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Published in:
Proceedings from Scandinavian Conference on Health Informatics

Publication date:
2014

A Belief Rule-Based (BRB) Decision Support System for Assessing Clinical Asthma Suspicion

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Abstract

Asthma is a common chronic disease that affects millions of people around the world. The most common signs and symptoms of asthma are cough, breathlessness, wheeze, chest tightness and respiratory rate. They cannot be measured accurately since they consist of various types of uncertainty such as vagueness, imprecision, randomness, ignorance and incompleteness. Consequently, traditional disease diagnosis, which is performed by a physician, cannot deliver accurate results. Therefore, this paper presents the design, development and application of a decision support system for assessing asthma under conditions of uncertainty. The Belief Rule-Based Inference Methodology Using the Evidential Reasoning (RIMER) approach was adopted to develop this expert system, which is named the Belief Rule-Based Expert System (BRBES). The system can handle various types of uncertainty in knowledge representation and inference procedures. The knowledge base of this system was constructed by using real patient data and expert opinion. Practical case studies were used to validate the system. The system-generated results are more effective and reliable in terms of accuracy than the results generated by a manual system.

Keywords: Belief Rule Base; Uncertainty; RIMER; Asthma Diagnosis; Asthma Suspicion; Decision Support System; Inference

Introduction

Asthma is a condition that affects the smaller airways of the lungs [1]. It is caused by inflammation of the airways. The inflammation irritates the muscles around the airways and causes them to constrict. This causes narrowing of the airways. It is more difficult for air to get in and out of the lungs. This leads to wheezing and breathlessness. When airways become inflamed and fill with mucus and the smooth muscles around the airways constrict, then chest tightness may be experienced. Asthma patients may cough because of the irritation inside the airways and the body's attempt to clean out the thick mucus. The respiratory rate is defined as the number of breaths a person takes in one minute. During an asthma attack, the respiratory rate often increases. The normal respiratory rate varies for different age groups, such as 30-60 breaths per minute for newborns and 12-18 breaths per minute for adults. Figure 1 illustrates airway inflammation and a cross-section of the airways during an asthma attack in the lungs and airways. Figure 1(A) shows the location of the lungs and airways in the body, Figure 1(B) illustrates the cross-section of a normal airway, and Figure 1(C) depicts a cross-section of an airway during an asthma attack.

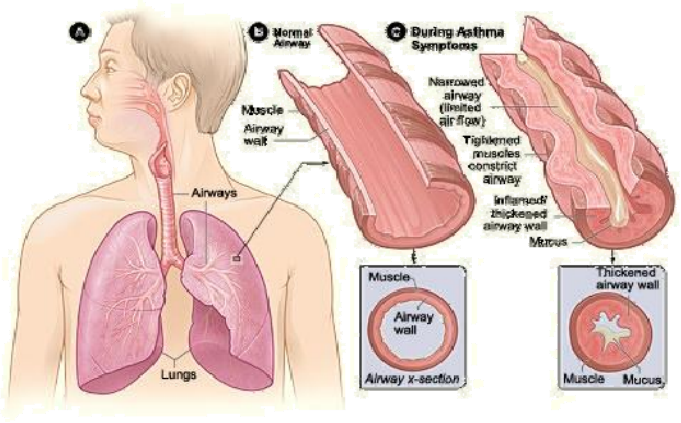

Figure 1- Mechanism of asthma[1]

Asthma may occur at any age but is most common in children [1]. It may also be due to hereditary factors [2]. The process for 'asthma suspicion' or diagnosis consists of observing a patient's signs and symptoms [3]. However, this asthma suspicion process contains errors because the signs and symptoms cannot be measured with 100% certainty. There are causal relationships among the signs and symptoms of asthma. These causal relationships can be represented by the If-Then rule.

An If-Then rule has an antecedent and a consequent part. The antecedent part takes input data while the consequent part shows the action to be taken. For example, signs and symptoms data are input data that is the antecedent part of various rules. Input data in a rule can differ in type and scale such as qualitative, quantitative etc. For example, a patient's breathlessness may be severe, moderate, mild or normal. This degree of illness is presented by qualitative data. These data are expressed as a linguistic term by patients and contains uncertainty due to vagueness and imprecision. However, a patient can have a respiration problem that can be within the range or out of the range. This can be measured with an optical breath rate sensor [4] that produces numeric or quantitative data. The result may be incorrect due to mishandling of the instrument, ignorance and randomness. Sometimes, a symptom such as

[1] Source: http://www.nhlbi.nih.gov/health/health-topics/topics/asthma/

cough may be hidden by patients, which arises out of ignorance and incompleteness. Therefore, various types of uncertainty can be associated with input data such as ambiguity, vagueness, imprecision, ignorance etc. Thus, the consequent part of the If-Then rule may contain uncertainty. For example, the initial belief degree can be imperfect since it contains incompleteness and ignorance.

Some expert systems for diagnosing asthma have been reported in the literature. A fuzzy rule-based expert system for assessing the severity of asthma was presented by [5]. The assessment of the severity of asthma by an expert system is illustrated by [6]. A clinical support system [7] was also developed to assess asthma. However, these systems cannot handle different types of uncertainty.

Diagnosing asthma is an example of a complex problem that can be handled by an expert system. An expert system has two components: the knowledge base and the inference engine. The knowledge base can be constructed with proportional logic (PL), first-order logic (FOL) or fuzzy logic (FL) [8,9]. Reasoning mechanisms such as forward chaining and backward chaining are used to develop the inference engine [10]. PL and FOL are not equipped to capture uncertainty. However, FL can handle uncertainty due to vagueness and ambiguity. However, FL cannot handle other types of uncertainty such as ignorance and incompleteness that may exist in signs and symptoms of asthma. Therefore, a knowledge base that can handle all types of uncertainty that exist with diagnosing asthma must be developed. A relevant inference mechanism must also be adopted. Uncertain knowledge in diagnosing asthma must be processed by using a refined knowledge base and an inference mechanism.

A recently developed Belief Rule-Based Inference Methodology Using the Evidential Reasoning (RIMER) approach [11,12] was used to design and develop the proposed decision support system. Uncertainty can be addressed by this methodology. This methodology consists of the Belief Rule Base (BRB) and the Evidential Reasoning (ER) algorithm. In RIMER, a rule base is designed with belief degrees embedded in all possible consequents of a rule. Inference in such a rule base is implemented using the evidential reasoning approach that can handle different types and degrees of uncertainty in signs and symptoms.

The rest of the paper is organized as follows. The next section provides an overview of the RIMER methodology. Then the stem architecture, design and implementation of the proposed BRBES are discussed. Experimental results and discussions are then presented. A conclusion is included to summarize the contribution.

Overview of RIMER Methodology

The RIMER approach consists of two components [10]. They are BRB to act as the knowledge base and ER to act as an inference engine.

Domain Knowledge Representation using BRB

Belief rules are the key elements of a BRB, which include belief degree. It is an extended form of traditional If-Then rules. A belief rule consists of an antecedent part and a consequent part. The antecedent attribute takes referential values, and each consequent is associated with belief degrees [12]. The knowledge representation parameters are rule weights, antecedent attribute weights and belief degrees in consequents, which can handle uncertainty. A belief rule can be defined as follows:

$$R_k : \begin{cases} IF\left(P_1 \text{ is } A_1^k\right)\Lambda\left(P_2 \text{ is } A_2^k\right)\Lambda.....\Lambda\left(P_{T_k} \text{ is } A_{T_k}^k\right) \\ THEN\ \left\{\left(C_1, B_{1k}\right),\left(C_2, B_{2k}\right),.....,\left(C_N, B_{Nk}\right)\right\} \end{cases} \quad (1)$$

$$R_k : \left(\beta_{jk} \geq 0, \sum_{j=1}^{N} \beta_{jk} \leq 1\right)$$

With a rule weight θ_k and attributes weight $\delta_{k1,}\delta_{k2,}\delta_{k3,}.....,\delta_{kT_k}$ *where* $k \in \{1,.....,L\}$, where $P_{1,}P_{2,}P_{3,}.....,P_{T_k}$ represent the antecedent attributes in the *k*-th rule. $A_i^k\ (i=1,.....,T_k \text{ and } k=1,.....,L)$ represents one of the referential values of the *i*-th antecedent attribute P_i in the *k*-th rule. C_j is one of the consequent reference values of the belief rule. $\beta_{jk}\ (j=1,.....,N \text{ and } k=1,.....,L)$ is the degree of belief to which the consequent reference value C_j is believed to be true. If $\sum_{j=1}^{N}\beta_{jk}=1$, the *k*-th rule said to be complete; *L* number of all belief rules in the rule base. *N* is the number of all possible consequents in the rule base. An example of a belief rule in the asthma suspicion/diagnosis BRB system prototype can be written in the following way:

$$R_k : \begin{cases} IF\left(Cough\ is\ Yes\right)and\left(Breathlessness\ is\ Moderate\right)and \\ \left(Wheeze\ is\ High\right)and\left(Chest\ tightness\ is Yes\right)and \\ \left(\text{Re}spiratory\ \ rate\ is\ Un-range\right) \\ THEN \\ Asthma\ Suspicion\ is \\ \left\{\begin{matrix}\left(Severe,(0.6)\right),\left(Moderate,(0.4)\right),\left(Mild,(0.0)\right), \\ \left(Normal,(0.0)\right)\end{matrix}\right\} \end{cases} \quad (2)$$

Where $\left\{\begin{matrix}\left(Severe,(0.6)\right),\left(Moderate,(0.4)\right),\left(Mild,(0.0)\right), \\ \left(Normal,(0.0)\right)\end{matrix}\right\}$ is a belief distribution associated with asthma consequents of the belief rule as represented in (2). The belief distribution states that the degree of belief associated with severe asthma is 60%, 40% degree of belief is associated with moderate asthma, 0% degree of belief is associated with mild asthma and 0% degree of belief is associated with normal asthma. Here, severe, moderate, mild and normal are the referential value of the consequent attribute "Asthma" of the belief rule. In this belief rule, the total degree of belief is (0.6+0.4+0+0) =1, and thus, the assessment is complete.

Inference Procedure in BRB

The inference procedure in the BRB inference system consists of various components such as input transformation, activation weight calculation, belief degree update mechanism and rule aggregation using ER. The input transformation of the antecedent attribute value distributes the value of a belief degree of different referential values of that antecedent. This is equivalent to transforming an input into a distribution on the referential values of an antecedent attribute by using their corresponding belief degrees [13]. At an instant point in time, the *i*-th value of an antecedent attribute P_i can equivalently be transformed into a distribution over the referential values of that antecedent attribute by using their belief degrees [11].

The *i*-th input value P_i, which is the *i*-th antecedent attribute along with its belief degree ε_i of a rule is shown below by (3). The belief degree is assigned to the input value by the experts.

$$H(P_i,\varepsilon_i)=\{(A_{ij},\alpha_{ij}),\ j=1,.....,j_i\},i=1,.....,T_k \quad (3)$$

Here, H is used to show the assessment of the belief degree assigned to the input value of the antecedent attributes. In this equation, A_{ij} (*i*-th value) is the *j*-th referential value of the input P_i. α_{ij} is the belief degree to the referential value, A_{ij} with $\alpha_{ij}\geq 0$. $\sum_{j=1}^{j_i}\alpha_{ij}\leq 1,(i=1,.....,T_k)$, and j_i is the number of the referential values.

The input value of an antecedent attribute is collected from the patient or from the physician in terms of linguistic values such as severe, moderate, mild and normal. These linguistic values are assigned a degree of belief ε_i using expert judgment. This assigned degree of belief is then distributed in terms of belief degree α_{ij} of the different referential values A_{ij}. There are five input antecedents: cough (A_1), breathlessness (A_2), wheezing (A_3), chest tightness (A_4) and respiratory rate (A_5). The referential values of these antecedent attributes consist of severe (S), moderate (Mo), mild (M) and normal (N). The devised rules are as follows:

$$IF(S\,value\geq input\,value\geq Mo\,value)THEN \quad (4)$$
$$Moderate=\frac{S\,value-input\,value}{S\,value-Mo\,value},Severe=1-Moderate,Mild=0.0,Normal=0.0$$

$$IF(Mo\,value\geq input\,value\geq M\,value)THEN \quad (5)$$
$$Mild=\frac{Mo\,value-input\,value}{Mo\,value-M\,value},Moderate=1-Mild,Severe=0.0,Normal=0.0$$

$$IF(M\,value\geq input\,value\geq N\,value)THEN \quad (6)$$
$$Normal=\frac{Mo\,value-input\,value}{Mo\,value-M\,value},Mild=1-Normal,Severe=0.0,Moderate=0.0$$

In the *k*-th rule, it is assumed that α_i^k is the belief degree of one of the referential values A_i^k (which is the element of A_{ij}) of the ith input P_i . This is called the individual matching degree. Here, α_{ij} can be calculated by using (4), (5), (6) and (7). When the *k*-th rule is activated, the weight of activation of the *k*-th rule, *ωk,* is calculated by using the flowing formula [10,11].

$$\omega_k=\frac{\theta_k\alpha_k}{\sum_{j=1}^{L}\theta_j\alpha_j}=\frac{\theta_k\prod_{i=1}^{T_k}(\alpha_i^k)^{\delta_{ki}^{'}}}{\sum_{j=1}^{L}\theta_j\left[\prod_{i=1}^{T_k}(\alpha_i^j)^{\delta_{ji}^{'}}\right]},\delta_{ki}^{'}=\frac{\delta_{ki}}{\max_{i=1,....,T_k}\{\delta_{ki}\}} \quad (7)$$

Here, δ_{ki} is the relative weight of P_i , which is used in the *k*-th rule and is calculated by dividing the weight of P_i by the maximum weight of all antecedent attributes of the *k*-th rule to normalize the value of δ_{ki} which means that its value should range between 0 and 1. The combined matching degree $\alpha_{ki}=\prod_{i=1}^{T_k}(\alpha_i^k)^{\delta_{ki}^{'}}$, which is calculated by using the multiplicative aggregation function. If the *k*-th rule as given in equation (1) is activated, the incompleteness of the consequent of the rule can also result from its antecedents due to the lack of data. The original belief degree β_{ik} in the *i*-th consequent C_i of the *k*-th rule is updated based on the actual input information in (8) as devised in [10].

$$\beta_{ik}=\overline{\beta_{ik}}\frac{\sum_{t=1}^{T_k}\left(\tau(t,k)\sum_{j=1}^{J_t}\alpha_{tj}\right)}{\sum_{t=1}^{T_k}\tau(t,k)} \quad (8)$$

Where

$$(t,k)=\begin{cases}1, if\ P_i\ is\ used\ in\ defining\ R_k(t=1,...,T_k)\\ 0, otherwise\end{cases}$$

Here, $\overline{\beta_{ik}}$ is the original belief degree, and β_{ik} is the updated belief degree. If ignorance occurs, then the belief degrees are updated. For example, if the input antecedent cough is ignored, then the initial belief degrees are updated. The updated belief degrees are shown in Table 1.

Table 1 - Belief degree update

Rule Id		Severe D1	Moderate D2	Mild D3	Normal D4	Dn
1	Initial	0.6	0	0	0.4	0
	Update	0.48	0	0	0.32	0.2
2	initial	0.8	0	0	0.2	0
	Update	0.64	0	0	0.16	0.2
3	Initial	0.4	0	0	0.6	0
	Update	0.32	0	0	0.48	0.2

All packet antecedents of the L rules are aggregated by using the ER approach to obtain the degree of belief of each referential value of the consequent attribute using the given input values P_i of the antecedent attributes. In this study, this aggregation is carried out using an analytical approach, which has been considered since it is more computationally efficient than the recursive approach [12,13]. The output O(Y), consisting of the referential values of the consequent attributes is generated by using the analytical ER algorithm [14]. This is illustrated in equation (9):

$$O(Y)=S(P_i)=\{(C_j,\beta_j),\ j=1,.....,N\} \quad (9)$$

Here, β_j denotes the belief degree associated with one of the consequent reference values such as C_j . β_j is calculated with the analytical format of the ER algorithm [11–14] as illustrated in (10).

$$\beta_j=\frac{\mu\times\left[\prod_{k=1}^{L}\left(\omega_k\beta_{jk}+1-\omega_k\sum_{j=1}^{N}\beta_{jk}\right)-\prod_{k=1}^{L}\left(1-\omega_k\sum_{j=1}^{N}\beta_{jk}\right)\right]}{1-\mu\times\left[\prod_{k=1}^{L}1-\omega_k\right]} \quad (10)$$

with

$$\mu=\left[\sum_{j=1}^{N}\prod_{k=1}^{L}\left(\omega_k\beta_{jk}+1-\omega_k\sum_{j=1}^{N}\beta_{jk}\right)-(N-1)\times\prod_{k=1}^{L}\left(1-\omega_k\sum_{j=1}^{N}\beta_{jk}\right)\right]^{-1}$$

The final output generated by ER is represented by $\{(C_1,\beta_1),(C_2,\beta_2),(C_3,\beta_3),.....,(C_N,\beta_N)\}$, where β_j is the final belief degree attached to the *j*-th referential value C_j of the consequent attribute, which is obtained after all activated rules in the BRB are combined by using ER. This output can be converted into a crisp/numerical value by as-

signing a utility score to each referential value of the consequent attribute [7,10], as shown in (11).

$$H(A^*) = \sum_{j=1}^{N} u(C_j)\beta_j \qquad (11)$$

Where $H(A^*)$ is the expected score expressed as a numerical value and $u(C_j)$ is the utility score of each referential value.

BRBES for Assessing Asthma Suspicion

This section presents the design, implementation, knowledge-base construction and interface of the BRBES for diagnosing asthma.

Architecture, Design and Implementation of the BRBES

The system architecture represents how its components consisting of input, process, and output are organized. The system also considers the pattern of the system organization, known as the architectural style. It consists of a user interface layer (used to get the input and produce system output), inference engine and knowledge base (consisting of the initial rule-base developed using BRB and facts including signs and symptoms of asthma).

The Relation Database Management System (RDBMS) was chosen to store data since this system has a flexible design and is portable in different system environments. PHP, which is available in Netbeans 6.9.1, was used to develop the user interface. The system architecture is shown in Figure 2.

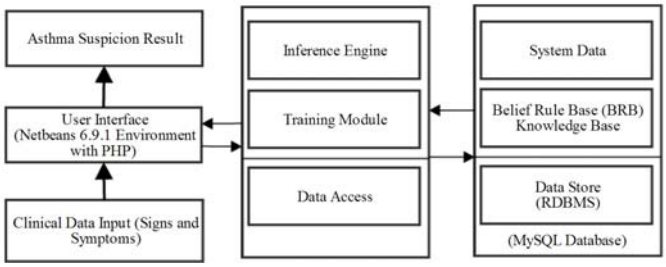

Figure 2- The BRBES system architecture

Knowledge Base Construction in BRB

To construct the knowledge base for this BRB system prototype, a BRB framework was used by following the British Guideline on the Management of Asthma. In the framework, the input factors that determine suspicion are A_1 = Cough, A_2 = Breathlessness, A_3 = Wheeze, A_4 = Chest tightness, A_5 = Respiratory rate and A_6 = Asthma. This BRB consists of only the Asthma ($A_{6)}$ rule base and is depicted in Figure 3. The rule base has five antecedent attributes. The total number of rules, L, is usually determined with the following method:

$$L = \prod_{i=1}^{T} J_i \qquad (12)$$

Here $J_1 = 2$, $J_2 = 4$, $J_3 = 3$, $J_4 = 2$, $J_5 = 2$, so L = (2*4*3*2*2) = 96. Thus, the entire BRB consists of 96 belief rules as illustrated in Table 2. It is assumed that all belief rules have equal rule weight and all antecedent attributes have equal weight. The initial belief base for the asthma suspicion BRB system is listed in Table 2.

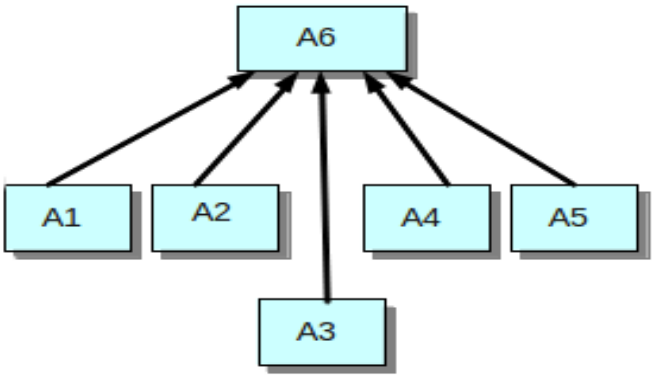

Figure 3- BRB framework for asthma suspicion

An example belief rule of this BRB system as follows:

$$R_1 : IF\,(Cough\ is\ Yes)\ and\ (Breathlessness\ is\ Severe)\ AND\ (Wheeze\ is\ High)\ AND\ (Chest\ tightness\ is\ Yes)\ AND\ (\mathrm{Re}spiratory\ \ rate\ is\ Out\ of\ \ range)$$
$$THEN$$
$$Asthma\ \ is\ \{S(1.00), Mo(0.00), M(0.00), N(0.00)\}$$

In this belief rule, the belief degrees are attached to the three referential values of the consequent attribute. For example, having 100 patients whose clinical information such as "*Cough* is Yes", "*Breathlessness* is Severe", "*Wheeze* is High", "*Chest tightness* is Yes" and "*Respiratory rate* is Out of Range". This means that if the clinical information of the antecedent parts of the rule is evaluated with a high referential value of the corresponding antecedent attribute of the rule, then all patients are judged as severe regarding a diagnosis of asthma. Consequently, the rule can assign initial belief degrees to the consequents in the rule such as "1" to "S", "0" to "Mo", "0" to "M" and "0" to "N" as shown in rule R1.

BRBES Interface

A system interface can be defined as the medium that enables interaction between the users and the system. Figure 4 illustrates a simple interface of the BRBES. Here, the input antecedent for cough is yes, breathlessness is moderate, wheezing is high, chest tightness is yes and respiratory rate is within the range. The BRB/RIMER system generates the fuzzy value of the referential value. Then the system converts the fuzzy value into one numerical value by multiplying four utility factors. The four reference values are 1.0 for the *Severe* referential value, 0.66 for the *Moderate* referential value, 0.33 for the *Mild* referential value and 0.0 for the *Normal* referential value. The fuzzy output of the system is Asthma (A6) :{(Severe, (23.67%)), (Moderate, (39.36%)), (Mild, (3.38%), (Normal, (33.59%))}. Severe referential value = (23.67%*1.00) = 23.67%, Moderate referential value = (39.36%*0.66) = 25.98%, Mild referential value = (3.38%*0.33) = 1.11%, and Normal referential value = (33.59%*0) = 0%. Thus, the total system output is (23.67%+25.98%+1.11%+0%) = 50.77%. The result of the system's diagnosis is 50.77% for the asthma suspicion. This result is shown in Figure 4.

Table 2 - Belief degree update

Rule ID	Rule Weight	IF					THEN			
		Cough	Breathlessness	Wheezing	Chest tightness	Respiratory rate	Asthma			
							S	Mo	M	N
R1	1	Yes	No limitation	High	Yes	Range	0.6	0	0	0.4
R2	1	Yes	No limitation	High	Yes	Out of range	0.8	0	0	0.2
R3	1	Yes	No limitation	High	No	Range	0.4	0	0	0.6
R4	1	Yes	No limitation	High	No	Out of range	0.6	0	0	0.4
R5	1	Yes	No limitation	Medium	Yes	Range	0.4	0.2	0	0.4
R6	1	Yes	No limitation	Medium	Yes	Out of range	0.6	0.2	0	0.2
R7	1	Yes	No limitation	Medium	No	Range	0	0.4	0	0.6
……	……..	……	……	…….	…….	……	…	…..	…..	…
R93	1	No	Severe	Low	Yes	Range	0.4	0	0	0.6
R94	1	No	Severe	Low	Yes	Out of range	0.5	0	0.3	0.2
R95	1	No	Severe	Low	No	Range	0.2	0	0	0.8
R96	1	No	Severe	Low	No	Out of range	0.3	0	0	0.7

Table 3- Asthma suspicion by BRBES and expert

Patient ID	Signs and Symptoms					Expert system/BRBES output	Expert opinion/ physician's opinion	Benchmark/ diagnostic result
	Cough	Breathlessness	Wheezing	Chest tightness	Respiratory rate			
P1	Yes	Moderate	Medium	No	Range	58.27%	65.0	1.0
P2	Yes	Mild	Medium	Yes	Out of range	79.48%	85.0	1.0
P3	No	No limitation	Low	Yes	Range	14.62%	24.0	0.0
P4	No	Severe	Medium	No	Out of range	68.67%	76.0	1.0
P5	Yes	Mild	High	Yes	Out of range	85.98%	90.0	1.0
P6	No	Moderate	High	Yes	Range	50.94%	57.0	1.0
P7	Yes	Mild	Low	Yes	Range	42.83%	50.0	1.0
P8	Yes	Moderate	High	Yes	Out of range	90.69%	95.0	1.0
P9	No	Moderate	Medium	Yes	Range	46.76%	56.0	0.0
P10	No	Severe	Low	Yes	Range	35.28%	45.0	0.0

Results and Discussion

In this research, leaf nodes data of the BRB were collected from patients who suffer from asthma. Then the patient data were used in the BRBES to assess asthma suspicion. Expert opinion on the asthma suspicion was also collected as shown in Table 3. If a patient has asthma, then the benchmark datum is 1; otherwise, it is 0. The data set consists of fifty samples. For simplicity, data for only ten patients is presented in Table 3.

The receiver operating characteristic (ROC) curve can help effectively analyze the performance of the suspicion/diagnosis tests that have ordinal or continuous results [16]. It can be used to test the results of the BRB Expert System and the manual system/expert opinion results by using the benchmark results. The system performance can be measured by calculating the area under the curve (AUC) [16–19]. If the AUC of the BRBES is larger than the expert opinion, then the BRBES produces more accurate and reliable results. Figure 5 shows the two ROC curves. One represents the suspicion performances of the BRB system prototype, and the other is the result of the manual system/expert opinion. The ROC curve with a red line in Figure 5 illustrates the BRB system asthma diagnosis while the curve with green line illustrates the manual system asthma diagnosis. The AUC for the BRB system prototype is 0.952 (95% confidence interval = 0.960–1.012), and the AUC for the expert opinion is 0.857 (95% confidence interval = 0.939–1.014). From the AUC of the BRBES and expert opinion, the AUC for the BRBES is greater than the

AUC for the expert opinion. This implies the results generated by the BRBES are better than the results generated by expert opinion. SPSS 16.0 was used to construct the ROC curve and to calculate the AUC of the curves.

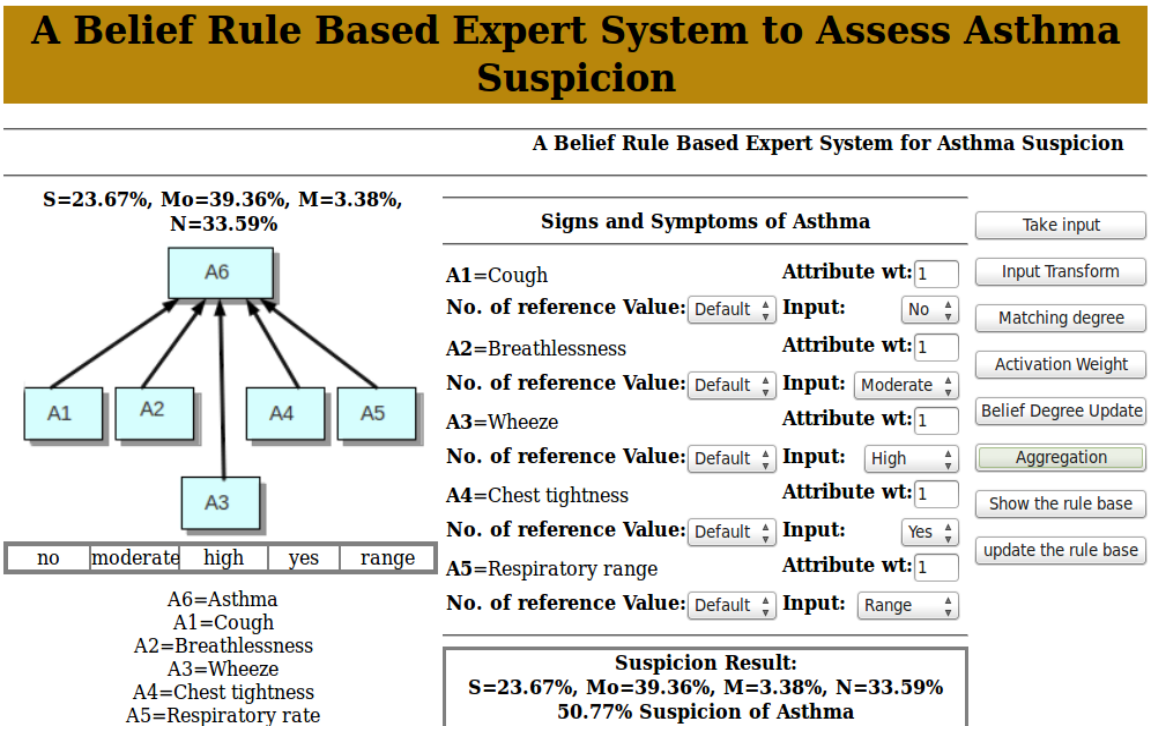

Figure 4- BRBES interface

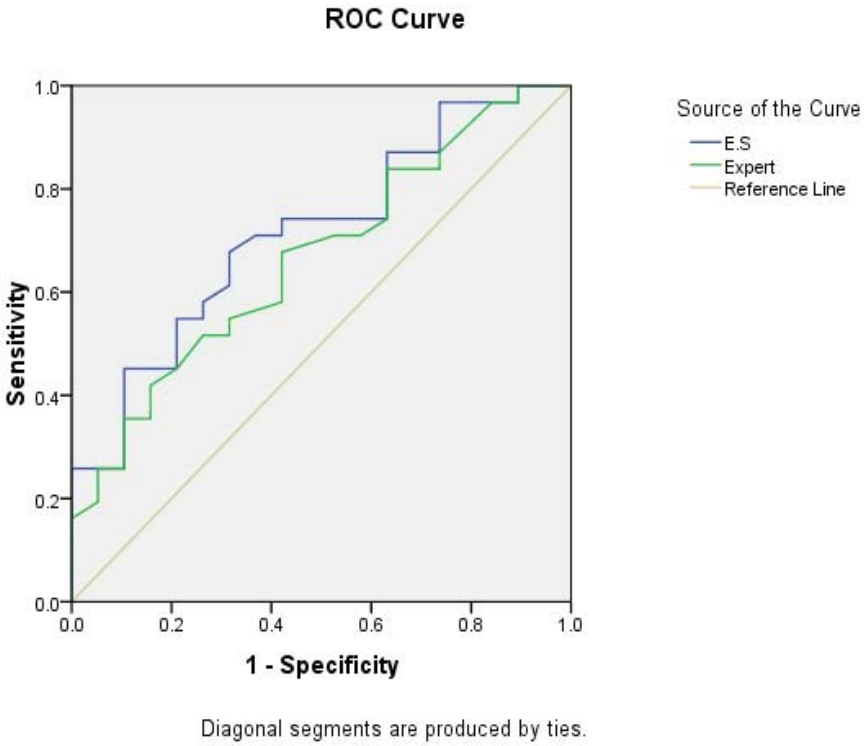

Figure 5- ROC curves of asthma suspicion between the BRBES and expert opinion (manual system)

The great achievement of our research is to overcome the uncertainty problem involved in diagnosing asthma, which cannot be overcome with the traditional rule-based system. The BRBES can handle various types of uncertainty such as ambiguity, vagueness, imprecision, ignorance etc.

Conclusion

In this paper, we demonstrated the development and application of a BRBES to diagnose asthma based on signs and symptoms. This BRBES used a methodology known as

RIMER that handles various types of uncertainty found in domain knowledge. The BRBES is a robust tool that can aid in assessing asthma suspicion. The system will help patients assess improvement in asthma severity as well. This BRBES provides a percentage of the assessment, which is more reliable and informative than from a traditional expert's opinion that given without a degree of belief that is weighted with percentage value. Results generated by the BRBES were more reliable than the traditional expert opinion.

The system has strong potential in developing countries in Africa and Asia, in addition to other countries, where there is a lack of healthcare resources, diagnosis machinery and expert physicians.

References

[1] Jeffery PK. Remodeling in Asthma and Chronic Obstructive Lung Disease. Am J Respir Crit Care Med 2001;164:S28–S38.

[2] Dold S, Wjst M, von Mutius E, Reitmeir P, Stiepel E. Genetic risk for asthma, allergic rhinitis, and atopic dermatitis. Arch Dis Child 1992;67:1018–22.

[3] Rahman S, Hossain MS. A Belief Rule Based System Prototype for Asthma Suspicion, Khulna, Bangladesh: 2013.

[4] Mathew J, Semenova Y, Farrell G. A miniature optical breathing sensor. Biomed Opt Express 2012;3:3325.

[5] Zolnoori M, Zarandi MHF, Moin M, Teimorian S. Fuzzy Rule-Based Expert System for Assessment Severity of Asthma. J Med Syst 2012;36:1707–17.

[6] Redier H, Daures JP, Michel C, Proudhon H, Vervloet D, Charpin D, et al. Assessment of the severity of asthma by an expert system. Description and evaluation. Am J Respir Crit Care Med 1995;151:345–52.

[7] Mishra N, Singh D, Bandil MK, Sharma P. Decision Support System for Asthma (DSSA). Int J Inf Comput Technol 2013;3:549–54.

[8] Angulo C, Cabestany J, Rodríguez P, Batlle M, González A, de Campos S. Fuzzy expert system for the detection of episodes of poor water quality through continuous measurement. Expert Syst Appl 2012;39:1011–20.

[9] Liu TI, Singonahalli JH, Iyer NR. Detection of Roller Bearing Defects Using Expert System and Fuzzy Logic. Mech Syst Signal Process 1996;10:595–614.

[10] Russell SJ, Norvig P, Davis E. Artificial intelligence: a modern approach. Upper Saddle River, NJ: Prentice Hall; 2010.

[11] Jian-Bo Yang, Jun Liu, Jin Wang, How-Sing Sii, Hong-Wei Wang. Belief rule-base inference methodology using the evidential reasoning Approach-RIMER. IEEE Trans Syst Man Cybern - Part Syst Hum 2006;36:266–85.

[12] Kong GL, Zu DL, Yang JB. An evidence-adaptive belief rule-based clinical decision support system for clinical risk assessment in emergency care, Bonn, Germany: 2009.

[13] Jian-Bo Yang, Pratyush Sen. A general multi-level evaluation process for hybrid MADM with uncertainty. IEEE Trans Syst Man Cybern 1994;24:1458–73.

[14] Wang Y-M, Yang J-B, Xu D-L. Environmental impact assessment using the evidential reasoning approach. Eur J Oper Res 2006;174:1885–913.

[15] Jian-Bo Yang, Jun Liu, Jin Wang, Guo-Ping Liu, Hong-Wei Wang. An optimal learning method for constructing belief rule bases. vol. 1, IEEE; 2004, p. 994–9.

[16] Body R. Clinical decision rules to enable exclusion of acute coronary syndromes in the emergency department. Doctoral Thesis. Manchester Metropolitan University, 2009.

[17] Skalska H, Freylich V. Web-bootstrap estimate of area under ROC curve. Aust J Stat 2006;35:325–30.

[18] Metz CE. Basic principles of ROC analysis. Semin Nucl Med 1978;8:283–98.

[19] Hanley JA. The Robustness of the "Binormal" Assumptions Used in Fitting ROC Curves. Med Decis Making 1988;8:197–203.

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