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. Maine 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 accurate 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, $\cdots$,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

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

Where
n=number of nodes in hidden layer;

x=input vector;
ci=center of the ith hidden node;
Wij=weight of the ith node of the hidden layer;
φ_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).

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

Where $w_i$is the weight vector, x_i is the input vector (i=1, 2… 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:

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

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*
1. Gender	Male	100(80)	25(20)	125	.002
	Female	32(58.2)	23(41.8)	56	
2. Age	<39.9	114(73.5)	41(26.5)	155	.960
	≥40	19(73.1)	7(26.9)	26	
3. Nationality	Iranian	97(69.3)	43(30.7)	140	.018
	Others	36(87.8)	5(12.2)	41	
4. Right iliac fossa pain	Yes	129(76.8)	39(23.2)	168	.000
	No	4(30.8)	9(69.2)	13	
5. Migratory right iliac fossa pain	Yes	79(83.2)	16(16.8)	95	.002
	No	54(62.8)	32(37.2)	86	
6. Anorexia	Yes	11(74)	39(26)	150	.728
	No	22(71)	9(29)	31	
7. Nausea or vomiting	Yes	103(78)	29(22)	132	.023
	No	30(61.2)	19(38.8)	49	
8. Fever	Yes	26(81.3)	6(18.8)	32	.272
	No	107(71.8)	42(28.2)	139	
9. Tenderness	Yes	118(79.2)	41(20.8)	139	.000
	No	15(46.9)	17(53.1)	32	
10. Rebound tenderness	Yes	71(78)	20(22)	91	.164
	No	62(68.9)	28(31.1)	90	
11. Right iliac fossa guarding	Yes	14(71.7)	5(26.3)	19	.983
	No	119(73.5)	43(26.5)	162	
12. Rovsing's Sign	Yes	58(84.1)	11(15.9)	69	.011
	NO	75(67)	37(33)	112	
13. Leukocytosis	$< 10 \times 10^9\ \mathrm{cell}/\mathrm{L}$	13(36.1)	23(63.9)	36	.000
	$< 10.0 - 14.9 \times 10^9\ \mathrm{cell}/\mathrm{L}$	90(80.4)	22(19.6)	112	
	$\geq 15.0 \times 10^9\ \mathrm{cell}/\mathrm{L}$	30(90.9)	3(9.1)	33	
14. Shift to the left of neutrophils	Yes	114(82)	25(18)	139	.000
	No	19(45.2)	23(54.8)	42	
15. CRP concentration	Minus	57(60.4)	36(39.6)	93	.000
	Plus	52(82)	12(19)	64	
	Plus Plus	24(100)	0(0)	24	
16. Negative urine analysis	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
Sex	1.038	.480	4.675	1	**.031**	2.824	1.102	7.235
Nationality	-.809	.646	1.568	1	.210	.445	.125	1.580
Right iliac fossa pain	1.891	.897	4.445	1	**.035**	6.628	1.142	38.457
Migratory right iliac fossa pain	.557	.446	1.558	1	.212	1.745	.728	4.186
Nausea or vomiting	.802	.494	2.636	1	.104	2.230	.847	5.874
Tenderness	.913	.636	2.061	1	.151	2.491	.717	8.656
Right iliac fossa guarding	-.836	.739	1.282	1	.257	.433	.102	1.843
Rovsing's Sign	-.116	.517	.050	1	.823	.891	.323	2.454
Leukocytosis	.656	.427	2.357	1	.125	1.927	.834	4.452
Shift to the left of neutrophils	.513	.544	.890	1	.345	1.670	.575	4.848
CRP concentration	1.136	.444	6.559	1	**.010**	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.

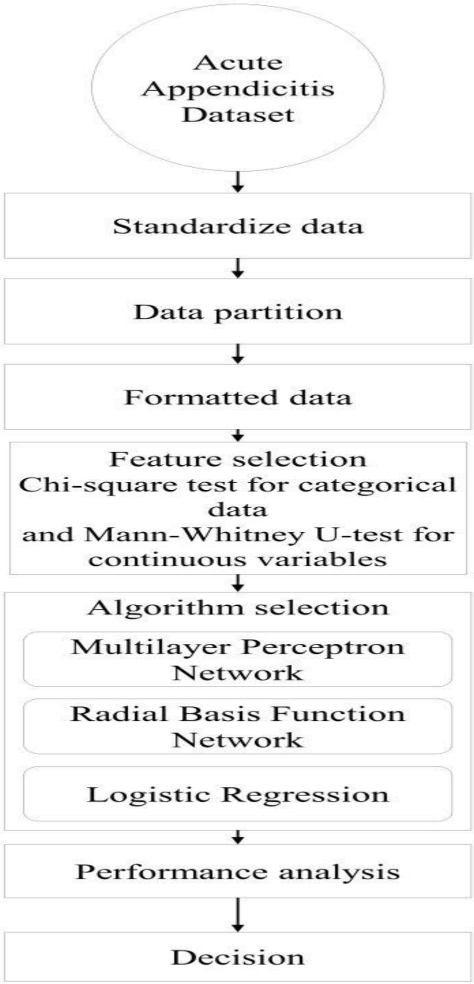

Figure 1. Flowchart of the implemented procedure of the current study

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)

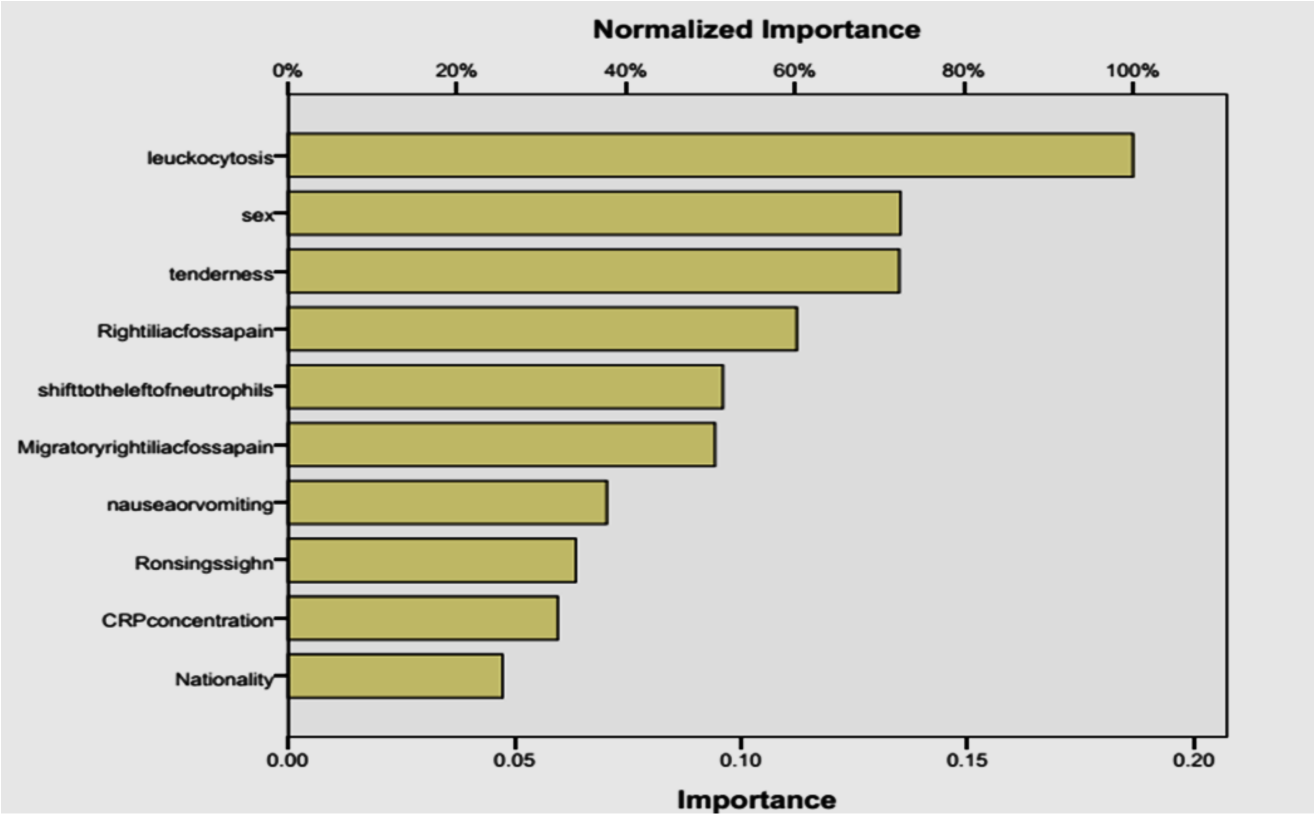

Figure 2. The importance of attributes in predicting acute appendicitis based on MLP model

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[1]	92.3%	64.2%	75.67%
	NPV[2]	93%	81.8%	86.01%
	AUC[3]	.832	-	.808

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

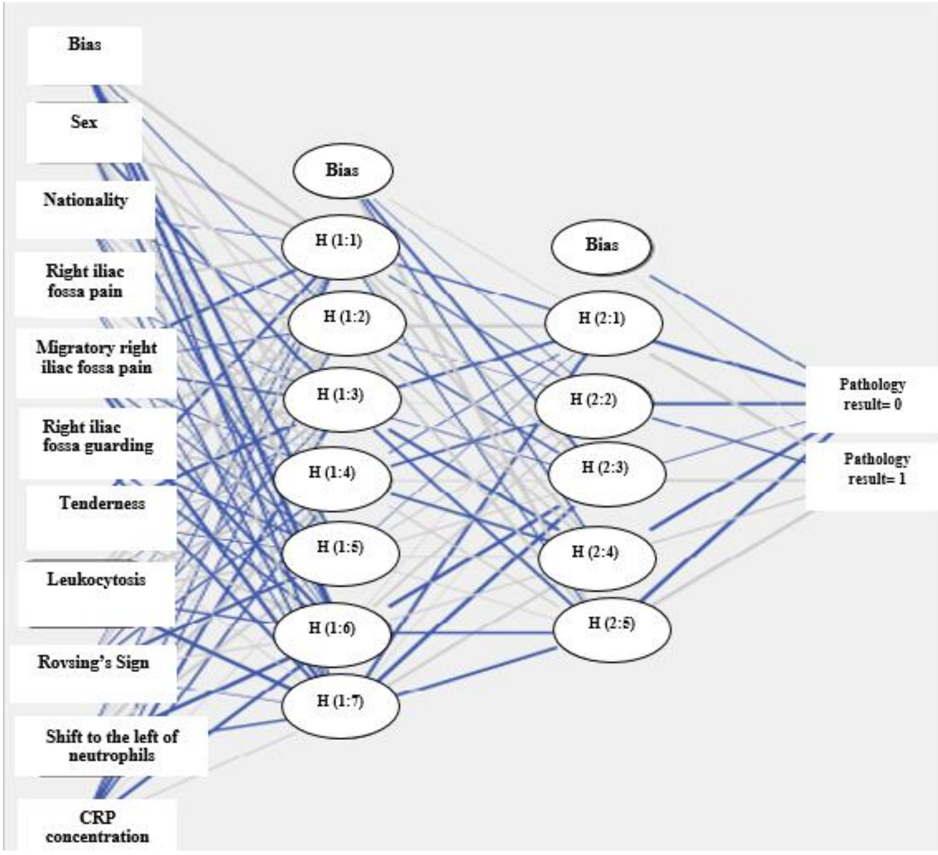

Figure 3. Multi-layer perceptron selected structure

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).

$$\mathrm{Ep}=-\sum_{k}[\mathrm{t_k}\ \log(y_k)+(1-\ t_k)\ \log(1-\ y_k)] \quad (4)$$

Where:

tk=the kth neuron's target value;

yk=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.

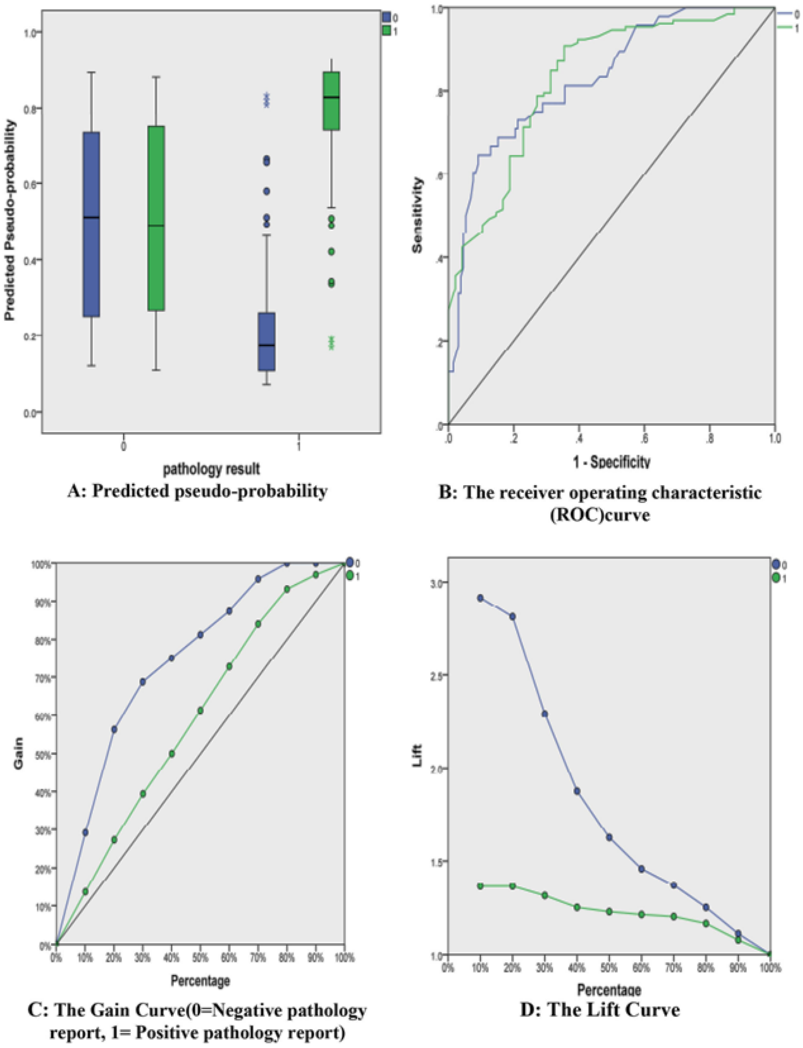

Figure 4. ThePredicted pseudo-probability (A), AUC (B), The Gain Curve (C) and The Lift Curve(D) generated by the MLP algorithm

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

Continuance of Table 4

Pesonen [1996]. [33]	**Features:** *Clinical history parameters*: 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. *Clinical sign parameters*: 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. **Classifier** : Artificial neural network.	Accuracy = 94%
Sakai et al. [2007]. [34]	**Features**: Age, gender, migration of pain, tenderness at RLQ, rebound tenderness, muscular guarding, body temperature, white blood cell count (WBC), CRP levels **Classifiers:** An artificial neural network, Logistic regression.	Accuracy= 91.80%
Ting et al. [2010]. [1]	**Features:** Age, gender, Migrating pain, Anorexia, Nausea, and vomiting, RLQ tenderness, Rebound pain, Temperature, WBC, Neutrophil count **Classifiers:** Decision tree	Sensitivity=94%
Hsieh et al. [2010].[6]	**Features:** 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. **Classifiers:** Random forest, support vector machine, artificial neural network	Sensitivity= 94%
Yun Park [2014].[35]	**Features:** 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 **Classifiers:** artificial neural network	Accuracy=98.81%
Current study	**Features:** 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. **Classifiers:** Logistic regression Multi-layer perceptron neural networks RBFN	Accuracy=92.90%

References

1. Ting HW, Wu JT, Chan CL, Lin SL, Chen MH. Decision model for acute appendicitis treatment with decision tree technology—a modification of the alvarado scoring system. J Chin Med Assoc 2010;73:401-6.
2. Akbulut S, Ulku A, Senol A, Tas M, Yagmur Y. Left-sided appendicitis: a review of 95 published cases and a case report. World J Gastroenterol 2010;16:5598.
3. Ferris M, Quan S, Kaplan BS, Molodecky N, Ball CG, Chernoff GW, et al. The Global Incidence of Appendicitis: A Systematic Review of Population-based Studies. Ann Surg 2017;266:237-41.
4. Zorman M, Eich HP, Kokol P, Ohmann C. Comparison of three databases with a decision tree approach in the medical field of acute appendicitis. Stud Health Technol Inform 2001;84:1414-8.
5. Memon ZA, Irfan S, Fatima K, Iqbal MS, Sami W. Acute appendicitis: diagnostic accuracy of Alvarado scoring system. Asian J Surg 2013;36:144-9.
6. Hsieh CH, Lu RH, Lee NH, Chiu WT, Hsu MH, Li YC. Novel solutions for an old disease: Diagnosis of acute appendicitis with random forest, support vector machines, and artificial neural networks. Surgery 2011;149:87-93.
7. Prabhudesai SG, Gould S, Rekhraj S, Tekkis PP, Glazer G, Ziprin P. Artificial neural networks: Useful aid in diagnosing acute appendicitis. World J Surg 2008;32:305-9.
8. Liu JL, Wyatt JC, Deeks JJ, Clamp S, Keen J, Verde P, et al. Systematic reviews of clinical decision tools for acute abdominal pain. Health Technol Assess 2006;10:1-167, iii-iv.
9. Kollár D, McCartan D, Bourke M, Cross K, Dowdall J. Predicting acute appendicitis? A comparison of the

Alvarado score, the Appendicitis Inflammatory Response Score and clinical assessment. World J Surg 2015;39:104-9.

10. Di Saverio S, Tugnoli G. The Challenge of Clinical Diagnosis of Appendicitis and Nonoperative Management of Patients With Right Lower Abdominal Pain. Ann Surg 2016;263:e22-e3.
11. Alter SM, Walsh B, Lenehan PJ, Shih RD. Ultrasound for the Diagnosis of Appendicitis in a Community Hospital Emergency Department has a High Rate of Nondiagnostic Studies. J Emerg Med 2017;52:833-6.
12. Cohen B, Bowling J, Midulla P, Shlasko E, Lester N, Rosenberg H, et al. The non-diagnostic ultrasound in appendicitis: is a non-visualized appendix the same as a negative study? J Pediatr Surg 2015;50:923-7.
13. Siegel Y, Kuker R, Banks J, Danton G. CT pulmonary angiogram quality comparison between early and later pregnancy. Emerg Radiol 2017;24:635-40.
14. Aggenbach L, Zeeman G, Cantineau A, Gordijn S, Hofker H. Impact of appendicitis during pregnancy: no delay in accurate diagnosis and treatment. Int J Surg 2015;15:84-9.
15. Sosner E, Patlas MN, Chernyak V, Dachman AH, Katz DS. Missed Acute Appendicitis on Multidetector Computed Tomography and Magnetic Resonance Imaging: Legal Ramifications, Challenges, and Avoidance Strategies. Curr Probl Diagn Radiol 2017;46:360-4.
16. Yilmaz O, Bozdana AT, Okka MA. An intelligent and automated system for electrical discharge drilling of aerospace alloys: Inconel 718 and Ti-6Al-4V. Int J Adv Manuf Technol 2014;74:1323-36.
17. Heydari M, Teimouri M, Heshmati Z, Alavinia SM. Comparison of various classification algorithms in the diagnosis of type 2 diabetes in Iran. Int J Diabet Dev Countries 2016;36:167-73.
18. Tseng CJ, Lu CJ, Chang CC, Chen GD, Cheewakriangkrai C. Integration of data mining classification techniques and ensemble learning to identify risk factors and diagnose ovarian cancer recurrence. Artif Intell Med 2017;78:47-54.
19. Dey S, Mohanta PK, Baruah AK, Kharga B, Bhutia KL, Singh VK. Alvarado scoring in acute appendicitis—a clinicopathological correlation. Indian J Surg 2010;72:290-3.
20. Nanjundaiah N, Mohammed A, Shanbhag V, Ashfaque K, Priya S. A comparative study of RIPASA score and ALVARADO score in the diagnosis of acute appendicitis. J Clin Diagn Res 2014;8:NC03.
21. Kang F, Li J, Xu Q. System reliability analysis of slopes using multilayer perceptron and radial basis function networks. Int J Numer Anal Methods Geomech 2017.
22. Nilashi M, Ahmadi H, Shahmoradi L, Mardani A, Ibrahim O, Yadegaridehkordi E. Knowledge Discovery and Diseases Prediction: A Comparative Study of Machine Learning Techniques. J Soft Compu Decis Support Sys 2017;4:8-16.
23. Hossain MS, Ong ZC, Ismail Z, Khoo SY. A comparative study of vibrational response based impact force localization and quantification using radial basis function network and multilayer perceptron. Exp Sys Appl 2017;85:87-98.
24. Nilashi M, Ibrahim Ob, Ahmadi H, Shahmoradi L. An analytical method for diseases prediction using machine learning techniques. Comput Chem Eng 2017;106:212-23.
25. Gholami A, Bonakdari H, Zaji AH, Michelson DG, Akhtari AA. Improving the performance of multi-layer perceptron and radial basis function models with a decision tree model to predict flow variables in a sharp 90 bend. Appl Soft Comput 2016;48:563-83.
26. Araujo P, Astray G, Ferrerio-Lage J, Mejuto J, Rodriguez-Suarez J, Soto B. Multilayer perceptron neural network for flow prediction. J Environ Monit 2011;13:35-41.
27. Delen D, Oztekin A, Kong ZJ. A machine learning-based approach to prognostic analysis of thoracic transplantations. Artif Intell Med 2010;49:33-42.
28. Huang ML, Chen HY, Huang WC, Tsai YY. Linear discriminant analysis and artificial neural network for glaucoma diagnosis using scanning laser polarimetry–variable cornea compensation measurements in Taiwan Chinese population. Graefes Arch Clin Exp Ophthalmol 2010;248:435-41.
29. Shen Y. Adaptive online state-of-charge determination based on neuro-controller and neural network. Energy Convers Manag 2010;51:1093-8.
30. Son CS, Jang BK, Seo ST, Kim MS, Kim YN. A hybrid decision support model to discover informative knowledge in diagnosing acute appendicitis. BMC Med Inform Decis Mak 2012;12:17.
31. Park SY, Kim SM. Acute appendicitis diagnosis using artificial neural networks. Technol Health Care 2015;23:S559-65.
32. Yoldaş Ö, Tez M, Karaca T. Artificial neural networks in the diagnosis of acute appendicitis. Am J Emerg Med 2012;30:1245-7.
33. Pesonen E, Eskelinen M, Juhola M. Comparison of different neural network algorithms in the diagnosis of acute appendicitis. Int J Bio Med Comput 1996;40:227-33.
34. Sakai S, Kobayashi K, Nakamura J, Toyabe S, Akazawa K. Accuracy in the diagnostic prediction of acute appendicitis based on the Bayesian network model. Methods Inf Med 2007;46:723-6.
35. Park SY, Lee S, Jeong JH, Kim SM. Application of artificial neural networks for diagnosing acute appendicitis. Appl Mech Mater 2014;479-480:445-50.

36. Yu CW, Juan LI, Wu MH, Shen CJ, Wu JY, Lee CC. Systematic review and meta-analysis of the diagnostic accuracy of procalcitonin, C-reactive protein and white blood cell count for suspected acute appendicitis. Br J Surg 2013;100:322-9.
37. Emmanuel A, Murchan P, Wilson I, Balfe P. The value of hyperbilirubinaemia in the diagnosis of acute appendicitis. Ann R Coll Surg Engl 2011;93:213-7.
38. Arji G. Safdari R, Ghazi saeedi M, Gharooni M, Nasiri M. Comparing performance of decision tree and neural network in predicting myocardial infarction. journal of Paramedical Sciences and Rehabilitation. 2014; 3 (2).
39. Abdar M, Yen N, Hung J. Improving the Diagnosis of Liver Disease Using Multilayer Perceptron Neural Network and Boosted Decision Trees. Journal of Medical and Biological Engineering. 2017. 38(6). pp 953–965.
40. Soleimani F, Teymouri R, Biglarian A. Predicting developmental disorder in infants using an artificial neural network. Acta Med Iran. 51(6):347-52.