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Diagnosing Appendicitis Using Backpropagation Neural Network and Bayesian Based Classifier

E.Sivasankar, Dr.R.S.Rajesh and Dr.S.R.Venkateswaran

Abstract— **The purpose of this study was to assess the role of a Bayesian classifier and back propagation neural network classifier in the diagnosis of severity of appendicitis in patients presenting with right iliac fossa (RIF) pain using Alvarado scoring method. The input parameters of the classifier are the pain site, pain nature, nausea, previous surgery, RIF Tenderness, Rebound Tenderness, Guarding, Rigidity ,Temperature, White blood cell count , Neutrophil count and the output parameters are different classes of appendicitis namely mild(Inflammation only), moderate(Inflammation, Faceolith and Turgid) and severe(Gangrenous and Perforated) appendicitis. The methodology used was a back propagation neural network and Bayesian classifier for diagnosing Appendicitis. The data set is based on the statistics already collected about the presence of appendicitis from patients data set of around 2230 records collected from BHEL Hospital, Tiruchirappalli, India. The conclusion is that Bayesian clas- sifier and back propagation neural network classifier can be used as an effective tool for accurately diagnosing the severity of appendicitis**.

Index Terms—**Data mining, Bayesian classification, Back propagation Neural Networks, Appendicitis.**

I. INTRODUCTION

Data mining is defined as"the nontrivial extraction of implicit, previously unknown, and potentially useful information from data". It is the science of extracting useful information from large data sets or databases. In data mining intelligent methods are applied to the data to discover knowledge or patterns. The two data mining tasks performed by our neural network based classifier are classification and prediction. Classification maps data into predefined groups or classes. It is often referred to as supervised learning, because the classes are determined before examining the data. Prediction is used for predicting a future state based on the past and current state.

Neural Networks A neural network is a system of programs and data structures that approximates the operation of the human brain. A neural network usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access to data in its local memory. Typically, a neural network is initially"trained" or fed large amounts of data and rules about data relationships. A program can then tell the network how to behave in response to an external stimulus or can initiate activity on its own. **Bayesian classification** Bayesian classifiers are statistical classifiers. They can predict class membership probabilities such as the probability that a given sample belongs to a particular class. Bayesian classifiers have exhibited high accuracy and speed when applied to large databases

Medical Data set -Appendicitis Appendicitis is an inflammation of the appendix. Once it starts, there is no effective medical therapy, so appendicitis is considered a medical emergency. When treated promptly, most patients recover without difficulty. If treatment is delayed, the appendix can burst, causing infection and even death. Appendicitis is the most common acute surgical emergency of the abdomen. Anyone can get appendicitis, but it occurs most often between the ages of 10 and 30.

II. RELATED WORK

S.G.Prabhudesai S.Gould and S.Rekhraj proposed that artificial neural networks can be an useful aid in diagnosing acute appendicitis .They used an back propagation algorithm and the weights of the connections were altered in an attempt to reduce the mean square error of the whole data set.Aleksander and Jan Komorowski proposed a computer model (Extended 1R), based upon clinical attributes with additional access to the results of certain biochemical tests which performed better then a classifier realized by probability estimates given by a team of physicians, based only upon the clinical attributes. Ikramullah Khan, Ata ur Rehman used an Alvarado scoring system which depends on the presence and absence of certain variables and which provides an accurate guide to whether or not the patient has the appendicitis.Mesut Tez and Selda Tez proved that neuro fuzzy systems can incorporate data from many clinical and laboratory variables to provide better diagnostic accuracy in acute appendicitis.

III. PROBLEM STATEMENT

This paper reports on an analysis of a database of patients operated for appendicitis. The main objective of this study has been to address the following two questions:

1) A computer based statistical model was built based on the clinical attributes and biochemical attributes that has been

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collected from the patients who are suffering with Appendicitis from BHEL Hospital, Tiruchirappalli.

2) Based on the statistical results a scoring System based on back propagation neural network and Bayesian classifier was proposed to detect the severity of appendicitis.

IV. Statistical Model for Appendicitis Data Set

We propose a computer based statistical model based on the statistics of clinical and biochemical attributes collected about the presence of appendicitis from a patient's data set from BHEL Hospital, Tiruchirappalli. From the dataset it was found that appendicitis occurs most often between the ages of 11 and 20 years. It is commonly found in patients with female sex. The pain site is usually right iliac fossa (RIF) pain and the pain nature is colicky. Fever and vomiting was usually present among the patients suffering with appendicitis. RIF tenderness and rebound tenderness was present among the patients with appendicitis. Based on the biochemical tests, it was found that high white blood cell count and neutrophil count indicates the severity of the appendicitis. Patients with high WBC and neutrophil count have a high probability of severe appendicitis.

TABLE I: Statistical Model built based on both clinical and biochemical attributes collected from the patients who are suffering with Appendicitis

Clinical Attributes		
Attribute	Description	Statistics
a1	Age(11-20 years)	40.57 %
a2	Sex(Female Sex)	60.70 %
a3	Pain Site(RIF)	93.28 %
a4	Pain Nature (Colicky)	63.91 %
a5	Nausea or vomiting(Present)	47.51 %
a6	Previous surgery(yes)	34.21 %
a7	Pain Shift(Present)	71.18 %
a8	Foetor(Present)	19.19 %
a9	Change of Micturition (Present)	11.74 %
a10	RIF Tenderness(Present)	93.04 %
a11	Rebound Tenderness(Present)	35.60 %
a12	Guarding(Present)	79.45 %
a13	Rigidity (Present)	45.24 %
a14	Temperature (Fever Present)	40.46 %
Biochemical Tests		
a15	White blood cell count (8000 and above)	57.36 %
a16	Neutrophil count (60 and above)	66.75 %
Diagnosis		
D	Diagnosis Appendicitis	

The Table -1 summarizes the statistics collected about the presence of appendicitis from a patient's data set of around 2230 patients collected from BHEL Hospital, Tiruchirappalli.

From the data analyzed we inferred that 23.23% of the patients were diagnosed with mild appendicitis, 57.30% of the patients were diagnosed with moderate appendicitis and 19.47 % of the patients were diagnosed with gangrenous appendicitis.

V. Existing Methods for Appendicitis Diagonosis

The diagnosis of appendicitis begins with a thorough history and physical examination. Patients often have an elevated temperature, and there usually will be moderate to severe tenderness in the right lower abdomen when the doctor pushes there. If inflammation has spread to the peritoneum, there is frequently rebound tenderness. Rebound tenderness is pain that is worse when the doctor quickly releases his hand after gently pressing on the abdomen over the area of tenderness.

A. White Blood Cell Count

The white blood cell count in the blood usually becomes elevated with infection. In early appendicitis, before infection sets in, it can be normal, but most often there is at least a mild elevation even early. Unfortunately, appendicitis is not the only condition that causes elevated white blood cell counts. Almost any infection or inflammation can cause this count to be abnormally high. Therefore, an elevated white blood cell count alone cannot be used as a sign of appendicitis.

B. Urinalysis

Urinalysis is a microscopic examination of the urine that detects red blood cells, white blood cells and bacteria in the urine. Urinalysis usually is abnormal when there is inflamma-tion or stones in the kidneys or bladder. The urinalysis also may be abnormal with appendicitis because the appendix lies near the ureter and bladder. If the inflammation of appendicitis is great enough, it can spread to the ureter and bladder leading to an abnormal urinalysis. Most patients with appendicitis, however, have a normal urinalysis. Therefore, a normal urinal- ysis suggests appendicitis more than a urinary tract problem.

C. Abdominal X-Ray

An abdominal x-ray may detect the fecalith (the hardened and calcified, pea-sized piece of stool that blocks the appen-diceal opening) that may be the cause of appendicitis. This is especially true in children.

D. Ultrasound

An ultrasound is a painless procedure that uses sound waves to identify organs within the body. Ultrasound can identify an enlarged appendix or an abscess. Nevertheless, during appendicitis, the appendix can be seen in only 50 percentage of patients. Therefore, not seeing the appendix during an ultrasound does not exclude appendicitis. Ultrasound also is helpful in women because it can exclude

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the presence of conditions involving the ovaries, fallopian tubes and uterus that can mimic appendicitis.

E. Computerized Tomography (CT) Scan

In patients who are not pregnant, a CT Scan of the area of the appendix is useful in diagnosing appendicitis and peri-appendicle abscesses as well as in excluding other diseases inside the abdomen and pelvis that can mimic appendicitis.

F. Laparoscopy

Laparoscopy is a surgical procedure in which a small fiber optic tube with a camera is inserted into the abdomen through a small puncture made on the abdominal wall.

Laparoscopy allows a direct view of the appendix as well as other abdominal and pelvic organs. If appendicitis is found, the inflamed ap appendix can be removed with the laparoscope. The disadvantage of laparoscopy compared to ultrasound and CT is that it requires a general anesthetic.

There is no one test that will diagnose appendicitis with certainty. Therefore, the approach to suspected appendicitis may include a period of observation, tests as previously discussed, or surgery.

VI. Scoring System for Appendicitis Investigation

A. Alvarado scoring system

Alvarado scoring system depends on the presence and absence of certain variables and which provides an accurate guide to whether or not the patient has the appendicitis.Table-2 summarizes the symptoms and their corresponding score in an Alvarado scoring system

TABLE II: ALVARADO SCORING SYSTEM FOR DIAGNOSING APPENDICITIS

Symptoms	Score
Migratory right iliac fossa pain	1
Nausea / Vomiting	1
Anorexia	1
Signs	
Tenderness in right iliac fossa	2
Rebound tenderness in right iliac fossa	1
Elevated temperature	1
Laboratory findings	
Leucocytosis	2
Shift to the left of neutrophils	1
Total	10

Aggregate score 7-10 (emergency surgery group): These patients were prepared and all underwent emergency appendicectomy.

Aggregate score 5-6 (observation group): These patients were admitted and kept under observation for 24 hours with frequent re-evaluation of the clinical data and reapplication of the score. Condition of some patients improved shown by a decrease in score and therefore they were discharged with the instructions that they should come back if symptoms persist or increase in intensity.

Aggregate score 1-4 (discharge home group): These patients, after giving initial symptomatic treatment, were discharged and sent home with the instructions, to come back if symptoms persist or condition become worse.

VII. Data Pre-processing:

Knowledge Discovery as a process consists of the following sequence of steps. Data cleaning is done to remove noise and inconsistent data .we use smoothing by bin means method to clean data. Data integration combines multiple data source formats into a uniform schema. Data relevant to the analysis task are retrieved by means of data selection methods. In the data transformation phase the data is consolidated into forms appropriate for mining. In data mining intelligent methods are applied in order to extract data patterns. The feature vectors are divided into two sets, the "training set" and the "test set". The training set is used to "train" the data mining algorithms, while the test set is used to verify the accuracy of any patterns found.

VIII. Appendicitis Diagnosis Using Backpropagation Neural Network and Bayesian Based Classifier

A. Back propagation neural network Algorithm

Neural Networks A neural network is a system of programs and data structures that approximates the operation of the human brain. A neural network usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access to data in its local Memory. Typically, a neural network is initially “trained” or fed large amounts of data and rules about data relationships. A program can then tell the network how to behave in response to an external stimulus or can initiate activity on its own.

Back propagation Neural Network

Back propagation is a supervised learning technique used for training artificial neural networks. The Steps in a BPN are

1) Present a training sample to the neural network
2) Compare the network’s output to the desired output from that sample. Calculate the error in each output neuron.
3) For each neuron, calculate what the output should have been, and a scaling factor, how much lower or higher the output must be adjusted to match the desired output. This is the local error.
4) Adjust the weights of each neuron to lower the local error.
5) Assign”blame” for the local error to neurons at the previous level, giving greater responsibility to neurons connected by stronger weights.
6) Repeat the steps above on the neurons at the previous level, using each one’s”blame” as its error.

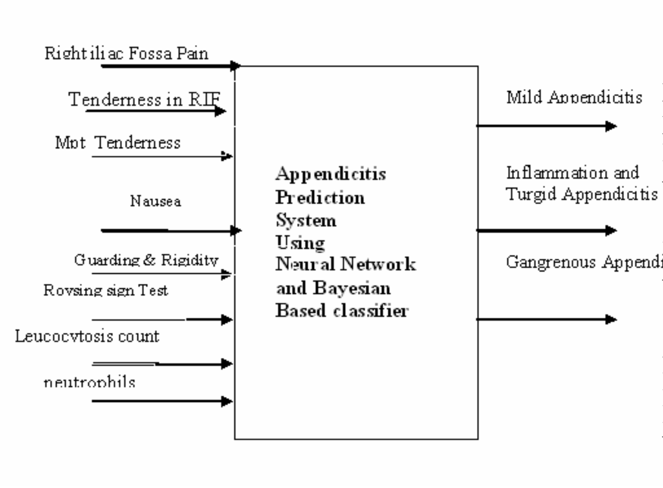

Figure 1 System Inputs and Outputs

Figure-1 summarizes the input and output parameters of the classifier. The input parameters of the BPN and Bayesian classifier are the pain site, pain nature,nausea, previous surgery, RIF Tenderness, rebound Tenderness, guarding, rigidity ,Temperature, White blood cell count , Neutrophil count and output parameters are different classes of appendicitis namely mild(Inflammation only), moderate(Inflammation, Faceolith and Turgid) and severe(Gangrenous and Perforated) appendicitis.

Back Propagation Network Algorithm Input:

D, a dataset consisting of the training tuples and their associated target values; I, the learning rate; Network, multilayer feed_forward network.

Output:

A trained neural network.

Method:

Initialize all weights and biases in network; while terminating condition is not satisfied {

for each training tuple X in samples {

//Propagate the inputs forward:

for each hidden or output layer unit j{

$I_j=\Sigma_i W_{ij}O_i + \Theta_j$;

//compute the net input of

unit j with respect to the previous layer, i

$O_j = 1/1+e^{\wedge}(-I_j)$;}

//compute the output of each unit j

//Back propagate the errors:

for each unit j in the output layer

$Err_j = O_j (1-O_j) (T_j - O_j)$;

//compute the error

for each unit j in the hidden layers, from the last to the first hidden layer

$Err_j = O_j (1-O_j) \Sigma_k Err_k W_{jk}$;

//compute the error with respect to the next higher layer, k

for each weight W_{ij} in network{

$\Delta W_{ij} = (l) Err_j O_i$; //weight increment

$W_{ij} = W_{ij} + \Delta W_{ij}$;}//weight update

for each bias Θj in the network{

$\Delta\Theta_j = (l) Err_j$; //bias increment

$\Theta_j = \Theta_j + \Delta\Theta_j$; //bias update

} }

B. *Bayesian classification*

Bayesian classifiers are statistical classifiers They can predict class membership probabilities such as the probability that a given sample belongs to a particular class. Bayesian classifiers have exhibited high accuracy and speed when applied to large databases. They have performance comparable with decision trees and neural networks. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called class conditional independence.

Bayes Theorem:

Let X be a data sample whose class label is unknown. Let H be some hypothesis such that the data sample X belongs to a specified Class C. For classification problems we need to determine P (H | X), the probability that the hypothesis H holds, given the observed data sample X.

P(H | X) is the posterior probability of H conditioned on X. P (H) is the prior probability of H.

By Bayes Theorem

$$P(H \mid X) = \frac{P(X \mid H)\,P(H)}{P(X)}$$

Bayesian Classifier Algorithm

1) Each data sample is represented by n-dimensional feature vector, $X=(x_1, x_2,\ldots,x_n)$ depicting measurements made on the sample from n attributes, A1,A2,……..An

2) Suppose there are m classes $C_1,C_2,\ldots,C_m$. Given an unknown sample, X which has no class label, the classifier will predict that X belongs to the class having highest posterior probability, conditioned on X.Bayesian classifier assigns an unknown sample X to class C_i if and only if

$$P(C_i \mid X) > P(C_j \mid X) \text{ for } 1\le j\le m,\ j \ne i.$$

We maximize $P(C_i \mid X)$.The class C_i for which $P(C_i \mid X)$ is maximized is called the maximum posteriori hypothesis.

By Bayes Theorem

$$P(C_i \mid X) = \frac{P(X \mid C_i)\,P(C_i)}{P(X)}$$

3) P(X) is constant for all the classes, only $P(X \mid C_i)\,P(C_i)$ need to be maximized. The class prior probabilities may be estimated by

$$P(C_i) = S_i / s$$

Where S_i=number of training samples of class C_i and s=total number of training samples

4) Class conditional independence presumes that the values of the attributes are conditionally independent of one another. Given the class label of the sample, there is no dependence relationship among the attributes

$$P(X \mid C_i) = \prod_{K=1}^{n} P(x_k \mid C_i)$$

5) An unknown sample X, is assigned to class C_i , if and only if

$$P(X \mid C_i)\ P(C_i) > P(X \mid C_j)\ P(C_j) \text{ for } 1 \le j \le m,\ j \ne i$$

IX. Experimental Results

The proposed Back propagation Neural Network and Bayesian classifier system was experimented for several test cases and the results obtained are graphically represented. For each test case, the experiment was executed at an average of 10 times to measure the performance of the heuristics. The graph in Figure-2, shows the comparison of the clinical attribute values for patients with different types of appendicitis and the graph in Figure-3 shows the comparison of the Biochemical attribute values for patients with different types of appendicitis for 10 runs of the sample test cases.

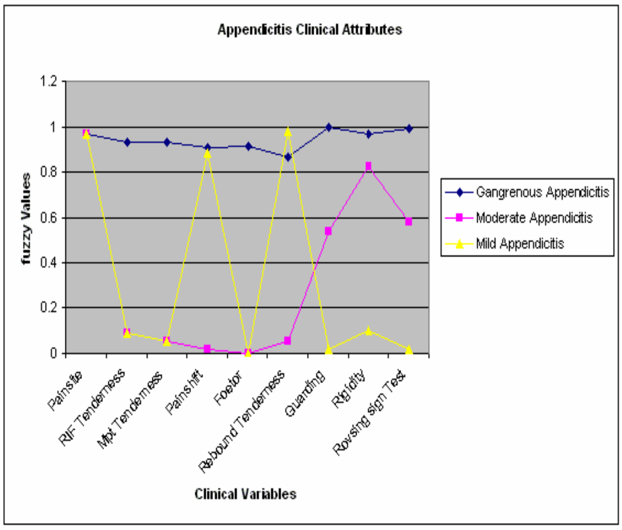

Fig. 2 Clinical attribute values for patients with different types of appendicitis

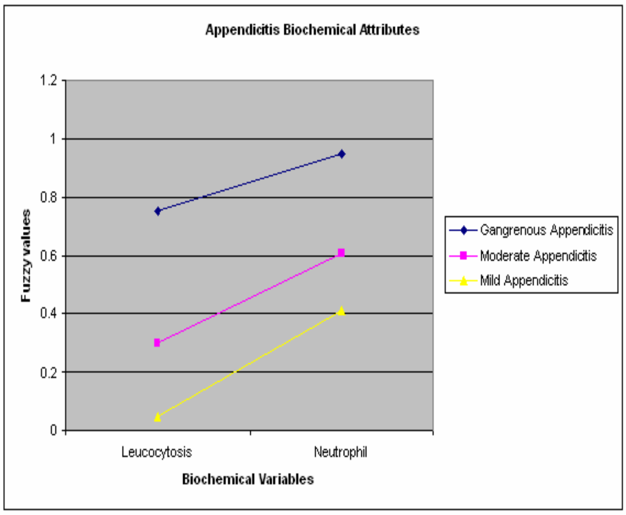

Fig. 3 Biochemical attributes values for patients with different types of appendicitis

X. Conclusion

Our study shows that Back propagation Neural Network can provide high degree more than of Positive predictive value and thus diagnostic accuracy in the prediction of the type of appendicitis. We were able to classify the patients to different classes of appendicitis namely mild, moderate and severe appendicitis based on the various input parameters namely the pain site, pain nature ,nausea, previous surgery, RIF Tenderness, Rebound Tenderness, Guarding, Rigidity, Temperature, White blood cell count and Neutrophil count with Gangrenous appendicitis .The Figure-6 gives the confusion matrix representation of the results obtained by different classifier.

Confusion matrix for Appendicitis prediction				
		Actual		
		Mild	Moderate	Gangrenous
Prediction by Back propagation Neural Network based classifier	Mild	94.82%	2.941%	0%
	Moderate	5.172%	92.15%	9.5%
	Gangrenous	0%	4.901%	90.5
Prediction by Bayesian classifier	Mild	91.37%	6.862%	0%
	Moderate	8.62%	87.25%	15%
	Gangrenous	0%	5.88%	85%

Fig. 4 Confusion Matrix representation of results by different classifier

From the results predicted by an Back propagation Neural network we inferred that the accuracy rate of prediction was 94.82% for the patients suffering with mild appendicitis, 92.15% for thee patients with moderate appendicitis and 90.5 % for the patients with Gangrenous appendicitis. The results predicted by an Bayesian classifier has the accuracy rate of 91.37% for the patients suffering with mild appendicitis ,87.25% for the patients with moderate appendicitis and 85 % for the patients. The Figure-4 gives the confusion matrix representation of the results obtained by different classifier.

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