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DESIGN OF AN INTELLIGENT SYSTEM TO DETECT TYPE OF PAIN USING ARTIFICIAL NEURAL NETWORK FOR PATIENTS WITH SPINAL CORD INJURY IN SHEFA NEUROSCIENCE RESEARCH CENTER

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Abstract:

Using artificial intelligence in computerized clinical systems helps physicians diagnose disease or choose treatment. Intelligent methods are constantly changed to be more effective and accurate for quick medical diagnosis. Neural networks are a powerful tool to help physicians. The tools can process a high number of data and minimize errors in ignoring patients' information. Intelligent system design based on artificial neural network was performed in 3 phases. Phase1: Designing the data recording and collection system. Phase2: Working with data and samples. Phase3: Artificial neural network design and analysis. Within 7 months, the data pertaining to 253 patients were collected and recorded in Shefa Neuroscience Center. Models of artificial neural network generated and for all models, the precision, sensitivity, attributes, positive reported value and negative reported value were calculated for comparison. 30 models of neural networks were generated. Performing various categorization methods on differing data shows that these methods do not have similar performance. At primary stage, model accuracy was 54%. We implemented the "Bagging" and "Boosting" performance improvement techniques in order to improve the values needed by the models. Accuracy model in secondary stage showed a 91% improvement in comparison with physician diagnosis. Neural network classifiers are very popular choices for medical decision-making, with proven effectiveness in clinical field. A number of studies have indicated that these networks may have significant prediction performance as compared to other methods. In the field of medicine, there are several practical challenges and restrictions regarding data collection.

Keywords: *Pain, Pain diagnosis, classification, Spinal Cord Injury, Artificial Intelligence, Artificial Neural Network.*

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INTRODUCTION:

Pain is a common problem in medicine and one of the major sources of personal and family sufferings; so that, in most cases it goes beyond the individual and becomes a social problem [1]. Pain is one of the main problems in people with Spinal Cord Injury(SCI)[2], and is one of the most common reasons of quality of life decline after SCI [3]. In many medical conditions, pain is a major symptom that is significantly associated with reduced quality of individual's life and his/her overall performance [4]. Nearly 8.2% of gross national income in developed countries is spent on direct and indirect treatment of pain [5]. Spinal cord injury is a damage to the spinal cord causing temporary or permanent functional changes [6]. Common causes of SCI include trauma or disease. Symptoms can vary widely from pain to paralysis and incontinence depending on the damaged part of the spinal cord and nerve roots [7]. Several reports have shown that severe pain can occur after SCI [8]. There is little consensus on the nature, terminology and definitions of various types of pain after SCI. This situation led to much differences in the reported incidence and prevalence of pain after SCI [2]. Health monitoring systems have grown rapidly in the past two decades, and have the potential to change the current medical care. Intelligent systems of "health monitoring" have a positive effect on automation of patient monitoring, improvement of treatment process, increasing medical staff efficiency, shortening waiting times for health services, and reduction of overall costs of health care [9]. Mechanized health information systems would collect and generate information required for integrated support of management decision-making processes [10, 11 and 12]. Using information technology in medicine reduces clinical errors (pharmaceutical and diagnostics) and leads to increased care effectiveness and saves time in caring the patients [13, 14]. Using artificial intelligence in computerized clinical systems helps physicians diagnose disease or choose treatment. Due to the memory limitations, physicians may not examine all symptoms and test results at a time, forget them and or may not seek information about them. However, it is unlikely for the mechanized systems to ignore or forget effective factors (since the relationships between variables are addressed in designing such systems)[15]. Like other intelligent systems, this intelligent system generally consists of five parts: 1.Choosing a classifier system, 2.Choosing effective features in classification, 3.Training 4.Validation, 5.Assessment [16]. Intelligent techniques are steadily changed to assist in accurate and rapid diagnosis [3]. Developed computerized systems aim to provide a tool for timely and more reliable decision for healthcare providers. According to the studies, the first step to produce such a device is to choose methods and algorithms for classification, such as neural network, support vector machine (SVM), genetic algorithms, rule-based systems, decision tree, and so forth [17]. With regard to specific clinical conditions, intelligent systems provide relevant information, necessary recommendations and analysis of conditions with the physicians, patients, and healthcare centers; however, judgment will be handled by physicians [18]. Intelligent methods are constantly changed to be more effective and accurate for quick medical diagnosis [19]. The machine learning intelligent systems can be grouped and classified in the three major groups of deductive learning using symbolic rules (e.g. rule induction, decision-making trees and logical programs), statistical or identification pattern methods (e.g. the nearest neighbors' *K* or based on learning, distinctive analysis and biz-classification) and artificial neural networks (e.g. back-propagation learning networks)[20]. Neural networks are widely used in medical decision support systems [21]. Neural networks are a powerful tool to help physicians. The tools can process a high number of data and minimize errors in ignoring patients' information. They also reduce the time spent on diagnosis. Neural networks strength has been proven in satisfactory diagnosis of various diseases. In addition, they help reaching a more reliable diagnosis which increases patients' satisfaction. However, neural network is a tool provided to help he physician and the physician is the one who should make the final decision [3].

Eq. 1. Output calculation method for each layer of neural network

$$net_j = \sum_{i=1}^{m} x_i \times w_{ij} + \theta_j \qquad (j = 1, 2, \ldots, n)$$

Eq. 2. Remainder of the squares for minimizing error

$$E = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}(y_{ij} - y_{ij}^{*})^2$$

Eq.3. the Chain rule of weight updating

$$\Delta w_{ij} = -\eta \frac{dE}{dw_{ij}}$$

Neural network is widely utilized in the programs related to various branches of science, including chemistry, physics and biology. Neural network is a simple mathematical model of the functionality of human brain neurons, and is capable of learning and extensibility. For this reason, neural network is part of the artificial intelligence widely used in studies, and is capable of modeling complex systems with unidentified variable relations in a non-linear manner [19]. For the first time in 1988, neural network was utilized in medicine. Neural networks are robust tools for aiding physicians. These tools have the capability to process large volumes of data, have proven their power for satisfactory diagnosis of diseases, and contribute to more reliable diagnosis, leading to higher patient satisfaction. Nevertheless, neural network is solely a tool at the physician's disposal, easing and shortening the process of decision-making, and the final decision lies with the physician [19]. Neural networks have been successfully implemented for real world classification applications in industry, business and science. Also, they have been implemented in various areas of medicine such as diagnostic counseling, medicine, biochemical analysis, image analysis and development of narcotic substances. Neural networks are used for medical image analysis for various imaging techniques. Some of their applications are tumor detection in sonography, detection and classification of micro-calcification in mammography, classification of thorax radiography and tissue classification for the magnetic resonance of images [22]. Among the neural network algorithms, the back-propagation algorithm is the most popular. While many types of neural networks can be used for classification purpose, Feed forward multilayer perception networks are widely studied and implemented. Back-propagation feed forward architecture was developed in the early 1970's. This architecture is among the most popular, most effective and simplest learning models of complex, multilayer networks, with great power at solving non-linear problems. Simple back-propagation network has an input layer, an output layer and at least, one hidden layer. There is no theoretical limitation for the number of hidden layers, but normally there are only one or two layers. Some of the conducted works indicate that at most five layers (one input layer, three hidden layers and one output layer) is needed for solving complexity problems. Each layer is completely connected to the subsequent layer [22].

MATERIALS and METHODS:

Intelligent system design based on artificial neural network was performed in 3 phases: **Phase 1.** Designing the data recording and collection system: At this stage, the best programming platform was selected based on the conducted studies. For this stage, the visual studio IDE and the C# programming language and the SQL Server database were utilized. The pain questionnaire used at the Shefa Neuroscience Research center of Tehran was developed by the expert physicians of this center; and has been in use for collecting the data and information regarding the pain of patients with spinal cord damage for nearly 10 years. The questionnaire was designed based on the internationally used Mc-Gill pain questionnaire (MPQ). MPQ is one of the tools used for measurement of pain, and has been used in hundreds of studies. The system was developed in 3 months based on the mentioned questionnaire. After that, by referring to the archives of the patients referred to the pain clinic, the records of the patients suffering from spinal cord damage pain were identified and marked for recording the patients' data in the system. Within 7 months, the data pertaining to 253 patients were collected and recorded.

Phase 2. Working with data and samples, all collected data were labeled, and in this research, the categorization technique which is among the supervised methods has been implemented. Also, this research used 30 neural networks to obtain the best network with the highest accuracy at the testing stage. The main stages of data collection and preparation for this research are summarized as follows:

- ***Attribute selection*:** at this stage, all attributes pertaining to the pain questionnaire of the Shefa Neuroscience Center of Tehran were collected and recorded in the system. At this stage, 386 attributes were collected for each sample.
- ***Database verification*:** for accuracy control and achieving certainty about the completion of recording, an analogical evaluation between the electronic data and the paper files was conducted. Finally, after complete updating, and Excel output was obtained from the collection system, and saved in the CSV (MS-DOS) format.
- ***Dimensionality reduction*:** reducing the number of attributes (dimensionality reduction) was undertaken in multiple stages.
  a) Combination of multiple attributes for obtaining a new attribute (Table 1).

b) According to the opinion of the expert physicians and the PCA technique, this is the best method for linear data dimensionality reduction. That is, by removing low-importance coefficients resulted from this conversion, the data loss is less that other methods. This results in an orderly list of attributes, from high-importance to low-importance. Here, if we intend to reduce data size, we can remove low-importance attributes, which is of course, accompanied by a slight loss of data. Finally after conducting dimensionality reduction, containing 34 attributes, was ordered using the Likert Scale.

- ***Sample balancing using the "Smooth" technique***: the system might have caused errors due to the non-uniformity of the distribution of the samples for the quad-level classes of pain types. For preventing such an error, we used the smooth method for the samples; in a way that frequency distribution for all 4 levels was of the same ratio and equal to the frequency of the highest level.
- ***Cleaning and pre-processing***: the pre-processing operation was used on the data prior to training the neural network. Also, the data was normalized in a range of [0-1]. In addition to normalization, data shuffling was also performed. The attributes below were subjected to normalization:

Age,
BMI,
Pain History,
Length of Attack Pain,
Number of Area,
HADS Anxiety,
HADS Depression,
PDI

Eq. 4. Data normalization formula $z = \frac{X - X\,min}{X\,max - X\,min}$

Phase 3. Artificial neural network design and analysis

- In categorization, all data were divided into 2 categories, in a way that 70% and 30% of the samples were utilized for training and testing the network, respectively. Sample selection was conducted via a completely randomized method by the network.
- The learning algorithms used for network design was the Gradient Descent Algorithm. We were after weights with the minimum possible error. The Gradient Descent Algorithm searches the space for a vector that minimized error. This algorithm starts from a custom value for the weight vector and at each stage, changes the weights in a way that error is reduced along the declining slope of the curve. We used feed-forward Back-propagation neural networks for network design. Each iteration of performing this algorithm for all of the data in the bank is called a "period". These periods iterate until the error value no longer changes. In this study, we used 2000 periods.
- For each iteration of performing the network operation and after witnessing the results of the training and testing the designed neural network, we frequently controlled the confusion matrix tables. This was done to make sure that the network performed well not only for the trained data, but also for other data sets. For elimination of this problem, we frequently performed network operation on the test data in addition to the experimental data, verifying the trend of error changes in them. We finally reached a point where error was increasing, while error for the experimental data was decreasing, so we stopped the training.
- ***Network structure***: for designing the neural network in question, the multilayer perceptron (MLP) was utilized. For all models, the precision, sensitivity, attributes, positive reported value and negative reported value were calculated for comparison using the following formulas.

FINDING:

The total number of the patients under study during the 7 month period was 253, and 83% of the patients were war veterans. In the process of recording and collecting patients' records, type of the pain, as diagnosed by the treating doctor, was also recorded (Table 2). The patients were classified in 8 diagnosis groups implying the types of their pain. By consulting 3 pain specialists with more than 5 years of work experience in Shefa Neuroscience Center, we could classify the pain experienced by the patients in 3 groups (Table 3). In this project, the Algorithm of artificial neural network categorization was used for modeling. 30 models of neural networks were generated and at the end, through accurate analogy between the networks, the model producing the highest accuracy and least errors was selected. In this project is called validation function within the neural network functions and four function contains, nominal to numerical: for continuous data into discrete data; neural network: to create a neural network model, Apply Model: For the use of neural network, performance:With the activation parameters (specificity, sensitivity, Accuracy, positive predictive value (PPV), negative predictive value (NPV) As the parameters of measurement accuracy, all in function are called (Table 4).

Table 1: Combination of multiple attributes

Name of Attribute	Number
HADS Anxiety	7
HADS Depression	7
PDI	7
BMI(Body Mass Index)	2

Table 2: Statistical data samples

Title	Number	Percent
The total number of participants	253	100
The number of war veterans	211	83
The number of participants with pain Nociceptive	62	24
The number of participants with pain Neuropathic	133	52
The number of participants with pain Psychosomatic	48	20
The number of participants with other types of pain	10	4
The average age of participants (years)	55	-
The least age of participants (years)	13	-
The most age of participants (years)	86	-
The average age of BMI	34.8	-
The longest history of pain in the participants (years)	34	-
The longest duration of pain attacks (day)	6	-

Table 3: Type of pain

Nociceptive	Nociceptive musculoskeletal pain
	Nociceptive visceral pain
	Other Nociceptive pain
Neuropathic	Neuropathic SCI pain
	Neuropathic pain- spinal canal/ foramina stenosis
	Neuropathic pain- stump/phantom pain
	Other neuropathic pain
Psychosomatic	Psychosomatic pain
Other	Cancer pain
	Other pain

Table 4: Criteria for comparison model

Accuracy	(TP+TN)/(TP+TN+FP+FN)
Sensitivity or true positive rate (TPR)	TP/(TP+FN)
Specificity or true negative rate(SPC)	TN/(TN+FP)
Positive Predictive Value (PPV)	TP/(TP+FP)
Negative Predictive Value (NPV)	TN/(TN+FN)

DISCUSSION:

After generating the respective neural network vial data imaging, we illustrated some diagrams for their evaluation. At this stage, model accuracy was 54%. Performing various categorization methods on differing data shows that these methods do not have similar performance, with each having proper performance for a specific set of data. Thus, considering the nature of the data and the intended application, various models must be extracted from the dataset and after that, performance improvement techniques must be administered for enhancing model accuracy. We implemented the "Bagging" and "Boosting" performance improvement techniques in order to improve the values needed by the models. Using the "Boosting" technique, model accuracy for data categorization showed a 91% improvement in comparison with physician diagnosis. Artificial neural networks have often been introduced with hopeful results in a vast number of medical journals [23]. The advantages of using neural networks include simplification of optimization and the resulting efficiency and flexibility of non-linear modeling, especially regarding large datasets, accuracy in prediction deduction and the potential for supporting clinical decision-making. These networks result in easier knowledge production along with explanations [23]. Among the other advantages of neural networks we can point out to less formal statistical data collection, the ability of unconditional detection of complex, non-linear relations between independent and dependent variables; the ability of detecting all possible interactions between the predicting variables and the accessibility of multifold algorithms. The disadvantages of neural networks include possessing a black-box nature, higher computational load and experience-based model development nature [24]. Computer-aided decision support system (CAD) are dependent on a wide range of classification methods such as statistical methods, Bayesian methods, deductive classifiers based on the state or case, decision-making trees and neural networks. Specially, neural network classifiers are very popular choices for medical decision-making, with proven effectiveness in clinical field [25]. Artificial neural networks are algorithms that can be used for non-linear statistical modeling. This method is mostly suited for the development of prediction models for split results in medicine [24] .A number of studies have indicated that these networks may have significant prediction performance as compared to other methods [24].

CONCLUSION:

In the field of medicine, there are several practical challenges and restrictions regarding data collection. First, data collection is time consuming and requires a great amount of time. Second, obtaining a large volume of data for patients afflicted with rare diseases is challenging due to the low occurrence rate of such diseases. This study showed that using an integrated model for dimensional reduction (reduction of attributes) alongside implementing artificial neural network is beneficial for developing automatic diagnosis systems, and may be utilized for other diseases also. We believe that artificial neural networks, as innovative, robust modeling tools, can increasingly be used for the development of prediction models for pain management for patients with spinal cord damage. When clinical information is scarce, ANN can be significantly beneficial. All things considered, this form of modeling can ultimately serve as a beneficial tool for clinical decision-making support.

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