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Medical training simulation system to assist novice physicians in diagnostic problem solving

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Abstract: - Medical diagnosis can be viewed as a task that allows physicians to make predictions about features of clinical situations and to determine appropriate course of action. Medical training simulations systems provide students and novices with opportunities to practice critical tasks. The main goal of this paper is investigate the feasibility of typical technique of Pattern Recognition for Meningitis classification in order to assist health professionals in diagnostic problem. We use non-linear mapping structures, which is based on the function of human brain, which so-called Artificial Neural Network (ANN). The early meningitis diagnosis is important as the treatment differ, depending whether meningitis is caused by a virus or bacterium and because of the high severity of illness. The results showed that the use of backpropagation learning with the topology and parameters adopt was able to classify accurately all-training set. Therefore, ANN models provided a robust tool for prediction meningitis diagnostic cluster. Future work will be oriented toward to investigate of structure of the data according to their interrelation, and the feasibility to reduce the feature space dimension.

Keywords: - Backpropagation; Artificial Neural Network; Medical Diagnosis; Meningitis.

1 Introduction

Medical diagnosis is essentially a reasoning and problem-solving task that can be quite difficult [3]. Even when the diagnosis is known, there are many challenging management decisions that test a General Practitioner's knowledge and experience [9]. Diagnostic reasoning is a key competence of physicians; in which medical students must learn to gather and interpret data, generate hypotheses, and make decisions. In this sense, training simulations systems provide students and novices with opportunities to realistically practice important tasks.

Especially in meningitis, medical diagnoses play an important hole. Knowing whether meningitis is caused by a virus or bacterium is imperative because the severity of illness and because the treatment differ. The cost can be quite severe and may result in brain damage, hearing loss, or death, it would be stressed that, every hour of delay the risks increase. If treated immediately, most people recover fully, it is vital, that treatment be started early in the course of the disease.

The use of computers to assist health professionals in their activities has been studied since the 1950s. Initial work was focused on the development of diagnostic systems. Ledley and Lusted [7] were the first to address this possibility. From an educational perspective, we recognize that education for most clinicians is an ongoing process intimately woven into clinical practice [1]. In this way, the learner acquires and uses the knowledge necessary for diagnostic reasoning. Furthermore, the learner should have an opportunity to actively perform diagnostic reasoning and to apply diagnostic strategies. Training simulations systems provide students and novices with opportunities to realistically practice important tasks [2].

In this paper, we investigate the feasibility of typical technique of Pattern Recognition for classification Meningitis, to assist novice physicians. In this sense, we use an artificial neural network in order to predict the "correct" diagnosis in a diagnostic problem.

This paper is organized as follows. The next section briefly describes the Theoretical part, e.g. the basics concept of ANN. The section three discusses the problem domain, the disease and its major characteristic. The following section explains the analysis of the data, in the section five we show the results, and finally, in the section six the conclusion and future work will be discussed.

2 ANN – basic concepts

Over the past few decades, a serious attempt has been made to design electronic circuits that closely resemble biological neural network and their attributes. An ANN Figure 2, more commonly known as a neural network or neural net for short, is a mathematical model for information processing based on a connectionist approach to computation. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data.

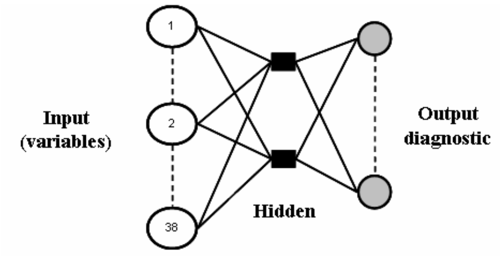

Figure 1: Neural Network basic structure

An ANN is represented by a set of nodes and arrows, which is a fundamental concept in graph theory. The original inspiration for the technique was from examination of bioelectrical networks in the brain formed by neurons and their synapses. In a neural network model, simple nodes (or "neurons" or "units") are connected together to form a network of nodes.

The general neuron has a set of n inputs Xj, where the subscript j takes values from 1 to n and indicates the source of the input signal. Each input Xj is weighted before reaching the main body of the processing element by the connection strength or the weight factor Wj. The output is expressed by:

$$O_i = f\left(\sum_{j=1}^{N}(x_{ij}w_{ij}) - \Theta_i\right) \quad (1)$$

Where xij is the incoming signal or stimulus at input j on the i th neuron, f is the nonlinearity, and Oi is the output response of the i th neuron. In this model the bias term Qi and the weight wij are assumed to have reached steady state.

Learning in ANN is highly important. Generally speaking, learning is the process by which the ANN adapts it self to stimulus (adjust its parameters), and eventually it produces a desired response. When the actual output response is the same as the desired one, the ANN has completed the learning (or training) phase; in other words, it has "acquired knowledge".

Because of its parallel-distributed architecture it can classify, convert, and learn patterns by recognizing significant features or attributes of the data. The computational advantages offered by them include knowledge acquisition under noise and uncertainty; flexible knowledge representation and fault tolerance.

This method has been particularly successful at narrow and well-defined clinical problems such as classifying textual output of images, diagnosis support [8] and prognosis evaluation [6].

For the purpose of our simulation, we select the BackPropagation Network – BPN with supervised learning. The BPN, also called multi-layer feed-forwards neural network or multilayer perceptron, is based on supervised procedure, i.e. the network constructs a model based on example of data with known and desired output. The network-learning rule in this case, is a kind of gradient descent technique with backward error (gradient) propagation. By using this method, it is possible to learn the weighting coefficients of units whose target values are not given directly. The BPN in essence learns a mapping from a set of input patterns to a set of output patterns and it was chosen because of its simplicity and popularity. An excellent general overview of some basic neural network topologies and their applications is given in [4] and [5].

3 Problem domain

Meningitis is an inflammation of the membranes (called meninges) that surround the brain and spinal cord. Meningitis is usually caused by a bacterial or viral infection of the spinal fluid (which is why the disease is called spinal meningitis). Meningitis can lead to permanent damage to the nervous system and can cause hydrocephalus.

The bacterial form of meningitis is an extremely serious illness that requires immediate medical care. If not treated quickly, it can lead to death or to permanent brain damage in about 30% of people. Bacterial meningitis is caused by any one of several bacteria, including Group B strep (in newborns), Hemophilus influenzae type b (in babies), meningococcus (mostly in young adults), Neisseria meningitidis (also called meningococcal meningitis) or Hib and pneumococcus (the most common for adults). Because of its myriad presentations, it is crucial that the emergency physician be able to diagnose Acute Bacterial Meningitis (ABM) and differentiate this condition from other disease processes that may cause or mimic meningitis.

Viral meningitis, also called aseptic meningitis, though more common, are much less likely to have permanent brain damage. Viral meningitis can be caused by a family of viruses known as enteroviruses.

Before performing a physical examination, doctors interview (medical history) the person. Doctors ask the person to describe current symptoms, telling precisely where and how often they occur, how severe they are, how long they last, and whether daily activities can still be performed. Many different symptoms can be caused by Neurologic disorders, but such symptoms can be caused by other disorders. When a Neurologic disorder is suspected, doctors usually evaluate all of the body systems during the physical examination but focus on the nervous system. The Neurologic aspect includes evaluation of mental status, cranial nerves, motor and sensory nerves, reflexes, coordination, stance, gait, regulation of internal body processes. A medical history and physical examination are useful but not specific enough to make the diagnosis.

The most common symptoms of meningitis, which may appear suddenly are: high fever, chills, severe and persistent headache, coma, stiff neck, nuchal rigidity (generally not present in children), nausea, vomiting, Kernig's sign (resistance to extension of the leg while the hip is flexed) and Brudzinski's sign (involuntary flexion of the hip and knee when the patient's neck is abruptly flexed while laying supine). With N. meningitidis may present a rash that begins as an erythematous macular rash, and then eventually progresses to petechiae and purpura (Septicaemia is the blood poisoning form of the disease). Besides, changes in behavior such as confusion, seizure, sleepiness, and difficulty waking up may occur.

Knowing whether meningitis is caused by a virus or bacterium is important because the severity of illness and the treatment differ. Viral meningitis is generally less severe and resolves without specific treatment, while bacterial meningitis can be quite severe and may result in brain damage, hearing loss, or learning disability. For bacterial meningitis, it is also important to know which type of bacteria is causing the meningitis because antibiotics can prevent some types from spreading and infecting other people. Every hour of delay in starting antibacterial (antibiotic) therapy increases the risk of complications and permanent neurological damage. If treated immediately, most people who have acute bacterial meningitis recover fully.

This study employs the collected sample from Investigation Spreadsheet at Epidemiological Surveillance Department of Teresópolis City Hall (Rio de Janeiro – Brazil).

4 Examining data

An exploratory data analysis was performed to identify the type and strength of relation between inputs. The purpose is to provide an overview of available data. The data examination process addresses three separate phases: (1) a graphical examination, (2) an evaluation process for understanding the impact missing data on the analysis, (3) an outlier identification.

A graphical examination showed a general shape of normal distribution and four outlier points. The low number of outlier unmakes the analysis. The next step to be conducted is to assess the normality of metric variables through the derivation of normal probability plots (the modified Kolmogorov-Smirnov test). Normality Test shown with 95% confidence interval that cannot reject the normality.

Furthermore, we determine the extent of missing data on each case, and delete the cases that have excessive levels (above 60 percent of missing values in the same row) and the cases that have not a complete set of exam mostly because of patient sudden death. Therefore, after examination phase the sample have 150 instances. It is important to emphasize that a sample size impairs the statistical strength, and may cause overffiting. Properly, a sample size of 150 produces a 91% confidence interval (see Figure 1) equal to the sample proportion plus or minus 0,06667.

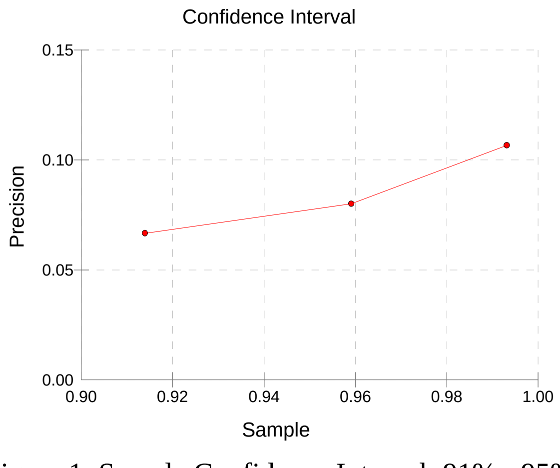

Figure 1: Sample Confidence Interval: 91% - 95% - 99%

The sample have the following distribution according to the diagnostic founded: Meningococcus - Group 1, Meningococcal Meningitis - Group 2, Non Specific Meningitis - Group 3, Tuberculosis - Group 4, Viral - Group 5, Pneumococcus - Group 6 and Hemophilus influenzae - Group 7.

For purposes of generalization, we divide the data into three sets called a Training set (114 records – 76%), Cross-Validation set (21 records – 14%) and a Test set (15 records – 10%) randomly selected. Diagnostic performance was measured by accuracy of diagnosis. The two commonly used performance measures of a neural network are: the Correct Classification Rate – CCR (the number of cases correctly classified divided by the total number of cases), precision required of 99 percent. The second is the lowest network Minimum Mean Squared Error, MSE = 0,000001, both selected as stop training condition. From the collected data, we get eighteen input variables according to their features, shown in Table 1.

After recognition the relevant input variables, it becomes necessary to encode these variables to make them useful. Encoding is the process of data conversion from user format to ANN format. It includes encoding of the categories for categorical data and normalization of numeric data.

Table 1: Clinical and laboratory features founded in patients spreadsheet with meningitis

Input	Features
X1	Age (days)
X2	CSF leucocytes count per µL
X3	CSF Polymorphonuclear - PMN (% of Neutrophilis) count per µL
X4	CSF Monocytes per µL
X5	CSF glucose in mg/dL
X6	CSF Protein in g/L
X7	Bacterioscopy
X8	CSF Culture (bacterial and mycobacterial culture)
X9	Latex Agglutination
X10	Headache
X11	Fever
X12	Nausea and Vomiting
X13	Seizures
X14	Nuchal rigidity
X15	Kernig's sign and Brudzinski's sign
X16	Bulging Fontanelle
X17	Petechiae and Purpura
X18	Coma

Categorical data can be automatically encoded using One-of-N. The One-of-N encoding means that a column with N distinct categories (values) encoded into a set of N categorical columns, with one column for each category, this approach is more resistant to noise because of more distributive information encoding. Originally, the sample contains eighteen variable (six numeric representing X1…X6 and thirteen categorical representing X13…X18), therefore after encoding, 38 inputs was obtained. As a result, the number of input units in input layer consists of 38 variables and the number of output units in output layer consists of 7 desired output or target response. The number of hidden units in hidden layers is much harder to determine. We tested hidden units of 15, 20, 25, 30, and 35. The best topology extensively achieved is then [38-15-7].

The activation level (Oj) of unit j is calculated by

$$O_j = \frac{1}{\left[1 + e^{-\left(\sum_i w_{ji} x_i - \theta_j\right)}\right]} \quad (2)$$

Where qj is the threshold on unit j

The learning algorithm is applied as follows:

1. Initialize all weight to small random values
2. Choose a training pair (x(k), T(k)) where x(k) is the input pattern and T(k) is the target or desired pattern.
3. Calculate the actual output from each neuron in a layer starting with the input layer and proceeding layer toward the output layer L:

$$O_j^l(k) = f\left(\sum_{m=0}^{N_{l-1}} (w_{jm}^l O_m^{l-1})\right) \quad (3)$$

4. Compute the gradient dli and the difference Dwlij for each input of the neuron in a layer stating with the output and backtracking layer by layer toward the input.
5. Update the weights
6. Repeat steps 2-5.

5 Results

To gain additional insights about how network performs under different conditions, several experiments were conducted using different learning rates, error function and classification method. The best output parameters fit were:

Error function: Sum-of-squares

Activation function: Sigmoid

Classification model: Winner-takes-all

Training algorithm: Quick Propagation

Learning rate = 0, 01

With these parameters, the network was stable and converged quickly.

Table 2: Matrix-confusion

		Network Output						
		G1	G2	G3	G4	G5	G6	G7
Target Output	G1	30	**1**	0	**1**	0	**1**	0
	G2	**3**	16	**1**	0	0	**6**	**1**
	G3	0	**1**	20	0	0	0	0
	G4	0	0	0	5	0	0	0
	G5	0	0	0	0	8	0	0
	G6	**1**	0	**1**	0	0	44	0
	G7	0	0	0	0	0	0	10

Table 2 gives an overview of confusion matrix for our classification problem. It is worthwhile to stress that a small portion of instances were classified incorrectly; the error rate was very low and is acceptable it can be seen in shading cells. Only Group 2 (Meningococcal Meningitis) has a small predicting accuracy 59% (16/27 cases), the remaining range between 90% and 100% in the matrix main diagonal.

Table 3 shows the acquired accuracy condition: the CCR and number of cases incorrectly classified in each set. Despite of CCR condition imposed (99%), the total CCR achieved was considered somewhat high (around 89%). From a medical point of view, it is more important to classify a subset of patients with a high accuracy than to obtain a global prediction for all patients. Hence, the global accuracy of 89% is less important compared to the high accuracy of (around) 94% in nearly more than a half of the instance (especially in training set).

Table 3: performance measures – Correct Classification Rate

Set	Mean CCR (%)	Error Quantity
Training	93,85	12
Validation	76,19	3
Test	66,00	2
Total	88,66	17

6 Conclusion

In this study, we investigate the feasibility of typical technique of Pattern Recognition for classification of diagnostic sets of the Meningitis. Results showed that the use of backpropagation learning with the topology and parameters adopt was able classify accurately all-training set. Hence, ANN models provided a robust tool for prediction meningitis diagnostic cluster. Diagnostic reasoning is a key competence of physicians and is at the core of medical practice. A major part of the undergraduate medical curriculum is dedicated to teaching the art and science of diagnosing illness and disease. Furthermore, when assessing the clinical competence of medical students, examiners must infer knowledge and reasoning skills from the behavior and the responses of the candidates.

In addition, finding ways to help students to become efficient in solving patients' problems is a central issue for medical educators. Research has shown that organization of knowledge is the key in the construction of clinical expertise. An important part of the acquisition of expertise is related to practice–theory–practice approach for medical education, in which questions pertinent to educational practice are built in the context of existing theory, and results are interpreted to confirm or refute these theories.

Future work will be oriented toward to investigate of structure of the data according to their interrelation, and the feasibility to reduce the feature space dimension to be considered in the medical analysis. In this sense, we propose to utilize a statistical method called factor analysis to simplify a dataset; it is used to study the patterns of relationship among many dependent variables with the goal of discovering something about the nature of the independent variables that affect them.

References:

[1] Barrows HS, Tamblyn RM.(1980). Problem-based Learning: An Approach to Medical Education, Series on Medical Education. New York: Springer Publishing Co, 1980.

[2] Bordage G, Williams RG. (1992).Theory and practice in medical education. Professions Educ Res Q.;14(2):1–5.

[3] Elstein, A.L., Shulman, L.S., & Sprafka, S.A. (1978). Medical Problem Solving - An Analysis of Clinical Reasoning. Cambridge: Harvard University Press.

[4] Haykin, S. (1994). Neural Networks: A Comprehensive Foundation, Prentice Hall International Editions, 1st ed.

[5] Fu, L. M. (1994). Neural Networks in Computer Intelligence, McGraw Hill, 1st ed.

[6] Heckerman DE, Horvitz EJ, Nathwani BN. (1992). Toward normative expert systems: Part I—the Pathfinder project. Methods Inf Med;31(2):90–105.

[7] Ledley RS, Lusted LB. (1959). Reasoning foundations of medical diagnosis. Science;130:9–21.

[8] Shortliffe E. H. (1987). Computer programs to support clinical decision-making. JAMA;258(1):61–6.

[9] Shortliffe, E. H. (1990). Medical informatics: computer applications in health care. Reading, MA: Addison-Welsley.