Abdominal Pain Estimation in Childhood based on Artificial Neural Network Classification

Dimitrios Mantzaris[1], George Anastassopoulos[1], Adam Adamopoulos[2]
Ioannis Stephanakis[3], Katerina Kambouri[4] and Stefanos Gardikis[4]

[1] *Medical Informatics Laboratory, Democritus University of Thrace, GR-68100, Alexandroupolis, Greece*
dmantzar@med.duth.gr anasta@med.duth.gr

[2] *Medical Physics Laboratory, Democritus University of Thrace, GR-68100, Alexandroupolis, Hellas*
adam@med.duth.gr

[3] *HellenicTelecom. Organization (OTE), GR-151 24, Athens, Greece*
stephan@ote.gr

[4] *Pediatric Surgery Department, Democritus University of Thrace, GR-68100, Alexandroupolis, Greece*
kakampou@med.duth.gr sgardik@med.duth.gr

Abstract

Artificial Neural Networks (ANNs) are particular implementations of AI (artificial intelligence) systems. ANNs have established themselves as powerful tools in clinical practice whenever disease prognosis is based upon the statistical analysis of a set of similar cases characterized by specific clinical data that describe the physical condition of the patient. This study examines the implementation of an ANN architecture for the estimation of abdominal pain in children, which is a critical factor in deciding upon performing a surgical operation of the abdomen. To our knowledge, this approach is the first computational intelligent method based on ANNs that deals with abdominal pain prediction. The proposed ANN implements a multilayer perceprton (MLP) architecture featuring an input layer of 16 nodes, a hidden layer of 5 neurons and an output layer of a single neuron. The decision between applying conservative treatment or performing a surgical operation depending upon the particular exhibits of each case is reached automatically by the output of the proposed ANN estimator of abdominal pain. The proposed ANN attains a percentage of 97% of successful prognosis in cases that belong to the testing set. All pathological cases belonging to the training set are classified correctly. The proposed method may be used as a software tool that assists surgeons in making a diagnosis speeding up thereby the entire examination procedure in emergency cases.

Key-Words: - Artificial Neural Networks, Non – symbolic artificial intelligence methods, Machine learning, Abdominal pain in childhood.

1 Introduction

Artificial intelligence (AI) engineering is a scientific field which attracts the vivid interest of various researchers. Symbolic Artificial Intelligence as well as Artificial Neural Networks, Genetic Algorithms and Fuzzy Logic are modern subfields of the emerging field of Computational Intelligence. Methods and algorithms derived from these subfields exhibit many advantages and suffer from certain drawbacks when applied to real-life problems.

The versatility of the problems [1 - 4] in which Artificial Neural Networks (ANNs) may be used yielding promising results, has led to their rapid proliferation throughout numerous applications. ANN implementations have been widely used over the last years on such applications as aerospace, telecommunications [5], robotics [6], image processing [6, 7], applied mathematics [8, 9], financial analysis [10], intrusion detection systems and others [11].

Medical prognosis is based upon the attempt of a physician to reach a valid decision upon the nature of a patient's disease, to predict its likely evolution and to foresee the chances of recovery based on an objective set of criteria that are applicable to the particular case. Clinician's decision is based on accurately classifying the findings of an examination into groups of high and low risk factors [12].

ANNs contribution into the ongoing research in such medical fields [2, 13 – 21] as oncology [14, 15], pneumonology, neurology [16], urology [17 – 21] and pediatrics [19] is substantial.

Abdominal pain diagnosis may employ fuzzy logic techniques and numerically scoring systems [22] as well in addition to the traditional methods (clinical, laboratory, imaging).

Close collaboration between computer engineers and pediatric surgeons specializing in the abdomen was necessary in the context of this research effort in order to implement ANN architectures for abdominal pain prognosis. Reliable and on-time detection of abdominal pain is crucial in the effective treatment of the disease and the avoidance of relapses. The proposed ANN architecture and its performance on testing clinical data are presented in the following sections of this paper.

2. Theoretical Framework

The proposed method for abdominal pain prognosis is based upon a non-symbolic computational intelligence method implemented by an ANN [19]. The details of the architecture of the ANN are crucial. An ANN featuring many neurons demonstrates poor generalization ability, i.e. its convergence during the training stage is slow or it may not converge at all. On the other hand an ANN which consists of few neurons may be incapable of distinguishing among all cases of interest, i.e. it attains low percentages of successful classification. The determination of the optimal ANN architecture should be carried out ad-hoc on a trial and error basis. ANNs have proved themselves very efficient in controlling complex, non-linear systems.

An ANN has the ability to learn from existent data. The acquisition of knowledge takes place during the training stage. An ANN's architecture is intended to implement a specific operation, which is defined upon a group of input data and the corresponding desired outputs, the so-called targets. Learning during the training stage consists of modifying the values of the synaptic weights between neurons in such a way that ANN's output conforms to the targets suggested by the specific problem. Learning rules are the algorithms according to which ANNs are trained. Unless the correlation between input data and desired outputs is high, ANN will not converge [23].

Combining ANN architectures with different learning schemes, results in a variety of ANN systems. The proper ANN is obtained by taking into consideration the requirements of the specific application as each ANN topology [1, 2, 23] does not yield satisfactory results in all practical cases.

3. Abdominal Pain as a Symptom of Appendicitis and Factors Related to the Prognosis

Appendicitis is the most common cause of surgery of the abdomen. Diagnosis and treatment have certainly improved during the last years but appendicitis still continues to cause significant morbidity and remains a cause of death (in some vary rare cases). [24].

Appendicitis in childhood occurs with a male-to-female ratio of 3:2 with a peak incidence between the ages of 6 to 12. Many terms have been used to describe the varying stages of appendicitis, including acute focal appendicitis, acute supurative appendicitis, gangrenous appendicitis and perforated appendicitis.

Acute Appendicitis (AA) manifests itself as a clinical case featuring a variety of evolving symptoms. Clinical experience and technological advances in diagnostic methods are not foolproof. A typical scenario of acute manifestation of appendicitis is the following: The child describes some mild gastrointestinal symptoms such as indigestion or "gastritis" before the onset of pain. It is typical in an early stage that the pain shall not be localized at the epigastric or umbilical region until after a few hours (4-6 hrs). Then it becomes localized at the lower right quadrant (LRQ) of the abdomen over the appendix. Anorexia, nausea and vomiting follow the onset of pain within a few hours in most cases. Localized tenderness in the LRQ (McBurney's point) is another essential symptom of appendicitis. Other symptoms suggesting acute appendicitis include: psoas muscle sign, obturator muscle sign, Rosving's sign and rebound tenderness. The appendix normally ruptures in about 24 to 48 hours after the onset of symptoms. This may not always be the case.

Leucocytosis (11,000 to 16,000/ mm3) with increased neutrophil population has been considered to be a significant indicator in patients with AA. Urinalysis is useful for detecting urinary tract disease; normal findings on urinalysis are of limited diagnostic value for appendicitis [24, 25].

To date, all efforts to find clinical features or laboratory tests - either standalone tests or combined tests - that are able to diagnose appendicitis with 100% accuracy have proven futile.

This study introduces artificial intelligence in appendicitis prognosis. In the present paper, the implementation of a specific purpose ANN is examined. It intends to estimate the existence or not of appendicitis.

The appendicitis diagnosis is based on 16 parameters that constitute the inputs of the implemented ANN. The result of the examination is the usefulness of an operative vs. a conservative treatment, so the number of ANN's output neurons is one. The estimation suggesting operative treatment is represented by an output value of 1 whereas the estimation suggesting conservative treatment is represented by 0.

The parameters that are used for appendicitis estimation, as well as their coding as input data of the ANN architecture, are summarized on Table 1. The values of the parameters "age" and "temperature" are numbers corresponding to the age and the body temperature of the patient. The coding of parameters Nr. 6 – 8, 10, 15 and 16 is based on the existence (+) or the absence (-) of each symptom. Should an aforementioned symptom exist, the corresponding value in ANN input layer will be set to 1, otherwise to 0.

This study employs a data-set consisting of 516 cases. 422 of them are normal/healthy cases whereas 94 underwent operative treatment. This data-set is separated into two sub-sets, one group of 400 records for training the proposed ANN and another sub-set of 116 cases for ANN testing. The patients' records are obtained from Pediatric Surgery Clinical Information System of the University Hospital of Alexandroupolis, Greece.

4. Proposed ANN Structure for Abdominal Pain Prognosis

The perceptron may be thought of as a net composed of elementary processors. It is a sort of binary classifier that maps its input x (a real-valued vector in the simplest case) to an output value f(x),which is used to classify x as either a positive or a negative instance. Since the inputs are fed directly to the output via the weights, the perceptron is considered as the simplest kind of feedforward network.

Perceptron network does not perform well in the case of non-separable patterns. This is resolved by Multi-Layer Perceptron (MLP) structures whose performance is unexceptionable in testing non-separable patterns as input data.

A MPL network is the ANN that is most commonly used for prediction [13 – 15, 23]. Input quantities are processed through successive layers of neurons. There is always an input layer, where the input nodes are present, with the number of neurons equal to the number of variables of the problem, and an output layer with the number of neurons equal to the desired number of quantities computed from the inputs (very often only one), which represents the results of the simulation [2]. The layers between input and output layers are called "hidden" layers.

Despite the fact that the number of neurons in input and output layers of a multi-layer feed forward network structure may be specified by the problem to be solved,, the determination of a large number of characteristics of a MPL architecture will be realized by trial and error.

As mentioned above, the neurons' number of input and output layers is defined by the problem. It is clarified in Section 3 that input parameters are 16 and output parameter is one;

consequently, in this study, the input layer consists of 16 neurons and the output layer has a neuron that determines the patients' operative or conservative treatment. The determination of the hidden layer is based on trial and error. The number of neurons in the hidden layer is varied and the performance of the specific ANN architecture is consequently evaluated.

Neural Networks Toolbox [www.mathworks.com]. This tool provides an integrated environment for developing, training and testing various ANN architectures and has a friendly and easy to use interface.

The ANN, which estimates the presence of appendicitis, consists of three layers and has a 16–5–1 structure, which is depicted in Figure 1. The output, denoted as **a**, of the proposed ANN results as:

$$a = \text{purelin}\left(W_2 \cdot \text{tansig}\left(W_1 x + b_1\right) + b_2\right) \quad (1)$$

where: purelin(x) = x, (2)

$$\text{tansig}(x) = \frac{2}{1+e^{-2x}} - 1, \quad (3)$$

Table 1. Abdominal pain clinical and laboratorial parameters and their values.

	PARAMETER	VALUES			
1	Sex	Boy	Girl		
2	Age				
3	Religion				
4	Demographic data	Alexandroupoli	Komotini	Xanthi	
5	Duration of Pain	<24 hours	>24 hours		
6	Vomitus	+	-		
7	Diarrhea	+	-		
8	Anorexia	+	-		
9	Tenderness	Diffuse	Right abdomen	Lower Right Quadrant	
10	Rebound	+	-		
11	Leucocytosis	3.500 – 10.800 K/μl			
12	Neutrophilia	40-75%			
13	Urinalysis	-	Non abnormal detected	microhematuria	pyuria
14	Temperature				
15	Constipation	+	-		
16	Admission	+	-		

The modification of the weights and the biases corresponding to the neurons of an ANN is called training and it is achieved using learning rules. In the present work, the Levenberg – Marquardt algorithm is used for the MLP training phase.

The performance of the ANN architecture is evaluated by appropriate criteria. The evaluation criterion applied to ANNs assessment is the Mean Squared Error (MSE).

5. Results

The Multi-Layer Perceptron Networks were implemented using the MATLAB®

W_1, b_1 are the weight matrix and the bias of the hidden layer, and **W_2, b_2** correspond to the weight matrix and the bias of the output layer.

The proposed ANN architecture performs well over the overall testing set as well as the overall training set. The performance of

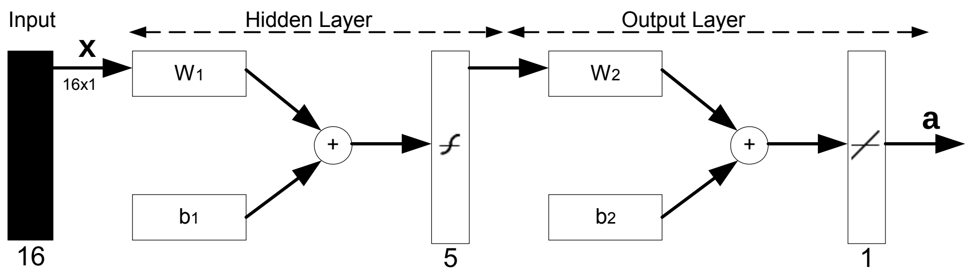

Figure 1. Artificial neural network architecture for appendicitis estimation in childhood.

implemented ANN architecture is presented in Table 2. This table summarizes the results of the values of the parameters for the best ANN structure for appendicitis prediction. An essential criterion is the percentage of successful prognosis over pathological cases for the testing set as well as for the training set.

The suggested artificial neural structure has the ability to predict all pathological cases in the testing set, whereas the percentage of correct prognosis over pathological cases in the training data is 97,4% (after simulation). The last value indicates that the proposed ANN does not suffer from overfitting. The overfitting problem occurs in cases in which the ANN memorizes the training data and does not have generalization ability.

Table 2. Experimental results of proposed artificial neural network architecture.

Criterion	Value (%)
Successful Prognosis Over the Training Set	99,0
Successful Prognosis Over the Testing Set	97,0
Successful Prognosis Over Pathological Cases of the Data Set	97,9
Successful Prognosis Over Pathological Cases of the Training Set	97,4
Successful Prognosis Over Pathological Cases of the Testing Set	100,0

The performance of the proposed technique is considered quite satisfactory and this method is used in Pediatric Surgery Department. This method exhibits certain advantages against existing techniques as ANN incorporates acquired knowledge that can be useful for a surgeon in order to estimate appendicitis in every new case of abdominal pain in children patients.

6. Discussion

ANN constitute a subfield of Computational Intelligence since they are able to embody knowledge within their structure. ANNs implement non-symbolic learning methods and try to emulate the behavior of biological neural networks related to information processing.

Neural networks are being currently used in many fields. Successful application in the medical field has being demonstrated in the areas of diagnostic applications, image processing and analysis, instrument monitoring, drug discovery and bioinformatics. In this study, various ANN architectures are implemented in order to face the problem of abdominal pain. The intention of the suggested implementation is not to replace the specialists, but rather to assist them in abdominal pain prediction, avoiding the unnecessary operative treatment of the disease.

A large number of computer experiments are performed in order to test different combinations of ANN structures, learning algorithms and transfer functions. The proposed ANN architecture faces the appendicitis prediction quite satisfactory, based on the obtained results in Table 2. This method achieves 100% successful prognosis over pathological cases as well as over pathological and non pathological testing cases. Compared to similar efforts to find clinical features or laboratorial tests, the proposed computational method constitutes a reliable non symbolic approach for appendicitis estimation. It avoids unnecessary surgery and proves the capability of artificial intelligence techniques to predict abdominal pain.

An artificial intelligent approach will be developed as part of a future work which will discriminate between and classify the different types of appendicitis (focal, phlegmonous, supurative, gangrenous, peritonitis). The scope of such a study will be the evaluation of the seriousness of the condition of a patient and the appropriate course of medical treatment.

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