

# Predicting Risk of Acute Appendicitis: A Comparison of Artificial Neural Network and Logistic Regression Models

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**Abstract-** Acute appendicitis is considered as one of the most prevalent diseases needing urgent action. Diagnosis of appendicitis is often complicated, and more precision in diagnosis is essential. The aim of this paper was to construct a model to predict acute appendicitis based on pathology reports. The analysis included 181 patients with an early diagnosis of acute appendicitis who had admitted to Shahid Modarres hospital. Two well-known neural network models (Radial Basis Function Network (RBFNs) and Multi-Layer Perceptron (MLP)) and logistic regression model were developed based on 16 attributes related to acute appendicitis diagnosis respectively. Statistical indicators were applied to evaluate the value of the prediction in three models. The predicted sensitivity, specificity, positive predicted value, negative predictive values, and accuracy by using MLP for acute appendicitis were 80%, 97.5%, 92.3%, 93%, and 92.9%, respectively. Main variables for correct diagnosis of acute appendicitis were leukocytosis, sex and tenderness, and right iliac fossa pain. According to the findings, the MLP model is more likely to predict acute appendicitis than RBFN and logistic regression. Accurate diagnosis of acute appendicitis is considered an essential factor for decreasing mortality rate. MLP based neural network algorithm revealed more sensitivity, specificity, and accuracy in timely diagnosis of acute appendicitis.

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**Keywords:** Acute appendicitis; Neural network; Multi-layer perceptron; Radial-based function; Logistic regression

## Introduction

Acute appendicitis is usually introduced as one of the prevalent causes of patient admission to hospital (1). It has been reported that 7% of people experience this condition during their life (2). Etiology of appendicitis is multifactorial, and adolescent and males are more likely to be diagnosed with acute appendicitis (3). Precise diagnosis of acute appendicitis is a challenging issue in the healthcare area, as it is difficult to discriminate between acute appendicitis and the other reasons for abdominal pain (4). Perforation rate is 13-20% in patients with acute appendicitis (5). Any false negative diagnosis or late diagnosis may lead to increase the length of stay and even mortality and morbidity rate (6,7). Therefore, appropriate detection and precise method for diagnosis of acute appendicitis is essential for accurate identifying of patients and applying care strategies (6). For this purpose,

there are different machine learning and diagnostic methods that can be applied for timely diagnosis of acute appendicitis.

A different approach for the correct diagnosis of acute appendicitis has been presented. Alvarado clinical scoring system was proposed in 1986; this scoring method is based on the specific symptom, sign and laboratory data (8). Various studies have reported the Alvarado's diagnostic accuracy up to 78-84% (9). Although, there is some contradictory conclusion about its accuracy (10). Among the other diagnostic methods, ultrasound is a noninvasive, safe, inexpensive and accessible method which is commonly used in clinical setting to the accurate diagnosis of acute appendicitis (11,12). Despite the numerous advantage of CT scanning in acute appendicitis diagnosis, there are also significant disadvantages; the patient is exposed to radioactive radiation, and the cost of this method is high. In the case

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of pregnant women, it cannot be used, some individuals are allergic to the contrast, it is not available in all health centers, and it takes more time than radiographic methods (13,14). Although the two aforementioned methods are commonly used in the diagnosis of acute appendicitis, the level of misdiagnosis has remained constant (15). It is possible that sometimes contradictions can be seen between different diagnostic methods and clinical observations. In order to tackle this issue, we can use some intelligent systems.

Applying intelligent systems in the management of acute appendicitis provides new capabilities for accurate diagnosis and decrease human errors (16,17). Medical diagnostic algorithms based on machine learning algorithms can capture the sophisticated relationship between data and provide promising medical diagnostic results (18). The aim of the current paper was to the establishment of the artificial neural network and a logistic regression model for correct prediction of acute appendicitis. In the development of artificial neural network (ANN) model, several configurations were evaluated, and the total performance of the model was optimized by means of modifying the number of hidden layers and neurons to achieve the suitable model for prediction of acute appendicitis. The remainder of this paper is organized as follow; In Section 2, we discussed the method. Section 3 provides more details about the obtained results and section 4 provides discussion in the current work. Finally, our conclusion is presented in section 5.

## Materials and Methods

### Patient characteristics

In the initial phase of the study, it was necessary to collect comprehensive information on the nature of the disease. Based on the literature, several scoring methods have been suggested to accurately diagnose of acute appendicitis. These systems include Alvarado's scoring system, Ripasa's scoring system, and acute appendicitis inflammatory scoring system (9,19,20). The parameters included in these systems are mainly based on patients' signs and symptoms, physical examination results, and laboratory tests that are somehow different in scoring systems. Variables that have been used in the current survey are based on this scoring system.

In the second phase, selected variables were gathered in the form of a questionnaire. After confirming the validity and reliability (Cronbach's alpha=75%) of the questionnaire, the forms were distributed among 17 general surgeons. To determine the variables

appropriateness to acute appendicitis diagnosis from the expert perspective statistical indicators of mean, variance and standard deviation were calculated. Finally, the 16 features that had greater diagnostic value for acute appendicitis were selected. The name of selected variables and their categories are demonstrated in table 1.

We retrospectively collected data from patients' medical records during 2015 in Shahid Modarres hospital which their diagnosis was confirmed by a pathology report. Patients diagnosed with complaints like acute cholecystitis or acute diverticulitis, incidental appendectomy and appendectomy due to chronic abdominal pain were excluded.

### Logistic regression

In the current paper, a logistic regression, as a linear mathematical model is applied for prediction of occurrence of acute appendicitis. The SPSS 21.0 was used to conduct the statistical analysis. In this study, the predictor variables ( $x_1, x_2, x_3, \dots, x_n$ ) were used as input variables. We also tested for significant interactions among attributes. At the output, a binary attribute was used that one class stand for a patient with a positive pathology result and the other one stands for a patient with a negative pathology result.

### Artificial neural network (ANN)

The artificial neural network is considered as an information processing system that consists of some processing units in order to store knowledge and distribute them to end users (21). The ANN structure is characterized by connection nodes, connection weights and activation function. In this research, we used the Radial Basis Function Network (RBFNs) and Multi-Layer Perceptron (MLP). An ANN model that is often used in disease prediction is RBFN (22). The RBFN structure comprises of input, hidden and an output layer. The first layer collects the raw data and transmits to the hidden layer. Hidden layer is considered as the core of RBFN that transfers the obtained results to the output layer. In RBFN only one hidden layer exists, and its neurons hold radial basis activation functions (23,24). Output of an RBF network is determined by the weighted sum of the hidden neurons' responses, which can be expressed as in Eq. 1

$$y_j = \sum_{i=1}^n W_{ij} \phi_i(\|x - c_i\|) + W_{oj}, j = 1, 2, \dots, n \quad (1)$$

Where

n=number of nodes in hidden layer;

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x=input vector;  
 ci=center of the ith hidden node;  
 Wij=weight of the ith node of the hidden layer;  
 $\varphi_i$ =radial basis function with ci beings its center;  
 And  $W_{oj}$ = bias of the ith node of outthe put layer.

The number of neurons in the input and output layer is equivalent to the input and output variables of the data set. However, the number of neurons in the hidden layer is usually determined based on a trial and error process (25).

Similar to the RBFN, Multilayer Perceptron (MLP) has input, hidden and output payer. Unlike RBFN, MLP can have multi hidden layers (21,25). Usually, the MLP by means of the back-propagation algorithm learns the relationship between a set of inputs and outputs by updating weights. The MLP algorithm is consisted of some neurons called perceptron. The perceptron

computes a single output from multiple inputs, by creating a linear combination based on its input weights. The mentioned function represented by equation 2, (26).

$$y = f \left( \sum_{i=1}^n w_i x_i + b \right) \quad (2)$$

Where  $w_i$  is the weight vector,  $x_i$  is the input vector ( $i=1, 2 \dots n$ ), b is the bias,  $f$  is the transfer function, and y is the output. The chosen logistic sigmoid transfer function may be defined as:

$$\frac{1}{(1 + e^{-x})} \quad (3)$$

**Table 1. Comparison of patient characteristics and categories based on pathology results**

	Variables and categories N (%)	Positive pathology result 133(73.48%)	Negative pathology result 48(26.51%)	Overall 181	P
<b>1. Gender</b>	Male	100(80)	25(20)	125	.002
	Female	32(58.2)	23(41.8)	56	
<b>2. Age</b>	<39.9	114(73.5)	41(26.5)	155	.960
	≥40	19(73.1)	7(26.9)	26	
<b>3. Nationality</b>	Iranian	97(69.3)	43(30.7)	140	.018
	Others	36(87.8)	5(12.2)	41	
<b>4. Right iliac fossa pain</b>	Yes	129(76.8)	39(23.2)	168	.000
	No	4(30.8)	9(69.2)	13	
<b>5. Migratory right iliac fossa pain</b>	Yes	79(83.2)	16(16.8)	95	.002
	No	54(62.8)	32(37.2)	86	
<b>6. Anorexia</b>	Yes	11(74)	39(26)	150	.728
	No	22(71)	9(29)	31	
<b>7. Nausea or vomiting</b>	Yes	103(78)	29(22)	132	.023
	No	30(61.2)	19(38.8)	49	
<b>8. Fever</b>	Yes	26(81.3)	6(18.8)	32	.272
	No	107(71.8)	42(28.2)	139	
<b>9. Tenderness</b>	Yes	118(79.2)	41(20.8)	139	.000
	No	15(46.9)	17(53.1)	32	
<b>10. Rebound tenderness</b>	Yes	71(78)	20(22)	91	.164
	No	62(68.9)	28(31.1)	90	
<b>11. Right iliac fossa guarding</b>	Yes	14(71.7)	5(26.3)	19	.983
	No	119(73.5)	43(26.5)	162	
<b>12. Rovsing's Sign</b>	Yes	58(84.1)	11(15.9)	69	.011
	NO	75(67)	37(33)	112	
<b>13. Leukocytosis</b>	< $10 \times 10^9$ cell/L	13(36.1)	23(63.9)	36	.000
	< 10.0 – 14.9 $\times 10^9$ cell/L	90(80.4)	22(19.6)	112	
	$\geq 15.0 \times 10^9$ cell/L	30(90.9)	3(9.1)	33	
<b>14. Shift to the left of neutrophils</b>	Yes	114(82)	25(18)	139	.000
	No	19(45.2)	23(54.8)	42	
	Minus	57(60.4)	36(39.6)	93	
<b>15. CRP concentration</b>	Plus	52(82)	12(19)	64	.000
	Plus Plus	24(100)	0(0)	24	
<b>16. Negative urine analysis</b>	Yes	123(75.5)	40(25.5)	163	.069
	No	10(55.6)	8(44.4)	18	

### Data analysis

At the first step, SPSS 21.0 which is installed on a windows system, was used for statistical analysis. Univariate correlation among clinical or laboratory variables was evaluated using the *Chi*-square test or Fisher's exact test, which are suitable for categorical data, and the Student t-test or Mann-Whitney U-test for continuous variables. A two-tailed  $P < 0.05$  was determined as the level of statistical significance.

### Results

There were 181 (126 men, 55 females) patients. According to statistical analysis average age in this study was 28-year-old. Male: female ratio in acute appendicitis was 2:1. Based on pathology reports the accuracy of correct diagnosis of acute appendicitis was 73.48 %. Meanwhile, 26.51% of patients had normal appendicitis. A significant difference ( $P < 0.05$ ) were observed in terms of sex, nationality, right iliac fossa pain, nausea and vomiting, tenderness, rovsing's sign, leukocytosis, shift to the left of neutrophil, CRP concentration among the positive and negative pathology result. The remaining

variables could not be used to differentiating positive pathology result from negative pathology result and acute appendicitis patients.

### Logistic regression analysis

Univariate regression analysis determined 10 pertinent variables for acute appendicitis prediction (Table 1). Among this variables sex, nationality, right iliac fossa pain, migratory right iliac fossa pain, nausea and vomiting, tenderness, rovsing's sign, leukocytosis, shift to the left of neutrophils and CRP concentration demonstrated differences between normal and positive pathology result significantly ( $P < 0.05$ ).

In the next step, all of the 10 variables were analyzed by means of multivariate logistic regression, three factors including sex, right iliac fossa pain, and CRP concentration were significantly correlated with acute appendicitis ( $P < 0.05$ ) (see Table 2). Then, these three factors were considered in the multivariable logistic regression as the predictor variables.

When logistic regression model analyzed based on confusion matrix, it had a sensitivity of 58.33%, specificity 93.18%, accuracy 83.9%, PPV 75.67%, NPV 86.01, and AUC .808, respectively.

**Table 2. Multivariate logistic regression analysis of variables for predicting acute appendicitis**

Variables	B	S.E.	Wald	df	Sig.	Exp (B)	95% C.I.for	
							EXP(B)	
							Lower	Upper
<b>Sex</b>	1.038	.480	4.675	1	<b>.031</b>	2.824	1.102	7.235
<b>Nationality</b>	-.809	.646	1.568	1	.210	.445	.125	1.580
<b>Right iliac fossa pain</b>	1.891	.897	4.445	1	<b>.035</b>	6.628	1.142	38.457
<b>Migratory right iliac fossa pain</b>	.557	.446	1.558	1	.212	1.745	.728	4.186
<b>Nausea or vomiting</b>	.802	.494	2.636	1	.104	2.230	.847	5.874
<b>Tenderness</b>	.913	.636	2.061	1	.151	2.491	.717	8.656
<b>Right iliac fossa guarding</b>	-.836	.739	1.282	1	.257	.433	.102	1.843
<b>Rovsing's Sign</b>	-.116	.517	.050	1	.823	.891	.323	2.454
<b>Leukocytosis</b>	.656	.427	2.357	1	.125	1.927	.834	4.452
<b>Shift to the left of neutrophils</b>	.513	.544	.890	1	.345	1.670	.575	4.848
<b>CRP concentration</b>	1.136	.444	6.559	1	<b>.010</b>	3.116	1.306	7.434

### Artificial neural network analysis

In the present work, after the feature selection process, we made use of MLP and RBFN. In order to achieve the

optimum model, the various steps have been followed according to workflow diagram shown in figure 1.

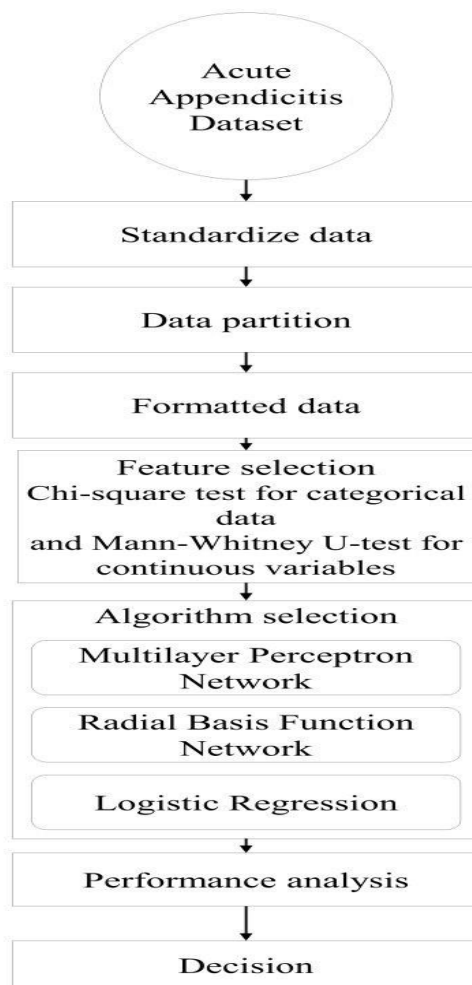


Figure 1. Flowchart of the implemented procedure of the current study

Following data preparation, the data set was randomly partitioned into two main sub-set (training and testing data). Determination of the number of hidden layers, number of neurons in each hidden layer, the neuron activation function are essential in artificial neural network modeling in this phase. The mentioned factors are usually determined via a trial and error process. We provide our results by applying RBFN and MLP in IBM SPSS statistics 21.

The overall performance of the RBFN and MLP

model was evaluated based on confusion matrix and applying standard measures such as accuracy, sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and the area under the curve (AUC). In the training phase of ANNs model, results revealed that leukocytosis, sex, tenderness, right iliac fossa pain were the important factors among all independent variables for acute appendicitis prediction, the normalized importance of them were 100%, 72.5%, 72.4%, and 60.2%, respectively (see Figure 2)

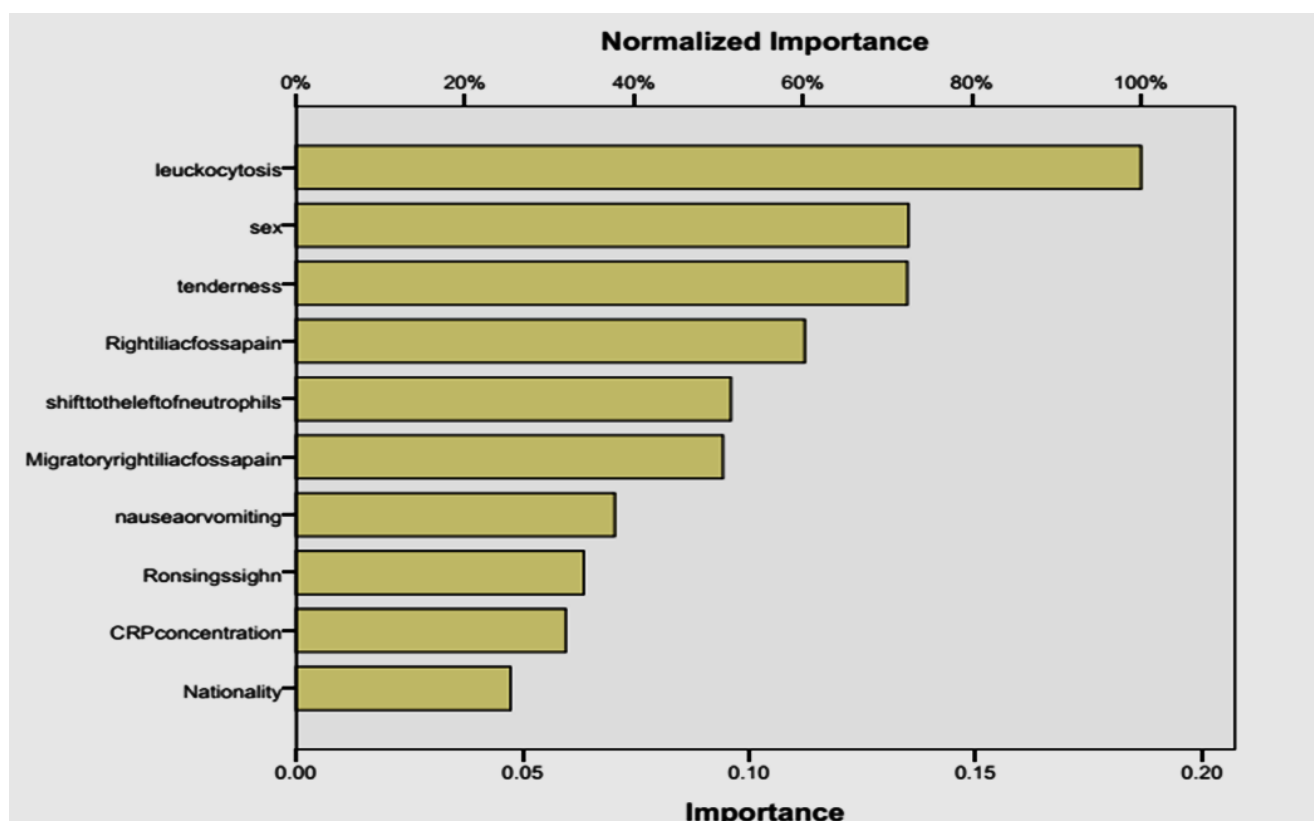


Figure 2. The importance of attributes in predicting acute appendicitis based on MLP model

In order to estimate the performance of neural network algorithms, we present the result pertaining to their application in the acute appendicitis data set. Table 3 demonstrates the values of the 6 metrics related to MLP, RBFN, and logistic regression algorithms.

According to table 3, it can be observed that the performance of MLP in all of the metrics is better than RBF and Logistic Regression. Therefore, MLP is selected

as an optimal algorithm for acute appendicitis prediction because of its high performance. The optimal architecture of the developed ANN is illustrated in figure 3. As can be observed, it is an MLP network architecture with two hidden layers and 7 and 5 neurons, respectively. In this architecture, the hidden layer activation function is a hyperbolic tangent, and output layer activation function is softmax.

Table 3. Evaluated parameters and their setting for MLP and RBFN in the current work.

Algorithms/Parameters		MLP	RBFN	Logistic regression
Setting parameters	The hidden layer activation function	Hyperbolic tangent	Softmax	-
	Output layer activation function	Softmax	Identity	-
	Rescale Method for Covariate	Adjusted normalized	Standardized	-
	Number of Hidden Layer	2	1	-
Evaluation parameters	Sensitivity	80%	28%	58.33%
	Specificity	97.5%	87.8%	93.18%
	Accuracy	92.9%	77.6%	83.9%
	PPV <sup>1</sup>	92.3%	64.2%	75.67%
	NPV <sup>2</sup>	93%	81.8%	86.01%
	AUC <sup>3</sup>	.832	-	.808

Note: 1= Positive Predictive Value (PPV), 2= Negative Predictive Value (NPV), 3= The area under the curve (AUC)

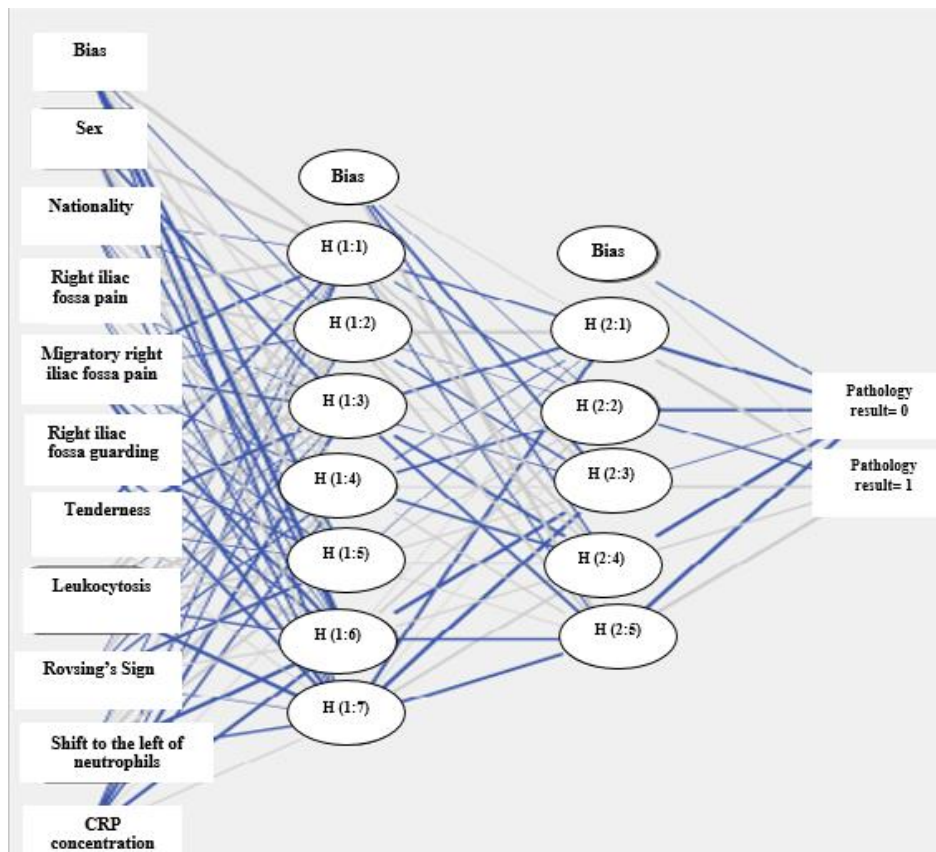


Figure 3. Multi-layer perceptron selected structure

Another significant metric to check the performance of methods in the current study is the Cross-Entropy Error (CEE). Based on the obtained outcomes in this section, Cross Entropy Error (CEE) for both training and testing steps were 60.95 and 16.65, respectively when the dependent variable was pathology result. Cross-Entropy Error (CEE) can be evaluated by equation 4 as below (27).

$$E_p = - \sum_k [ t_k \log(y_k) + (1 - t_k) \log(1 - y_k) ] \quad (4)$$

Where:

$t_k$  = the  $k$ th neuron's target value;

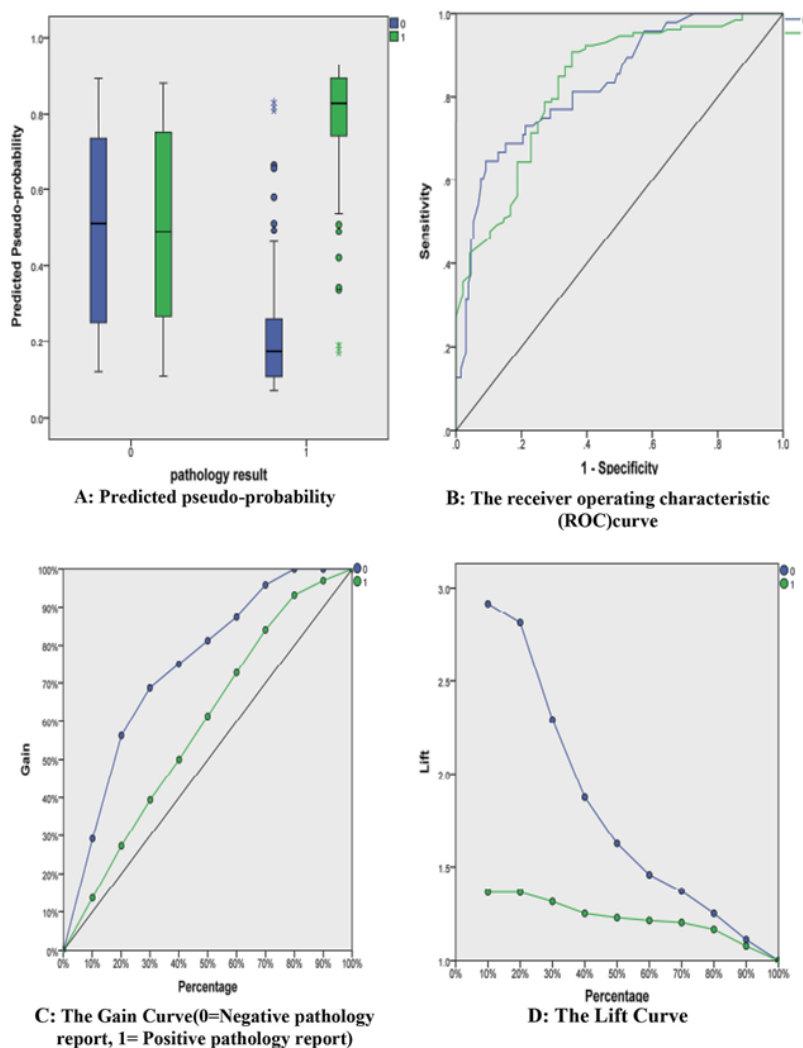
$y_k$  = its output.

Other important metrics for evaluation of the MLP model include predicted pseudo-probability, AUC, Gain Curve, and Lift Curve. These curves are presented in figure 4.

Predicted pseudo-probability (A) is demonstrated in the box-plot which illustrate the good predictive value of the MLP model. The AUC curve (B) for MLP is .832; this

means that 83.2% of the total area is explained by our model successfully. In the current paper, we compared the accuracy of prediction for negative pathology result and positive pathology result by means of cumulative gain charts (C), the outcome revealed that the degree of fitting in negative pathology result is suitable than positive pathology result. Totally, it is observed that the MLP model is more appropriate for prediction of normal pathology result rather than a positive one (Figure 4).

The evaluation indicators of the ANNs models and logistic regression model were compared (Table 3). There were notable differences between the ANN and logistic regression models in terms of sensitivity, specificity, accuracy, positive predicted value and the negative predicted value. The area under the curve (AUC) value for identifying acute appendicitis when using the MLP model showing more accurate overall performance than the logistic regression model.



**Figure 4.** The Predicted pseudo-probability (A), AUC (B), The Gain Curve (C) and The Lift Curve (D) generated by the MLP algorithm

## Discussion

Logistic regression is a statistical modeling technique in which the probability of occurrence an outcome is associated with a series of potential predictor variables. However, logistic regression models have some limitations, this method requires more formal statistical training to the development of the model, they cannot completely reveal complicated nonlinear relationships among predictor and target variables, and they are not able to determine all probable relationship between independent attributes. In comparison with logistic regression technique in mentioned aspects, the artificial neural network can overcome some of these restrictions.

Neural network algorithms have been used in several studies for disease prediction (27-29,38,40). There are several methods for the diagnosis of acute appendicitis such as clinical scoring systems and laboratory test.

However, due to the complex clinical protocols, these methods have not shown stable performance. Alvarado scoring system has shown contradictory results in a different study (5,19). There are various studies in the literature denoting recent advances in machine learning application in acute appendicitis diagnosis. Table 4 summarizes studies carried out on the automated diagnosis of acute appendicitis.

In this study, the sensitivity, specificity, accuracy, PPV, and NPV of the MLP model were significantly better than the logistic model. Moreover, the AUC value for recognizing acute appendicitis using MLP model was superior to logistic regression. Furthermore, predicted pseudo-probability curve, gain curve, and lift curve were in a reasonable performance, which demonstrates a more accurate prediction of acute appendicitis using neural networks. That is because the independent attributes in ANN mainly experience a nonlinear transformation at



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each hidden layer and an output layer, and so an artificial neural network can model complicated nonlinear relationships better than a logistic regression model.

Feature selection is one of the main steps in model development (39). In the present study, we applied statistical analysis for the determination of variables that significantly appropriate for acute appendicitis diagnosis. This method uses some of the potential subsets of attributes that greatly compatible with the complete features. Logistic regression model revealed that three factors including sex, right iliac fossa pain, and CRP concentration were identified significant correlated with acute appendicitis. Moreover, based on the variable importance factor in the MLP model, leukocytosis, sex, tenderness, right iliac fossa pain were the essential features between all independent factors for acute appendicitis prediction.

Analysis of results demonstrates that CRP is an important factor in the acute appendicitis diagnosis, especially by using the logistic regression model. Based on literature review, CRP may not have been applied in acute appendicitis diagnosis (36). A probable cause for this disagreement between studies is the time of the laboratory investigation for patients. Clinically CRP appears 12 to 24 h after the beginning of acute appendicitis symptoms (37). Although related studies have revealed that leukocytosis rate was the best laboratory test for early diagnosis of acute appendicitis, as determined in the MLP model (37). Leukocytosis, sex, tenderness, right iliac fossa pain seems to be effective variables that can be applied to the early diagnosis of acute appendicitis in emergency care. In this paper, the positive predictive value rate in MLP was better than RBFN and logistic regression. Misclassifying a patient

who has acute appendicitis as a healthy person (FN error) can be worse than misclassifying a healthy person as a disease one (FP). It would be more beneficial to reduce misdiagnosis rate.

The data structure in the current study is more suitable for an ANN model than a logistic regression model because the sample size is somewhat small. Despite that, the diagnostic accuracy of the MLP model in the current study was 92.90%, but the models were mainly based on clinical and laboratory findings. The previous studies recommended that an accurate diagnosis of acute appendicitis, cannot be made without the application of imaging techniques. As a result, caregivers should be educated to the prerequisites of the suggested model prior to using it.

Early and accurate diagnosis and intervention for acute appendicitis are one of the main principals in minimizing the morbidity and mortality rate. Nevertheless, acute appendicitis diagnosis in the initial stage remains difficult. This study proposed a framework to use the MLP algorithm to predict acute appendicitis. For this purpose, some well-known algorithms such as MLP, RBFN, and logistic regression were applied. Variable importance analysis was used to determine which predictors were essential to acute appendicitis prediction. Based on the results, we observed that factors such as leukocytosis, sex, tenderness, right iliac fossa pain were the essential variables among all independent variables for acute appendicitis prediction. Furthermore, this study provides an MLP model instead of the traditional logistic regression model, which is revealed more sensitivity, specificity, and accuracy of medical diagnostic.

**Table 4. Summary of studies carried out to the automated diagnosis of acute appendicitis**

Author [year]	Methodology	Best Performance
Sik Son [2012].[30]	<b>Features in univariate analysis:</b> lymphocytes, urine glucose, total bilirubin, total amylase, chloride, red blood cell, neutrophils, eosinophils, white blood cell, complaints, basophils, glucose, monocytes,	Accuracy=78.87%
	activated partial thromboplastin time, urine ketone, and direct bilirubin.	
	<b>Features in multivariate analysis:</b> neutrophils, complaints, total bilirubin, urine glucose, and lipase	
Yun Park [2015]. [31]	<b>Classifiers:</b> C5.0 decision tree algorithm	Accuracy RBF= 99.80%
	<b>Features:</b> Pain location, migration of RLQ, tenderness of RLQ, Rebound tenderness of RLQ, bowel sound, nausea, vomiting, body temperature, WBC counts	
	<b>Classifiers:</b> Radial basis function neural network (RBF), Multilayer neural network (MLNN), Probabilistic neural network (PNN).	
	<b>Features:</b> Sex, the intensity of pain, relocation of pain, pain in the right lower abdominal quadrant, vomiting, body temperature, guarding, bowel sounds, rebound tenderness.	
Yoldaş [2012]. [32]	<b>Classifiers:</b> Artificial neural network	Sensitivity=100%

## Continuance of Table 4

<b>Pesonen [1996]. [33]</b>	<p><b>Features:</b>  <i>Clinical history parameters:</i> Age, sex, the location of initial pain, the location of pain in diagnosis, duration of pain, the intensity of abdominal pain, the progression of pain from the onset to diagnosis, type of pain, aggravating factors, relieving factors, previous similar pain, nausea, vomiting, appetite.  <i>Clinical sign parameters:</i> mood, color, tenderness, scar, distention, abdominal movement mass, rebound, guarding, rigidity, murphy's positive, bowel sound, renal tenderness, rectal digital tenderness, body temperature, leukocyte count, urine.</p> <p><b>Classifier :</b>  Artificial neural network.</p>	Accuracy = 94%
<b>Sakai et al. [2007]. [34]</b>	<p><b>Features:</b>  Age, gender, migration of pain, tenderness at RLQ, rebound tenderness, muscular guarding, body temperature, white blood cell count (WBC), CRP levels</p> <p><b>Classifiers:</b>  An artificial neural network,  Logistic regression.</p>	Accuracy= 91.80%
<b>Ting et al. [2010]. [1]</b>	<p><b>Features:</b>  Age, gender, Migrating pain, Anorexia, Nausea, and vomiting, RLQ tenderness, Rebound pain, Temperature, WBC, Neutrophil count</p> <p><b>Classifiers:</b>  Decision tree</p>	Sensitivity=94%
<b>Hsieh et al. [2010].[6]</b>	<p><b>Features:</b>  The operation, age, sex, Migration of pain, anorexia, Nausea/vomiting, RLQ tenderness, RLQ tenderness, Rebounding pain, Diarrhea, the progression of pain, Right flank pain, Body temperature, WBC, Neutrophil, CRP, Urine occult blood, Hemoglobin.</p> <p><b>Classifiers:</b>  Random forest,  support vector machine,  artificial neural network</p>	Sensitivity= 94%
<b>Yun Park [2014].[35]</b>	<p><b>Features:</b>  age, sex, migratory right iliac fossa (RIF) pain, anorexia, nausea/vomiting, tenderness, right iliac fossa, rebound tenderness RIF, bowel sound, abnormal wall rigidity, elevated temperature, leukocytosis, shift to the left of neutrophil, and CRP</p> <p><b>Classifiers:</b>  artificial neural network</p>	Accuracy=98.81%
<b>Current study</b>	<p><b>Features:</b>  Sex, Nationality, Right iliac fossa pain, migratory right iliac fossa pain, nausea and vomiting, tenderness, right iliac fossa guarding, Rovsing's Sign, leukocytosis, shift to the left of neutrophils, CRP concentration.</p> <p><b>Classifiers:</b>  Logistic regression  Multi-layer perceptron neural networks  RBFN</p>	Accuracy=92.90%

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