Bees Reproduction Cycle: A Solution to Diagnosis of Acute Appendicitis

Amir Jamshidnezhad [1], Mohammad Mehdi Lotfinejad [2], Saeed Shirali [3]
Vahideh Ziagham [4], Mahsa Attarzadeh [4]

[1]*Department of Health Information Technology, Faculty of Allied Health Sciences, Ahvaz Jundishapur University of Medical Sciences, Ahvaz, Iran*
[2]*Department of Computer Engineering and Information Technology, Payame Noor University(PNU), P.O. Box, 19395-3697, Tehran, Iran*
[3]*Department of Laboratory Sciences, Faculty of Allied Health Sciences, Ahvaz Jundishapur University of Medical Sciences, Ahvaz, Iran*
[4]*Department of Health Information Records, Ahvaz Imam Educational Hospital, Ahvaz, Iran*

***Abstract*- For centuries, the natural laws have been the source of human creativity. Recently, simulation of the animal life and behavior as the algorithms have been studied in the optimization problems. In this article, an evolutionary algorithm was proposed to diagnosis a challenging disease which deals with several factors. The proposed algorithm was developed according to the honeybee reproduction cycle (HBRC) to create the fuzzy decision rules in an acute appendicitis diagnostic system. In this article thus, the useful clinical factors available in the first hours of the pain were explored and the diagnosis knowledge was discovered using an evolutionary algorithm in a Fuzzy-rule based system. The optimization process in the algorithm decreases the chance of local optima in comparison with other techniques such as genetic algorithms. Experimental results showed that the proposed algorithm improves considerably the optimization performance in the diagnostic problem**.

***Keywords:* Clinical decision support systems, Genetic algorithms, Evolutionary algorithms, Acute appendicitis, Fuzzy systems.**

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Corresponding author: Amir Jamshidnezhad
1Department of Health Information Technology, Faculty of Allied Health Sciences, Ahvaz Jundishapur University of Medical Sciences, Ahvaz, Iran
Email: jamshidnejad-a@ajums.ac.ir

1. Introduction

Appendicitis is the most common abdominal emergency. There is a diagnostic risk of acute appendicitis due to similarity of signs, symptoms and experiment data with other diseases in the first hours of presentation [1], [2], [3]. Clinical decision to diagnosis of appendicitis is often made based on physicians' intuition and experience. Overlapped symptoms of appendicitis cause involuntary biases, risks and medical costs and expenses for medical centers and patients. Generally, diagnostic accuracy of Acute Appendicitis ranges from 58% to 92% which shows the higher risk in female patients [4]. Therefore, the clinical decision support systems could decrease these diagnostic errors as well as unwanted practice variation and improve the patients treatments in terms of times and costs [5]. Alvarado score test as a clinical scoring system is a diagnostic tool for analyzing the acute appendicitis signs and symptoms [6]. However, the sensitivity of 72 % was only demonstrated for the diagnosis of appendicitis. This method has developed in the further studies to improve the accuracy rate for acute appendicitis detection [7], [8], [9].

Nowadays, artificial intelligence techniques are used extensively in the CDSSs. Neural networks (NNs) are the popular methods used in the clinical diagnostic systems as the learning techniques. In recent years, NNs and Fuzzy systems made a hybrid model to decrease the appendicitis diagnosis errors. [1]. Experimental results showed that the Neuro-Fuzzy systems are the useful techniques to detection of acute appendicitis [1], [10], [11]. However, current studies still have restrictions to model accurately a diagnostic system while limited clinical items and laboratory measurements are available.

Moreover, many computational or multi- object optimization problems cannot be answered simply with using classical mathematical techniques as they need to handle a lot of complex solutions. Therefore, sometimes the results will be local optima rather than global optima [12]. On the other hand, the traditional methods can be used for just a specific problem and are not enough intelligent to use in every conditions as a resistance solution.

Genetic Algorithms (GAs) are popular computational techniques that follow the natural evolution to find the best or approximate solutions among the huge number of solutions [13]. Local optima limitation is the main drawback reported for GAs in some complex problems [14].

To improve the GAs, in recent years the intelligent behavior of animals and insects in colony have been studied in various domains for optimization problems. Researchers have found out that modelling of animal and insects behaviors in the group and colony can improves the optimization algorithms in many cases [14]. Honeybee behavior is a popular area which is used for optimization problems. The simulated Honey bee algorithm called Bees Royalty Offspring Algorithm (BROA) considerably improves the accuracy of the classical GAs in the complicated fields [15].

In the current study, an evolutionary-Fuzzy system was proposed to classify the patients with Right Iliac Fossa (RIF) pain into patient and non-patient groups. In this model, the Honeybee Reproduction Cycle (HBRC) was used to create the rules in order to optimize the Fuzzy knowledge base. In the next sections the proposed hybrid model as well as its parts and performance for the purpose of Acute appendicitis diagnosis are described in details.

1.1 Clinical aspects of Acute Appendicitis

Appendicitis is the most common abdominal emergency. The lifetime risk of developing appendicitis is around 7% from 10 to 30 years old patients which usually requires surgery [16]. Generally, the diagnostic error in the appendectomy patients is approximately between 8% to 45% and varies based on the sex [17], [18].

2. Fuzzy rule-based systems

In this research, fuzzy rule-based approach was the proposed classification technique while a genetic-based algorithm was used in the fuzzy knowledge base to create and tune the rules for diagnosing of appendicitis [14]. The input parameters for the proposed evolutionary-fuzzy classifier system are age, first abdominal pain time, initial pain site, Right Lower Quadrant (RLQ) abdomen shift, white blood cell (WBC) count and neutrophil count. Clearly, the selected features were a few of the signs and symptoms showed in Table 1. Therefore, the proposed model was aimed to diagnose the appendicitis with small numbers of features to limit the processing cost and time in terms of computational process. Figure 1. shows the Architecture of the proposed diagnostic classification system.

Table 1: Anthropometry, physical examinations and laboratory factors for diagnosing of acute appendicitis

Factors	
Age	Foetor
Sex	Change of micturition
Pain site	RIF tenderness
Pain nature	Rebound tenderness
Pain time	Guarding
Nausea or vomiting	Rigidity
Previous surgery	Temperature
Pain shift	White blood cell count (WBC)
Neutrophil count	

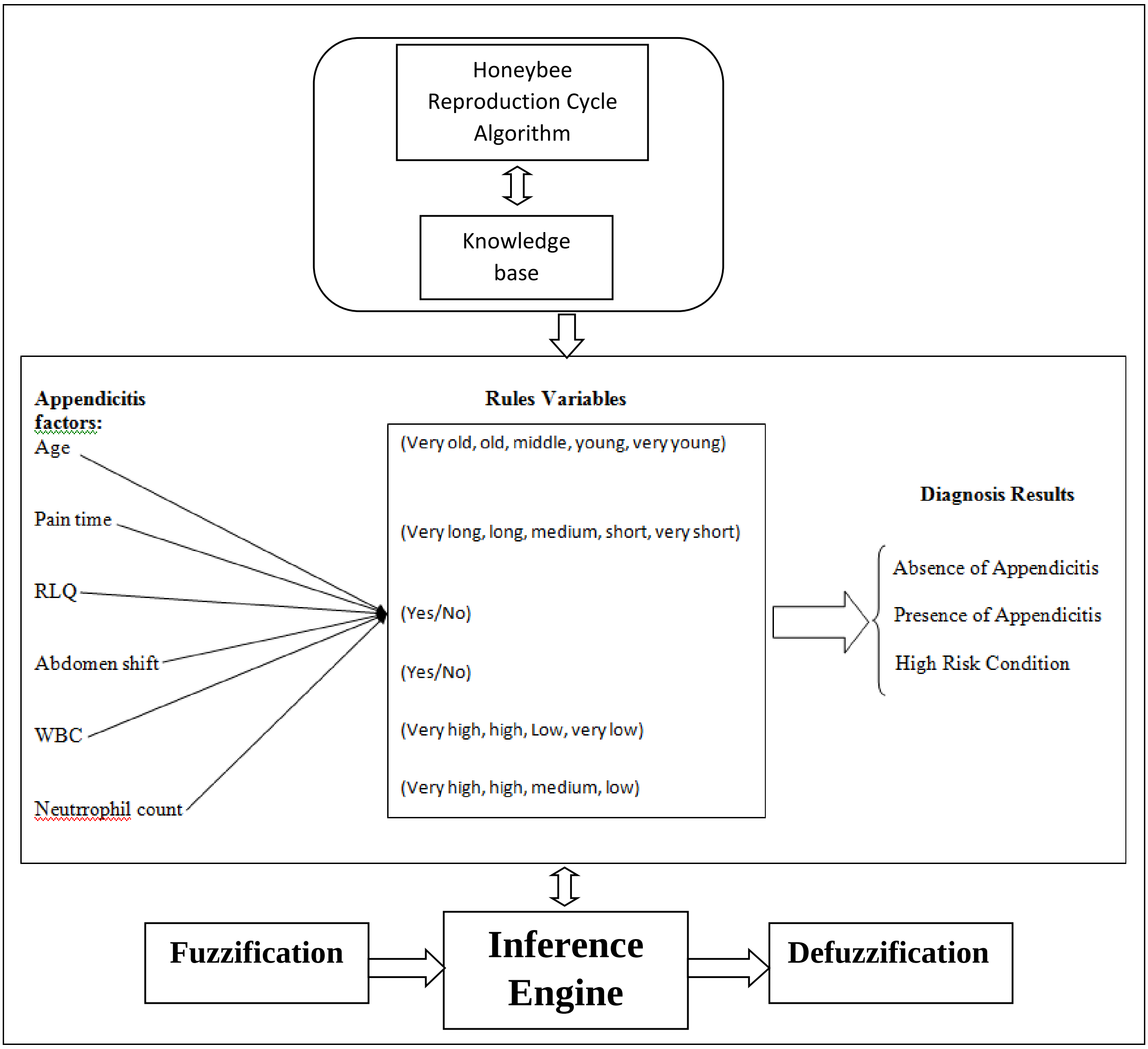

Figure 1.Architecture of the proposed diagnostic classification system

2.1 Knowledge base

The computational procedure of fuzzy inference system based on the knowledge base to predict the new conclusion is implemented in the inference engine. Therefore, the knowledge of fuzzy diagnostic model was determined and optimized in the knowledge base component by the HBRC to find the best rules set for diagnosis of appendicitis.

In this model the rules were trained to classify the input data into three classes which showed the Presence, Absence and High risk diagnostic conditions.

2.2 Defuzzification

In this research, the consequent of defuzzification process is classification of each expression to one of four emotions, while the Fuzzy outputs include three Gaussian membership functions for indicating Presence of Appendicitis, Absence of Appendicitis, and High risk condition.

2.3. Evolutionary optimizing algorithm

For the purpose of improving the performance of the fuzzy diagnostic system, a Genetic-based algorithm as an evolutionary technique was used. Genetic algorithms are popular learning methods to answer the optimization problems.

Holland is well known to introduce and develop Genetic Algorithms to solve the complex problems based on the evolutionary computation [19]. Therefore, Genetic Algorithms with the search in the solutions space find the best or approximately results in a process of several generations [20]. Nowadays, numerous applications for Genetic Algorithms are known in the different areas such as engineering, management, medicine, humanity sciences and computer science [21].

In the current study, HBRC as an evolutionary algorithm was proposed to create and optimize the fuzzy knowledge base. Therefore, although the fuzzy rules are normally set by the experts, due to diversity of features as well as their effects on the diagnosis of appendicitis the rules were created in the training process.

Moreover, the achieved results were also compared with the Sonography findings while the data of the patients with acute abdomen suspicious of acute appendicitis from hospitals in Iran were used.

In the following parts, the process of HBRC performed on the classification problem is described and compared with other scenarios. Figure 2. briefly shows the proposed evolutionary algorithm as an optimizing process.

3. Honeybee reproduction cycle algorithm

Solutions were encoded as the strings of gens consist of fuzzy rules, extracted features and linguistic terms. Therefore, six selected features along with the linguistic terms formed the fuzzy inference system structure. Therefore, each string of chromosome contained a sequence of gens, *C*i= (*G*1, *G*2… *Gn*), in form of real values. As a result, each chromosome made a set of fuzzy *If then* rules which defuzzified as a decision.

3.1. Creation of initial population

Initial population created randomly included 50 chromosomes. The fuzzy rules as the gene values were determined randomly to make the initial results. The results were considered based on the fitness function to measure reaching the objective solution. Therefore, fittest values were the criterion for selection. Fitness function was determined based on the following objective function:

$$\text{Max}\, f(x) = \sum_{n=1}^{3} \left(\frac{d_n}{t_n}\right)$$

Where d_n is the number of correct diagnostic prediction in the Acceptance, Rejection or Highly acceptance of acute appendicitis. t_n is total number of abdominal data in *nth* class. As a result, the optimum value is computed according to the following equation:

$$\sum_{n=1}^{3} \left(\frac{d_n}{t_n}\right) = 1$$

3.2 Parent selection

Parent selection process was operated in the phases of parent selection and selection of new population. Ten chromosomes were used as the parents based on the best results.

3.3 Crossover operation

Crossover was operated with the pair of parent chromosomes. In this article, the crossover was performed in two main phases: Queen and Princess crossover. Queen chromosome is the optimum solution from the first generation of parent crossover. In this step, crossover was operated on each pair of chromosomes to create the offspring. The elite solution from previous generation is called Queen. The combination of Queen with other chromosomes generates the Princess. The crossover on Princess and other chromosomes makes the offspring. Figure 3. shows the crossover process in HBRC algorithm.

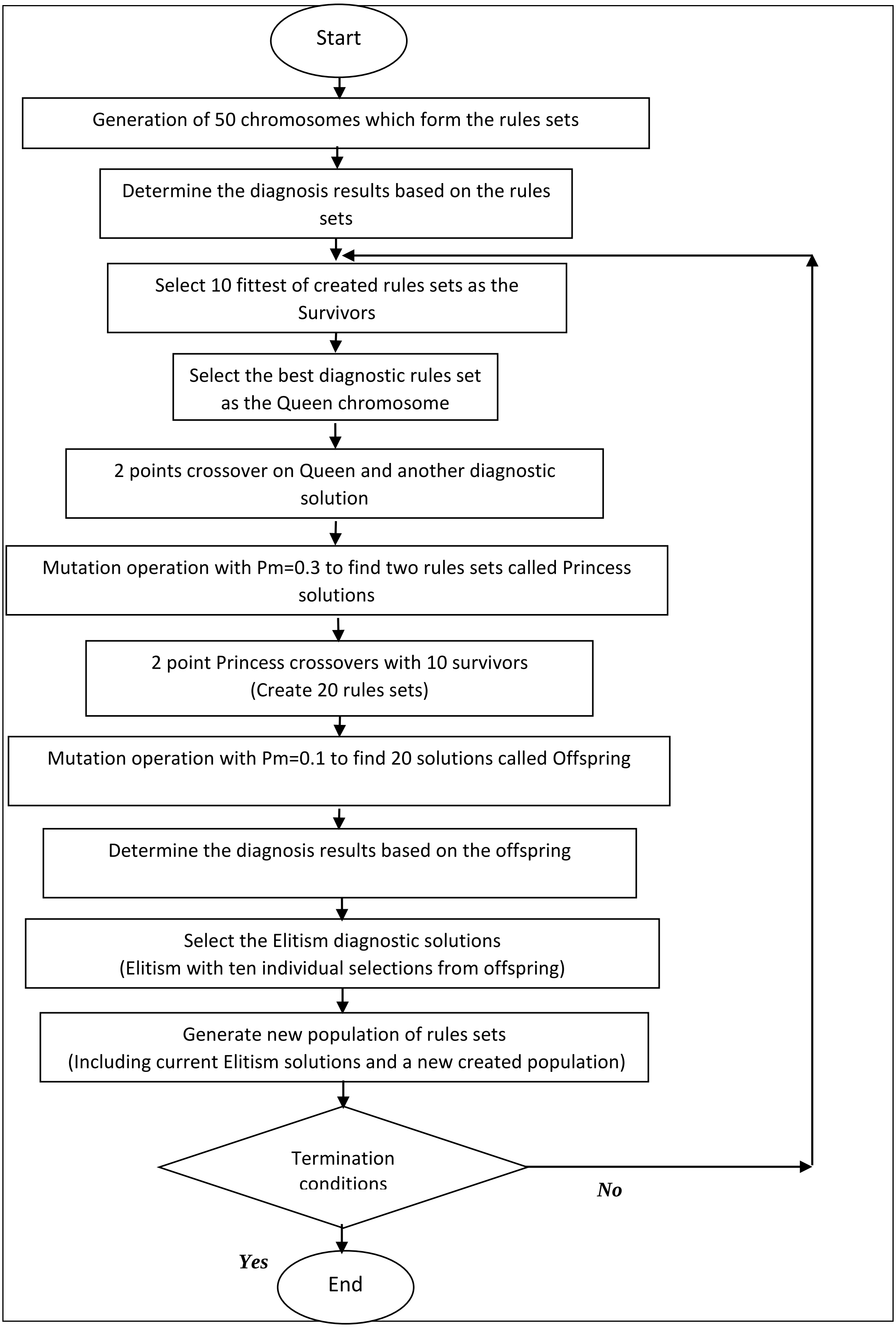

Figure 2. Proposed evolutionary algorithm to create the Fuzzy knowledge base

Queen Crossover:

a'_{11}	b'_{11}	c'_{11}	a'_{21}	b'_{21}	c'_{21}	….	a'_{nm}	b'_{nm}	c'_{nm}	Queen Chrom
a_{11}	b_{11}	c_{11}	a_{21}	b_{21}	c_{21}	….	a_{nm}	b_{nm}	c_{nm}	Fittest Chrom1

a'_{11}	b'_{11}	c'_{11}	a'_{21}	b'_{21}	c'_{21}	….	a'_{nm}	b'_{nm}	c'_{nm}	Queen Chrom
a_{11}	b_{11}	c_{11}	a_{21}	b_{21}	c_{21}	….	a_{nm}	b_{nm}	c_{nm}	Fittest Chrom2

Princess Crossover:

a_{11}	b_{11}	c_{11}	a_{21}	b_{21}	c_{21}	….	a_{nm}	b_{nm}	c_{nm}	Princess
a'_{11}	b'_{11}	c'_{11}	a'_{21}	b'_{21}	c'_{21}	….	a'_{nm}	b'_{nm}	c'_{nm}	Chrom1

a_{11}	b_{11}	c_{11}	a_{21}	b_{21}	c_{21}	….	a_{nm}	b_{nm}	c_{nm}	Princess
a'_{11}	b'_{11}	c'_{11}	a'_{21}	b'_{21}	c'_{21}	….	a'_{nm}	b'_{nm}	c'_{nm}	Chrom2

Figure 3. The Proposed Recombination of Princess and Selected Chromosomes

3.4 Mutation operation

For the purpose of simulation the small changes in the genetic structure of creatures, mutation operation with the probability (Pm) of 0.3 was performed on the offspring.

3.5 Selection of new population

New generation was created from the higher fitness values among offspring and parents. Therefore, fifteen chromosomes as the rule sets were selected as a part of new generation. Moreover, fifty chromosome sets randomly created in the new iteration were added to the selected fifteen solutions to make the new population. Therefore, each new iteration (from second iteration to end) included sixty populations.

3.6 Termination conditions

Termination conditions were satisfied based on the number of iterations for generating results or reaching to the proper solution with optimum fitness value. For the purpose of optimizing the obtained results from the training data two termination conditions included the generation numbers of 50 or the fitness value higher than 95%.

4. Abdominal dataset

To evaluate the accuracy of the proposed model for diagnosing of appendicitis, a collection of data was gathered from abdominal patients with the age between 3 to 60 years who referred to the educational hospitals of Ahvaz, a metropolis in south west of Iran, from 2014 to 2015 . This dataset included some features such as patient's signs and symptoms, biochemical tests as well as physicians' first diagnosis and final diagnosis about the acute appendicitis. Only 6 features were used to evaluate the reliability and validity of the model in the experimental process. Therefore, two training and testing set were randomly selected from the dataset. The testing set consists of about 30% of total data in the abdominal dataset. For the purpose of evaluating model deviation and its reliability, the training process was repeated ten times and every time the validity of the model was considered with the testing independent dataset.

In this study, the achieved results were compared with the Sonography findings while the data of the patients with acute abdomen suspicious of acute appendicitis from hospitals in Iran were used.

5. Experimental results

Table 2. shows the overall outcomes from optimizing process by using the proposed Evolutionary algorithm on the testing set. The achieved results are also compared with Alvarado test as well as other techniques in Table 3.

According to Table 2., the highest predication rate was related to the Presence class which approves the appendicitis. Therefore, the model has the best performance to diagnose for the patients suffering with acute appendicitis while it had only 8% error to predict the positive acute appendicitis. However, the accuracy rate for the abdominal patients who were rejected finally from the appendicitis was 80%. Similarly, only 80% of the high risk patients were predicted accurately in the proper class. Overall, the--accuracy rate to classify the abdominal patients into three categories was around 90%.

Table 2. Accuracy rate of classification by Meta heuristic-fuzzy model

Confusion Matrix for Diagnosis of Appendicitis				
	Presence	High Risk	Reject	*Overall Accuracy rate*
Presence	92%	4%	4%	92%
High Risk	10%	90%	0	90%
Reject	12.5%	0	87.5%	87.5%
Average				89.9%

5.1 Sonography tests

Medical ultrasound is widely used throughout the world for diagnosis of Acute appendicitis in recent years. Influence of ultrasound on clinical decision making in Acute appendicitis in Iranian hospitals was determined in several studies [22,23,24]. In this study, the achieved results from abdominal Sonography screening of suspected appendicitis as a reliable detection method before surgery is compared with the results of the proposed computer based model. Findings showed that the medical ultrasound method has the sensitivity and specificity of 74 and 43 percent, respectively. Screening results illustrated that the Sonography is more valuable for acute appendicitis diagnosis when not more than 48 hours have passed from the abdominal signs [25].

5.2 Other diagnostic techniques

According to Table 3. Neural networks is a popular technique to classify the presence of acute appendicitis from its absence for the data of the abdominal patients. However, neural networks needed to use large size of features including clinical and nonclinical examination factors as the input variables to show the accurate performance. Neural networks are not robust when the input factors are less than 10 features. Moreover, the Alvarado Scoring system as the most cited model is not as valid as other techniques for acute appendicitis prediction [25]. On the other hand, although the SVM showed a good performance in detection of acute appendicitis, it needs at least 10 factors to classify the patients with acute appendicitis from non-acute appendicitis [26]. The proposed model including evolutionary algorithm in this study resulted into a performance with 90% accuracy which improved the fuzzy model for diagnosis of pediatrics [29]. Although the achieved result in this study was lower than the accuracy of some algorithms used in the existing research, it used only 6 input factors for prediction. Moreover, the model analyzed the data from abdominal patients into three classes including presence and absence of acute appendicitis or high risk for acute appendicitis. Moreover, in regard to the fact that determining larger number of the input factors needs more laboratory tests or nonclinical examination, time costing is one of the weak points of the existing research in comparison to the proposed model. Figure 4. Shows a view of dispersion of the selected features belonging to three diagnostic conditions. According to Figure 4, the distribution of the data overlap among three classes. This diversity in the

Table 3. Comparison of the diagnostic models for acute appendicitis prediction

Diagnostic model	Number of used factors	Accuracy rate
Alvarado Clinical Scoring System(ACSS) [26].	9	66.4%
Multi Layer Neural Networks [26].	8	92.89%
SVM [27].	10	99%
Neural Networks [28].	10	90%
Neural Networks [25].	9	74%
Neural networks [11].	11	97%
Hybrid Fuzzy Model [29].	6	71%
Proposed model	**6**	**89.9%**

-patients' signs complicated the classification process. As a result, the robustness of the proposed diagnostic model showed a proper performance in the ambiguous conditions. Therefore, the evolutionary-fuzzy model not only decreases the diagnosis time and costs in terms of collecting laboratory and examination data but also improves the processing time and robustness of Decision Support System (DSSs) in the complex clinical problem.

The model also showed a valuable performance in comparison with physician's primary diagnosis for acute appendicitis. According to the reported diagnosis for acute appendicitis in the dataset, the presence of acute appendicitis for 23% of patients with acute appendicitis was rejected in the primary diagnosis while the acute appendicitis was found in the final diagnosis. Therefore, the primary diagnosis by physicians showed around 77% accuracy for accepting the acute appendicitis.

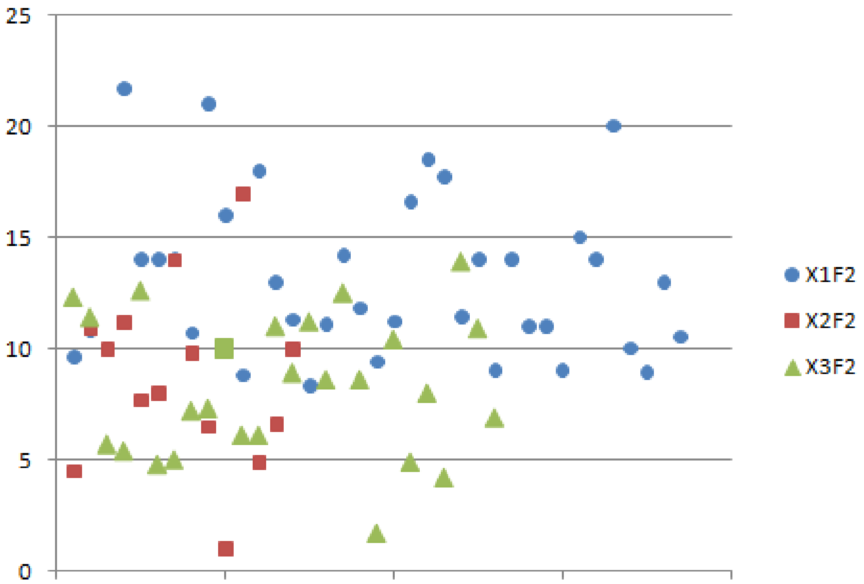

Figure 4. A sample of dispersion of the feature among three classes

6. Conclusion

Medical Diagnosis in terms of time and accuracy has the vital role to patients' life. In this study a fuzzy decision support system was used to diagnose the acute appendicitis. The knowledge base in the fuzzy rule based system was created by the proposed evolutionary algorithm. The proposed optimizing algorithm increased the accuracy of prediction with improving the knowledge base in the fuzzy rule based system. The results showed a proper performance for classification of the presence of acute appendicitis from the patients in the high risk position and absence of the acute appendicitis. The diagnostic acceptable performance was achieved while a limited range of factors as the input parameters were used in the hybrid model. Therefore, the model improves the processing time as well as the treatment costs to diagnosis of acute appendicitis.

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