use trial and error to improve the model (19). Compared with those of studies in which ANN was used for disease prediction, the classification performance of our model seems to be high.

In addition, experiments performed using ANN; determined that the test success rate increased with the use of inputs such as age, duration of employment in group 1 jobs, number of days spent working underground, year the worker began his employment, total number of days worked, smoking status, and occupational category; that being the case, these variables were included in the model. The departments in which the workers labored during their employment with the corporation and the time they spent working underground varied. Periods of performing active work (such as the number of days spent working underground) could be incorporated into the model.

However, because most workers rotated through various positions within the corporation, even those with long tenures may not have spent much time in roles with high dust exposure. The number of years that the workers were employed with the corporation probably did not reflect the level of dust exposure, thereby reducing the model's performance; for this reason, that variable was not used in the model.

Therefore, in our study, instead of using the duration of employment with the corporation as a variable, we used the number of days worked underground and the duration of

Table 2. Comparison of workers with and without pneumoconiosis in terms of age and occupational background

	With pneumoconiosis (n=144) Mean ± standard deviation	Without pneumoconiosis (n=576) Mean ± standard deviation	Total (n=720) Mean ± standard deviation
Age (years)*	40.7±4.7	36.2±7.1	37.1±6.9
Age at first dust exposure (years)**	25.9±2.9	25.9±14.2	25.9±3.8
Number of days spent working underground*	4380.0±1808.8	2604.7±2141.9	2959.7±2196.5
Total number of days worked*	5041.3±1879.7	3505.5±2535.0	3850.5±2489.3
Duration of employment in group 1 jobs (years)***	6.6 ± 4.3	5.2±5.1	5.5±4.9

*P<.001, **P >.05, ***P=.002

employment in group 1 jobs, as these 2 variables may have led to provided a higher success rate since they are better measures of dust exposure.

In a study in which Aydın used logistic regression to evaluate the risk of developing pneumoconiosis in coal workers in Zonguldak, a difference in occupational categories was found among surface workers. It was stated that the greater the number of years of employment and the higher the duration of dust exposure were, the higher the incidence of coal workers' pneumoconiosis was. In addition, compared to the first 10 years of employment, the likelihood of developing coal workers' pneumoconiosis is 5 times higher for those with 10 to 15 years of work experience and 20 times higher for those with 15 to 20 years. It was also found that as the educational level of the workers increased, the development of coal workers' pneumoconiosis decreased. Aydın's study suggested that this may be due to the better compliance of workers with higher levels of educational levels with measures such as the use of dust filters and masks or due to the fact that they were engaged in jobs with less dust exposure (20). In a study conducted by Shen et al. in China, the 40-year cumulative incidence rates according to occupational categories were listed, in decreasing order, as follows: tunneling workers, miners, workers in combined jobs, and those working in auxiliary jobs (1).

Finally, the effect levels of input variables on pneumoconiosis risk were also assessed in this study. The most influential input variable of pneumoconiosis risk was age, and the second most important was the duration of employment in group 1 jobs. Although age is known to be associated with pneumoconiosis risk, the data on whether this is linked to an increase in the age-related duration of dust exposure or whether it can really be considered as a risk factor is controversial. It is known that pneumoconiosis is a disease that develops over a number of years as a result of cumulative dust accumulation. In the study, the increased duration of working in coal production jobs with the highest exposure to dust, classified as group 1 jobs, was the second most important variable. In a study conducted in China by Liu et al., the 2 most important variables affecting the prediction of coal workers' pneumoconiosis were the duration of dust exposure and occupational category (11). In their study, Zhang et al. investigated the effect of different factors on the onset of coal workers' pneumoconiosis and found that the most influential variable of pneumoconiosis onset was the duration of dust exposure (3). Wang et al. found that the most important variables were the duration of dust exposure followed by the type of dust, the years of exposure to dust, and age (2).

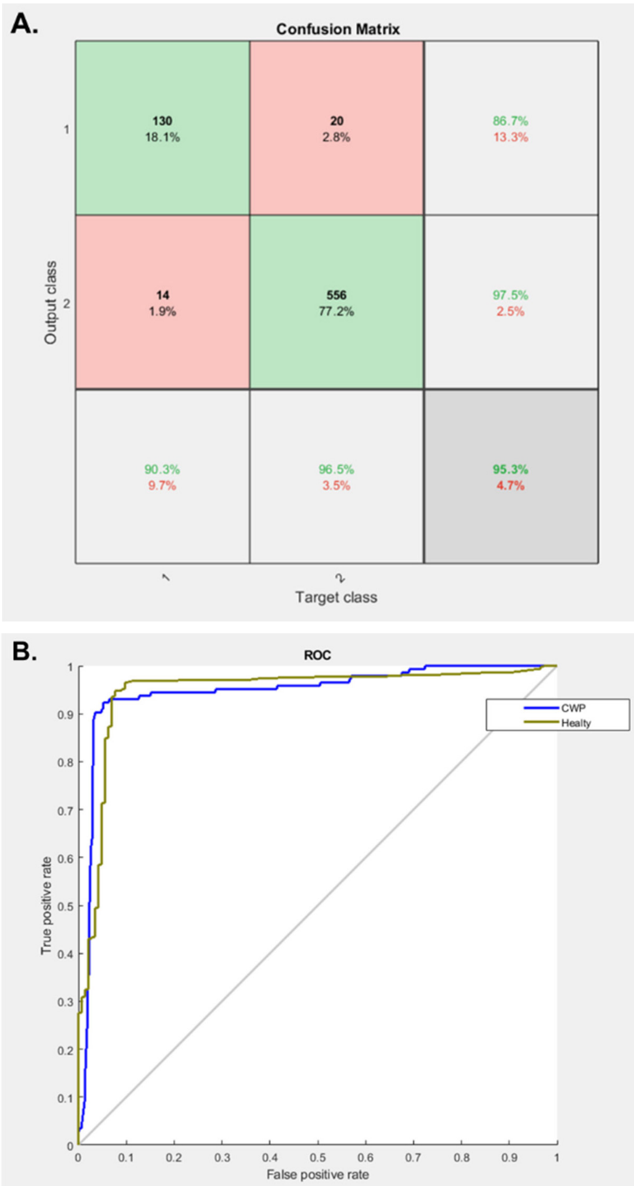
There were several potential limitations to using health record data in this study. Health record data is regularly kept for each worker at Turkish Coal Enterprises. Each worker undergoes a yearly examination, the results of which are recorded in that worker's digital file. Data quality was sufficient to build the model. However, it was difficult to create spesific occupational categories, because most of workers had worked in different job groups, including having been assigned to both underground and aboveground labor for different periods of his working life. Also data on smoking status were limited. In particular, information on daily cigarette consumption was not available in the files of some of the workers. Some workers' files contained only information on whether they smoked or not. However, because there are no studies in the literature on the role of smoking in ANN-based models of coal workers' pneumoconiosis, we wanted to at least add smoking status to the model as an innovation.

To summarize, this study is important since it is the first to investigate the use of ANN for predicting the risk of pneumoconiosis development in Turkey. In addition, this research covered workers employed at all locations of the Turkish Coal Enterprises, which is the corporation doing the bulk of the hard coal production in Turkey, and is thus very important in terms of the generalizability of the results and the model's scope of use. The results of this study have great potential for global occupational health and safety applications and should provide important innovation in the development of occupational health management and preventive strategies. The ANN model has been used quite successfully to predict the risk of developing serious, widespread occupational diseases, such as pneumoconiosis, in coal mining workers.

This study determined that variables such as age, duration of employment in group 1 jobs, number of days spent working underground, year the worker began his employment, total number of days worked, smoking status, and occupational category can be included in an ANN model to predict the risk of pneumoconiosis development. The success rate of the model was 95.3%; the sensitivity was 90.3%, and the specificity was 96.5%. According to the model, the most influential input variable of pneumoconiosis was age followed by the duration of employment in coal production jobs, which we classify as group 1 jobs.

A very high success rate was achieved by the model and its predictive power can enhance the effectiveness of preventive measures by enabling the early diagnosis of diseases such as pneumoconiosis, thereby helping to protect the health of workers.

Figure 3. (A) Confusion matrix for the optimal performance network. (B) Receiver operator characteristic curve of the optimal performance network



Current strategies for the prevention of pneumoconiosis are generally reactive and are aimed at intervening when symptoms of the disease appear. The opportunity offered by this ANN-based model is to aid in the development of preventive approaches and implement proactive interventions. Thanks to the model, workers at high risk can be identified before they develop the disease and appropriate position changes can be made, or special health checks can be arranged for these workers at more frequent intervals. For example, the disease risks of these workers can be minimized by shifting them to work areas where they will be less exposed to dust or by more strictly monitoring their use of personal protective equipment. Workers who reach a certain cumulative dust concentration can be transferred to other work areas and undergo more frequent examinations.

Another important application of the model in practice is that it allows the health of workers to be monitored not only during their active periods of work but also during their breaks. The symptoms of diseases such as pneumoconiosis usually develop over a period of years due to cumulative dust exposure and can continue to have an effect during retirement. In this context, this ANN-based risk prediction model can contribute to the prevention of further complications by ensuring that the health status of retired workers is monitored and disease is diagnosed early. Alternately, periodic follow-ups (to be carried out during retirement) can be tailored to spesific risk groups, and thus unnecessary frequent examinations or, conversely, deficiencies in follow-up can be prevented. In both cases, the model can be used as an important tool in planning the health services to be provided, particulary for retired workers.

Artificial neural networks are increasingly used in biomedical data analysis and excel in disease prediction thanks to their ability to learn and generalize complex relationships. The ANN model used in this study has significant advantages over traditional risk assessment methods in terms of occupational health and safety. For example, the model's ability to consider multiple variables simultaneously, tolerate errors, and function with missing data allows occupational health assessments to be more realistic and flexible. While traditional methods focus on a specific group of risk factors, ANN models can analyze complex and multiple relationships and make more comprehensive assessments. These features make the ANN model an important innovative tool, especially in occupational health and safety management.

In many countries, the mining sector is an area with a high risk of occupational diseases and pneumoconiosis is a common health

Table 3. Order of importance of the input layer weights by the sum of the absolute values

Inputs	Age	Year the worker began his employment	Number of days spent working underground	Total number of days worked	Smoking status	Duration of employment in group 1 jobs	Occupational category
Input layer weights by the sum of the absolute values	58.19973	51.32426	55.41777	42.25968	42.10587	55.82865	39.60478
Order of importance	1	4	3	5	6	2	7

problem. Therefore, the applicability of such ANN-based models not only in a specific region or country but also at a global level offers an important opportunity for improving occupational health and safety policies.

As a result, the use of prediction models to determine risk of occupational diseases can provide a valid basis for planning and implementing healthier and safer programs to improve working conditions. The use of an ANN-based pneumoconiosis risk prediction model has great potential for protecting the health of workers in high-risk occupations by preventing occupational diseases and strengthening occupational safety management. The integration of such models into global occupational health policies will enable the development of more scientific, innovative, proactive and effective strategies in occupational health services.

Resumen

Objetivos: Este estudio tuvo como objetivo crear un modelo para predecir el riesgo de neumoconiosis en trabajadores del carbón mediante redes neuronales artificiales (RNA). Métodos: Se desarrolló un modelo basado en RNA utilizando los historiales médicos de una población de trabajadores del carbón. Las neuronas de entrada incluyeron la edad actual, la edad de reclutamiento, la categoría ocupacional, el número de días de trabajo subterráneo, el total de días de trabajo, la duración del empleo en el trabajo subterráneo (es decir, en un trabajo del grupo 1) y el tabaquismo. Las neuronas de salida incluyeron los estados de tener neumoconiosis y estar libre de ella. Resultados: El estudio determinó que un modelo de RNA que incorpora las variables edad, duración del empleo en un trabajo del grupo 1, el número de días de trabajo subterráneo, la edad de reclutamiento, el total de días de trabajo, el tabaquismo y la categoría ocupacional puede utilizarse para estimar el riesgo de neumoconiosis. La tasa de éxito del modelo fue del 95,3%; la sensibilidad, del 90,3%, y la especificidad, del 96,5%. La variable de entrada más influyente para la neumoconiosis fue la edad, seguida por la duración del empleo en los trabajos del grupo 1. Conclusión: Predecir el riesgo de neumoconiosis en mineros ofrece grandes ventajas para el seguimiento estratégico de los mineros y el desarrollo de programas de salud preventiva. Se deben desarrollar modelos de RNA, integrarlos en la práctica de la medicina del trabajo y utilizarlos para evaluar el estado de salud de los trabajadores.

References

1. Shen F, Yuan J, Sun Z, et al. Risk identification and prediction of coal workers' pneumoconiosis in Kailuan Colliery Group in China: a historical cohort study. PLoS One. 2013;8(12):e82181. Published 2013 Dec 23. doi:10.1371/journal.pone.0082181
2. Wang X, Wu J, Yin S, Wang G, Guo Z. Forecasting incidence age of coal workers' pneumoconiosis based on BP neural networks. In: Yang Y, Ma M, eds. Proceedings of the 2nd International Conference on Green Communications and Networks 2012 (GCN 2012): Volume 1. Vol 223. Lecture Notes in Electrical Engineering. Springer; 2013:657-664. doi:10.1007/978-3-642-35419-9_77
3. Zhang Y, Zhang Y, Liu B, Meng X. Prediction of the length of service at the onset of coal workers' pneumoconiosis based on neural network. Arch Environ Occup Health. 2020;75(4):242-250. doi:10.1080/19338244.2019.1644278
4. Wu J, Wang X, Guo X, Wang G, Su Y, Zhou L. Forecasting incidence seniority of coal workers' pneumoconiosis based on BP neural network. In: Yang Y, Ma M, eds. Proceedings of the 2nd International Conference on Green Communications and Networks 2012 (GCN 2012): Volume 4. Vol 226. Lecture Notes in Electrical Engineering. Springer; 2013:559-564. doi:10.1007/978-3-642-35440-3_73
5. Shen F, Liu H, Yuan J, et al. Cost-Effectiveness of Coal Workers' Pneumoconiosis Prevention Based on Its Predicted Incidence within the Datong Coal Mine Group in China. PLoS One. 2015;10(6):e0130958. Published 2015 Jun 22. doi:10.1371/journal.pone.0130958
6. Suarthana E, Moons KG, Heederik D, Meijer E. A simple diagnostic model for ruling out pneumoconiosis among construction workers. Occup Environ Med. 2007;64(9):595-601. doi:10.1136/oem.2006.027904
7. Suarthana E. Predicting occupational lung diseases, Utrecht University; Drukkerij Ridderprint, Ridderkerk; 2008:105-108.
8. Öztemel E. Artificial Neural Network. 3rd ed. İstanbul: Papatya Yayıncılık Eğitim; 2012:203-206.
9. Renganathan V. Overview of artificial neural network models in the biomedical domain. Bratisl Lek Listy. 2019;120(7):536-540. doi:10.4149/BLL_2019_087
10. Delen D, Sharda R, Kumar P. Movie forecast Guru: A Web-based DSS for Hollywood managers. Decis Support Syst. 2007 Aug 1;43(4):1151-1170. https://doi.org/10.1016/j.dss.2005.07.005
11. Liu H, Tang Z, Yang Y, et al. Identification and classification of high risk groups for Coal Workers' Pneumoconiosis using an artificial neural network based on occupational histories: a retrospective cohort study. BMC Public Health. 2009;9:366. Published 2009 Sep 29. doi:10.1186/1471-2458-9-366
12. Zhang L, Rong R, Li Q, et al. A deep learning-based model for screening and staging pneumoconiosis. Sci Rep. 2021;11(1):2201. Published 2021 Jan 26. doi:10.1038/s41598-020-77924-z
13. Baxt WG, Skora J. Prospective validation of artificial neural network trained to identify acute myocardial infarction. Lancet. 1996;347(8993):12-15. doi:10.1016/s0140-6736(96)91555-x
14. Astion ML, Wilding P. Application of neural networks to the interpretation of laboratory data in cancer diagnosis. Clin Chem. 1992;38(1):34-38.
15. Er O, Yumusak N, Temurtas F, Tanrikulu AC, Abakay A. Chronic obstructive pulmonary disease diagnosis using radial based function neural network. e-LSE. 2009;5(2):1-8.
16. Er O, Temurtas F. A study on chronic obstructive pulmonary disease diagnosis using multilayer neural networks. J Med Syst. 2008;32(5):429-432. doi:10.1007/s10916-008-9148-6
17. Golub R, Cantu R Jr, Tan M. The prediction of common bile duct stones using a neural network. J Am Coll Surg. 1998;187(6):584-590. doi:10.1016/s1072-7515(98)00241-5
18. Mansour R, Eghbal K, Amirhossein H. Comparison of artificial neural network, logistic regression and discriminant analysis efficiency in determining risk factors of type 2 diabetes. World Appl Sci J. 2013;23(11)1522-1529. doi:10.5829/idosi.wasj.2013.23.11.1119
19. Farhadian M, Mahjub H, Aliabadi M, Musavi S, Jalali M. Prediction of workers pulmonary disorder exposed to silica dust in stone crushing workshops using logistic regression and artificial neural networks techniques. Jundishapur J Health Sci. 2013;5(2):141-148.
20. Aydin H. Evaluation of the risk of coal workers pneumoconiosis (CWP): A case study for the Turkish hardcoal mining. Sci Res Essays. 2010;5(21):3289-3297.