A Belief Rule Based Expert System to Diagnose Measles under Uncertainty

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Abstract - Measles is a highly infectious child disease that causes serious complications and death worldwide. Measles is generally diagnosed from its signs and symptoms by a physician, which cannot be measured with 100% certainty during the diagnosis process. Consequently, the traditional way of diagnosing measles from its signs and symptoms lacks the accuracy. Therefore, a belief rule-based inference methodology using evidential reasoning approach (RIMER), which is capable of handling various types of uncertainties has been used to develop an expert system to diagnose measles under uncertainty. The results, generated, from the system have been compared with the expert opinion as well as with a Fuzzy Logic based system. In both the cases, it has been found that the Belief Rule Based Expert (BRBES), presented in this paper, is more reliable and accurate.

Keywords: Measles, Expert System, Belief Rule Base, Uncertainty, Evidential Reasoning

1 Introduction

Measles is a highly contagious infection caused by measles virus. It is a common disease in developing countries like Bangladesh. Almost every organ system can be affected by the complications from measles [1]. Physical contact, coughing and sneezing can spread the infection. Moreover, infected droplets of mucus can remain active and contagious for around two hours. This means that the virus can live outside the body - for example, on surfaces, pens, pencils etc. A survey said that, before the introduction of measles vaccines, the disease occurred in 95%–98% of children by the age of 18 years [2][3]. After an incubation period of 8–12 days, measles begins with increasing fever (to 39°C–40.5°C) and cough, coryza, and conjunctivitis [4][5]. Symptoms intensify over the 2–4 days before the onset of rash and peak on the first day of rash [6]. The rash is usually first noted on the face and neck, appearing as discrete erythematous patches 3–8 mm in diameter. The lesions increase in number for 2 or 3 days, especially on the trunk and the face, where they frequently become confluent. Discrete lesions are usually seen on the distal extremities, and with careful observation, small numbers of lesions can be found on the palms of 25%–50% of those infected. The rash lasts for 3–7 days and then fades in the same manner as it appeared, sometimes ending with a fine desquamation that may go unnoticed in children who are bathed daily. An exaggerated desquamation is commonly seen in malnourished children [5][7][8]. Fever usually persists for 2 or 3 days after the onset of the rash, and the cough may persist for as many as 10 days. Koplik’s spots usually appear 1 day before the onset of rash and persist for 2 or 3 days. These bluish-white, slightly raised, 2- to 3-mm-diameter lesions on an erythematous base appear on the buccal mucosa, usually opposite the first molar, and occasionally on the soft palate, conjunctiva, and vaginal mucosa [9][10]. Koplik’s spots have been reported in 60%–70% of persons with measles but are probably present in most persons who develop measles [11]. An irregular blotchy exanthem may be present in other areas of the buccal mucosa. Photophobia from iridocyclitis, sore throat, headache, abdominal pain, and generalized mild lymphadenopathy are also common. Measles is transmitted by the respiratory route and is highly infectious. Infectivity is greatest in the 3 days before the onset of rash, and 75%–90% of susceptible household contacts develop the disease [12][13][14]. The early pre-rash symptoms are similar to those of other common respiratory illnesses, and affected persons often participate in routine social activities, facilitating transmission. The outbreaks of measles occur when children in the first few days of illness attend school and other events like sports [15]. Outbreaks also occur when ill children are brought to a doctor’s office or emergency room for evaluation for fever, irritability, or rash [16][17].

Medical diagnosis is a process to detect a disease by measuring its specific signs and symptoms. Signs are observed by a physician while symptoms are expressed by the patient. However, patients may not able to precisely express their feelings on the symptoms and doctors may not always sure about the condition of signs. Therefore, various types of uncertainties may be noticed during the diagnosis process of a disease. These uncertainties should be carefully handled, enabling the accurate diagnosis of a disease.

The main signs and symptoms associated with measles consist of fever, cough, coryza, conjunctivitis, koplík’s spot and rash [18][19]. These signs and symptoms cannot be measured with 100% certainty during the diagnosis process. The reason for this is that they are expressed both by the patients and the doctors in linguistic terms such as “high”, “medium” and “low”. Such linguistic terms inevitably contains uncertainty such as vagueness, imprecision and ambiguity. Sometime, it is not possible to obtain data on the above signs and symptoms and hence, this causes uncertainty due to ignorance and incompleteness in the diagnosis process. Consequently, the traditional way of diagnosing the measles
is incapable of producing the accurate diagnostic results because of the absence of appropriate method of handling the issue of uncertainty that exists with the signs and symptoms. Problem of this nature could be well handled by developing an expert system [20], which emulate the human decision making process. However, this system employed traditional IF-THEN rules to develop knowledge base, which can capture assertive knowledge not the uncertain knowledge. Therefore, a knowledge representation schema is required which could be used to develop the expert system with the capability of capturing various types of uncertainties that exist with the signs and symptoms of measles. Hence, belief rule base knowledge representation schema, which has the ability to represent uncertain knowledge, has been considered to develop an expert system along with the evidential reasoning as the inference engine [21].

The remaining of the paper is structured as follows. Section two presents the related works. Section three provides an overview of the methodology used to develop the belief rule based expert system (BRBES) known as RIMER. Section four describes the design and implementation of the BRBES. Section five presents the results and discussions. Section six concludes the paper.

2 Literature Review

Expert systems are widely used to diagnose diseases. This is a computer system that nearly earns the decision making ability of a human expert. The goal of designing an expert system is to solve a complex problem by reasoning with knowledge rather than by conventional procedural codes. An expert system consists of two parts namely, the inference engine and the knowledge base [22]. Knowledge base of an expert system dedicated to represent the knowledge about a domain. Various knowledge representation schemas such as Propositional Logic (PL), First Order Logic (FOL), Fuzzy Logic (FL), Frames, Semantic Net, Case Based Reasoning and Bayesian Belief Network are widely used to build the knowledge base of an expert system. Both PL and FOL are used to acquire assertive knowledge and hence, unable to represent various types of uncertainties [23]. Semantic Net is a directed or undirected graph, which represents semantic relations between concepts [24] but not the uncertainty. Bayesian Belief Network or BNN is a directed acyclic graph representing the facts using conditional probability. Given relationships between diseases and symptoms, the network can compute the probabilities of the presence of various diseases. The idea of conditional probability is very useful here. In spite of remarkable power of BNN it has some limitations such as it is difficult to compute result for previously unknown network. A Bayesian network is only useful when a priori knowledge is reliable [25]. However, the diagnosing of measles requires the consideration of a posteriori signs and symptoms. Fuzzy logic is suitable to represent lexical knowledge and can address uncertainties such as vagueness, imprecision and ambiguity but is not equipped enough to handle uncertainty due to ignorance or incompleteness. Belief rule-base [21] is a new knowledge representation schema uses a belief structure where belief degrees are embedded with all possible terms of the consequent part of a rule. It can handle various types of uncertainties such as vagueness, ambiguity, imprecision, ignorance and incompleteness.

Inference is the process of reasoning from the factual knowledge in order to derive logical conclusions. Examples of inference procedures are Forward Chaining (FC), Backward Chaining (BC), Modus Ponens (MP), evidential reasoning(ER) etc. MP is the simplest form of inference procedure, enables the deductive reasoning. It is interesting to note that both FC and BC developed based on MP. Forward chaining begins with the available fact or input and searches the rules until the rule is found where the if-clause is known to be true. When such a rule is found, the process may conclude or forward to the then-clause for further inference. The process is iterated until a goal is reached. On the other hand backward chaining works backward from the goal. It begins with a list of goals and searches the rules until it finds a rule, which contains a desired goal in then-clause. BC is a goal driven mechanism while FC is a data driven mechanism for inference. However, they are not equipped with the mechanism to handle uncertainties. On the other hand Evidential Reasoning, which is used as an inference mechanism can process various types of uncertainties mentioned previously, especially the ignorance and incompleteness. Therefore, belief rule base along with evidential reasoning, known as RIMER, has been considered to develop the expert system to diagnose measles under uncertainty.

Therefore, in order to ensure a most correct detection of measles under uncertainty, an expert system needs to be developed by using BRB for knowledge base, along with the ER approach for inference mechanism.

3 Overview of RIMER

RIMER consists of two parts. The first part is concerned with building the knowledge base using BRB while the second part is concerned with the inference procedures consisting of input transformation, rule activation weight calculation, belief degree update and rule aggregation using evidential reasoning.

3.1 Domain knowledge representation using BRB

BRB is an extended form of traditional IF-Then rule. In a BRB, the antecedent part consists of antecedent attributes that take referential values, while the referential values of the consequent of the consequent part is attached with belief degrees. In this way, the later part forms a belief structure as shown in equation (1). The BRB also includes learning parameter such as rule weight and antecedent attribute weight.
\( R_k: \ \text{if} \ (S_{k1} \text{ is } A_{k1}^k) \land (S_{k2} \text{ is } A_{k2}^k) \land \ldots \land (S_{k_T} \text{ is } A_{k_T}^k), \)

\( \text{then} \ \{(D_1 \text{ is } \beta_{1k}), (D_2 \text{ is } \beta_{2k}), \ldots, (D_N \text{ is } \beta_{Nk})\} \)

with a rule weight \( \theta_k \) and

attribute weights \( \delta_{k1}, \delta_{k2}, \ldots, \delta_{k_T} \)

\( k \in \{1, \ldots, L\} \)

..... (1)

Here, \( S_{k1}, S_{k2}, \ldots, S_{k_T} \) stand for the antecedent attributes in \( k^{th} \) rule and each \( A_i^k \) (\( i \in \{1, \ldots, T_k\} \)) is one of the referential values of \( S_{ki} \). \( T_k \) is the total number of antecedent attributes in the \( k^{th} \) rule. \( \beta_{jk} (j = 1, \ldots, N, k = 1, \ldots, L) \) is the degree of belief to which the consequent reference value \( D_j \) 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 consequent in the rule base. For example, in the case of measles diagnosis, a belief rule can be written as follows:

\( R_k: \ \text{if} \ (\text{Fever is } \text{Medium}') \land (\text{Rash is } \text{High}') \land \)

Here, \( \{(\text{High, 0.90}), (\text{Medium, 0.10}), (\text{Low, 0.00})\} \) is a belief distribution associated with the measles diagnosis. This belief distribution states that, it is 90% sure that the condition of the measles is ‘high’ and 10% sure that it is ‘medium’. In this belief rule, the total degree of belief is \((0.90+0.10+0) = 1\) and hence, the assessment is complete.

### 3.2 Inference Procedures

Following the schema of BRB as represented by equation (1) the knowledge base of an expert system is developed, which is known as initial rule base. This rule base is stored in the static memory or in the long-term memory. However, in order to diagnose the measles, it is necessary to get its values of the signs and symptoms, collected either from the patients or from the physicians. These values considered as the input values of the BRBES. Basically, these signs and symptoms considered as the antecedent attributes of a rule. Each input value needs to be distributed over the referential values of an antecedent attribute to demonstrate what amount of this input value match with each of the referential value. This is shown in equation (2). The referential values of each antecedent attribute may by “High”, “Medium” and “Low”, which are similar to the signs and symptoms of the measles as expressed by the patients or the physicians in terms of these linguistic terms.

\[ (S_{k1} \text{ is } A_{k1}^k, \alpha_{k1}^k) \land (S_{k2} \text{ is } A_{k2}^k, \alpha_{k2}^k) \land \ldots \land (S_{k_T} \text{ is } A_{k_T}^k, \alpha_{k_T}^k) \]\n
where \( \alpha_{k_i}^k \) is the matching degree of the input value to the referential value \( A_{ki}^k \) of an antecedent attribute \( S_{ki} \) in the \( k^{th} \) rule (\( i = 1, \ldots, T_k \)). This is important to note that when the matching degree is assigned to the referential values of the attributes of a rule then it is said to be activated. This phenomenon is also called packet antecedent of a rule. In other way, it can be argued that the rule is in the RAM or on the short term memory. The total degree or the combined matching degree \( \alpha_i \) to which the input matches the whole antecedent part of \( k^{th} \) rule, can be calculated by using the following formula:

\[ \alpha_k = \text{aggr}((\delta_{k1}, \alpha_{k1}^k), \ldots, (\delta_{k_T}, \alpha_{k_T}^k)) \]

where \( \text{aggr} \) is an aggregation function which should be selected carefully. In the case of a rule defined as in (3), following simple weighted multiplicative aggregation function can be used:

\[ \alpha_k = \prod_{i=1}^{T_k} (\alpha_i^k) \]

where \( \delta_{ki} = \sum_{i=1}^{T_k} \delta_{ki} \)

The activation weight \( w_k \) for \( k^{th} \) rule can be generated by the following equation:

\[ w_k = \theta_k \alpha_k / \sum_{i=1}^{L} \theta_i \alpha_i \]

This activation weight will be zero if the \( k^{th} \) rule is not activated.

The incompleteness of the consequent of a rule can also be occurred by its antecedents because of the lack of data. Such incompleteness should be taken into account in the inference process. Therefore, the existing belief degree is updated using the actual input information.

\[ \beta_{ik} = \bar{\beta}_{ik} \sum_{t=1}^{T_k} (\lambda(t, k) \sum_{j=1}^{T} \alpha_{ij}) / \sum_{t=1}^{T_k} \lambda(t, k) \]

where

\[ \lambda(t, k) = \begin{cases} 1, & \text{if } t^{th} \text{ attribute is used in defining } R_k \\ 0, & \text{otherwise.} \end{cases} \]

ER approach is used to aggregate all the packet antecedents of the \( L \) rules to obtain the degree of belief of each referential values of the consequent attribute by taking account of given input values \( P_i \) of antecedent attributes. This aggregation can be carried out either using recursive or analytical approach. Accordingly, for each \( D_i \) the generated belief degree will be calculated as:

\[ \beta_i = \frac{\lambda_i(t, k)}{1 - \lambda_i(t, k)} \]

Thus, the final result generated by aggregating all rules can be represented as

\[ F = \{D_i, \beta_i\}; i = 1, \ldots, N \]

The entire result can then be converted into a crisp value by calculating the expected score \( u(F) \).
\[ u(F) = \sum_{i=1}^{N} \beta_i u(D_i) \quad \ldots (9) \]

\( u(D_i) \) denotes the score of an individual consequent \( D_i \).

## 4 BRBES for Measles Diagnosis

This section presents the design, implementation, knowledge-base construction, interface of the BRBES to diagnose measles.

### 4.1. Architecture, design and Implementation of the BRBES

The design of a system consists of data structure and program components that are essential to build a computer based system. It also considers the system organization pattern, which is known as architectural style. The architecture of the BRBES consists of user interface, data management layer and application processing as shown in Figure 1. User interface interacts to system user to get input data and to receive system generated output. Data management layer includes designing the knowledge base containing the rules and facts about measles.

![Figure 1. Architecture of BRBES](image)

The application processing layer is concerned with input transformation, rule activation weight calculation, belief degree update and the aggregation of the rules. The data management layer and application processing layer has been implemented using Microsoft Excel 2010 spreadsheet programming. The interface layer has been implemented using VBA (visual basic application) programming [27][28][29][30][31][32].

### 4.2. Knowledgebase Construction in BRB

Figure 2 illustrates the BRB tree, which has been developed in consultation with the physicians. The BRB tree represents a multilevel hierarchical structure of the knowledge base. Each sub tree with a root and its leaf nodes represents a sub-rule-base of the knowledge base.

The leaf nodes becomes the antecedent attributes of a rule and the parent node becomes its consequent attribute. The number of sub rule-bases can be determined from the number of parent nodes. The BRB tree as illustrated in Figure 2 has two parent nodes i.e. \( A_3 \) and \( A_4 \). Therefore, there should be two sub-rule-bases namely sub-rule base \( A_4 \) and sub-rule-base \( A_8 \).

![Figure 2. The BRB Framework to Diagnose Measles](image)

### Sub-Rule-Base \( A_4 \)

This sub rule base consist of three antecedent attributes namely \( A_1 \), \( A_2 \) and \( A_3 \). Each attribute has three referential values, namely high (H), medium (M) and low (L). Therefore, this sub-rule-base consists of 27 rules.

### Sub-Rule Base \( A_8 \)

Four antecedent attributes \( A_4 \), \( A_5 \), \( A_6 \) and \( A_7 \) exist in this sub-rule-base. Three of them consist of three referential values high (H), medium (M) and low (L). However, \( A_7 \) has two referential values such as high (H) and low (L). Therefore this sub-rule-base should have \( 27 \times 2 = 54 \) rules. Table 1 illustrates the initial rule base for the sub rule base \( A_8 \).

**TABLE 1. INITIAL SUB-RULE-BASE \( A_8 \)**

<table>
<thead>
<tr>
<th>Rule id</th>
<th>Rule Weight</th>
<th>IF</th>
<th>THEN</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is H ^ ( A_6 ) is L</td>
<td>( A_8 ) is {(H,1.00),( (M,0.00),( (L,0.00))}</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is H ^ ( A_6 ) is M</td>
<td>( A_8 ) is {(H,0.9),( (M,0.10),( (L,0.00))}</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is H ^ ( A_6 ) is L</td>
<td>( A_8 ) is {(H,0.80),( (M,0.20),( (L,0.00))}</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is M ^ ( A_6 ) is H</td>
<td>( A_8 ) is {(H,0.9),( (M,0.1),( (L,0.0))}</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is M ^ ( A_6 ) is M</td>
<td>( A_8 ) is {(H,0.5),( (M,0.5),( (L,0.00))}</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is M ^ ( A_6 ) is L</td>
<td>( A_8 ) is {(H,0.2),( (M,0.8),( (L,0.00))}</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is L ^ ( A_6 ) is H</td>
<td>( A_8 ) is {(H,0.8),( (M,0.2),( (L,0.0))}</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>( A_1 ) is H ^ ( A_3 ) is H ^ ( A_5 ) is L ^ ( A_6 ) is M</td>
<td>( A_8 ) is {(H,0.2),( (M,0.8),( (L,0.0))}</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>54</td>
<td>1</td>
<td>( A_1 ) is L ^ ( A_3 ) is L ^ ( A_5 ) is L ^ ( A_6 ) is L</td>
<td>( A_8 ) is {(H,0.00),( (M,0.00),( (L,1.00))}</td>
</tr>
</tbody>
</table>

An example of a belief rule taken from Table 1 is illustrated below.

\( R1: IF \) Koplik’s Spot is High AND Rash is high AND Fever is High AND ‘Three C Symptoms’ is High THEN Measles\{(High,1),(Medium,0),(Low,0)\}.}
In the above belief rule, the belief degrees are attached to the three referential values. The weight of each rule has been considered as ‘1’.

4.3. BRBES Interface

A system interface can be defined as the media, enabling the interaction between the users and the system. Figure 3 illustrates a simple interface of the BRBES. This interface facilitates the acquiring of the leaf nodes (antecedent attributes) data of the BRB framework (fig 2). The system interface enables the displaying of the measles diagnosing results (the top node). For example, Figure 3 illustrates the result for the data of leaf nodes (A1 = mild, A2 = moderate, A3 = mild, which appears in the signs and symptoms dialogue box of the BRBES’ interface) associated with sub-rule-base A4.

Figure 3. User Interface of BRBES to Diagnose Measles

From Figure 3 it can be observed that the ‘Three C Symptoms’, which is the consequent attribute named as “A4” of this sub-rule-base is 50%. This data has been calculated by the system by applying equations (7-9). The child node of the sub rule base A8 consists of A4, A5, A6, and A7. However, A5, A6 and A7 are the leaf nodes and the input data related to these nodes as shown in the signs and symptoms dialogue box of the system interface are ‘103 degree F’, ‘Spread Moderately’ and ‘Found’ respectively. These linguistic data have been distributed over the referential values of the leaf node attributes by using equations (2). Figure 3 illustrates the overall assessment of the measles which is 50% high, 50% medium and 0% low. This is obtained by using equation (8) while by using equation (9) the assessment in terms of crisp value i.e. 75% has been achieved.

5 Result and Discussion

In this research, the leaf nodes data of the BRB framework (fig 2) have been collected from the patients. The patient’s data have been used in the BRBES to diagnose measles. Expert’s opinion on the measles diagnosis of the patients is also collected as shown in Table 3. The data set consists of 200. For simplicity, only ten patient’s data set are presented in Table 2. Column 8 of Table 2 illustrates BRBES’ generated output in percentages, which is calculated by using utility equation (9). For example, the overall system output of measles diagnosis is 75.28% can be obtained, by using a degree of belief associated with referential values such as {High (0.6191), Medium(0.2674), Low(0.1134)}.

The Receiver Operating Characteristic (ROC) curve can be used to analyze effectively performances of diagnosis of measles having ordinal or continuous results [33][34][35][36][37]. It can be used to test the reliability of the BRBES’s output in comparison with manual system by taking account of benchmark data. The real laboratory test results of the patients have been considered as the benchmark data. For example, if the measles is found positive then it is considered as “1”, otherwise it is “0” as shown in the column 10 of the Table 2. The performance of the system can be measured by calculating the Area under Curve (AUC). A larger AUC refers to a more accurate and reliable result. Fig 4 shows the two ROC curves; one represents the performances of the BRBES and the other for the manual system. The performance of the BRBES has also been compared against the physician’s opinion, as shown in Fig 5.

TABLE II. DATASET FOR SYSTEM TESTING

<table>
<thead>
<tr>
<th>S.no.</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A5</th>
<th>A6</th>
<th>A7</th>
<th>System Opinion (%)</th>
<th>Expert’s Opinion (%)</th>
<th>State variance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mild</td>
<td>Mild</td>
<td>Mild</td>
<td>103.0</td>
<td>Spread moderately</td>
<td>Found</td>
<td>82.00</td>
<td>90.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>Mild</td>
<td>Normal</td>
<td>Normal</td>
<td>102.0</td>
<td>Spread moderately</td>
<td>Found</td>
<td>67.50</td>
<td>65.00</td>
<td>1.00</td>
</tr>
<tr>
<td>3</td>
<td>Normal</td>
<td>Normal</td>
<td>Moderate</td>
<td>99.5</td>
<td>Spread moderately</td>
<td>Found</td>
<td>64.50</td>
<td>60.00</td>
<td>1.00</td>
</tr>
<tr>
<td>4</td>
<td>Mild</td>
<td>Normal</td>
<td>Normal</td>
<td>102.5</td>
<td>A few rashes</td>
<td>Found</td>
<td>72.50</td>
<td>70.00</td>
<td>1.00</td>
</tr>
<tr>
<td>5</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>99.5</td>
<td>A few rashes</td>
<td>Not found</td>
<td>1.50</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>102.0</td>
<td>A few rashes</td>
<td>Found</td>
<td>86.00</td>
<td>85.00</td>
<td>1.00</td>
</tr>
<tr>
<td>7</td>
<td>Severe</td>
<td>Normal</td>
<td>Normal</td>
<td>103.5</td>
<td>A few rashes</td>
<td>Found</td>
<td>65.50</td>
<td>65.00</td>
<td>1.00</td>
</tr>
<tr>
<td>8</td>
<td>Mild</td>
<td>Normal</td>
<td>Normal</td>
<td>102.0</td>
<td>A few rashes</td>
<td>Found</td>
<td>86.00</td>
<td>85.00</td>
<td>1.00</td>
</tr>
<tr>
<td>9</td>
<td>Severe</td>
<td>Normal</td>
<td>Normal</td>
<td>104.0</td>
<td>A few rashes</td>
<td>Found</td>
<td>65.50</td>
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<td>10</td>
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<td>Normal</td>
<td>99.5</td>
<td>A few rashes</td>
<td>Not found</td>
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<td>1.50</td>
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<td>11</td>
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<td>Normal</td>
<td>Normal</td>
<td>99.5</td>
<td>A few rashes</td>
<td>Not found</td>
<td>1.50</td>
<td>1.50</td>
<td>0.00</td>
</tr>
<tr>
<td>12</td>
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<td>Normal</td>
<td>Normal</td>
<td>103.5</td>
<td>A few rashes</td>
<td>Found</td>
<td>27.50</td>
<td>27.00</td>
<td>0.00</td>
</tr>
<tr>
<td>13</td>
<td>Normal</td>
<td>Normal</td>
<td>Moderate</td>
<td>99.5</td>
<td>Spread moderately</td>
<td>Found</td>
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<td>60.00</td>
<td>1.00</td>
</tr>
<tr>
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<td>Mild</td>
<td>Normal</td>
<td>Normal</td>
<td>102.5</td>
<td>Spread moderately</td>
<td>Found</td>
<td>72.50</td>
<td>65.00</td>
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</tr>
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<td>Mild</td>
<td>Normal</td>
<td>Normal</td>
<td>101.5</td>
<td>Spread moderately</td>
<td>Found</td>
<td>67.50</td>
<td>60.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

5.1. Reliability of BRBES against Expert Opinion

The ROC curve plotted by the blue line in fig 6 is carried out by using the results generated by the BRBES, which AUC is 0.849 (95% confidence intervals 0.729 - 0.970). The ROC curve plotted by the green line in fig 6 is obtained from the result set manually produced based on the physician’s opinion, and its AUC is 0.811 (95% confidence intervals 0.675 - 0.947). The 95% confidence interval means that the parameter value in estimation can remain within the range of estimated interval with 95% certainty [38]. The results show that the AUC of BRBES is greater than that of physician
opinion. This implies that, under clinical uncertainties, the diagnostic performance of the BRBES is better than manual judgment made by a physician.

Figure 4. ROC curves of Measles Diagnosis between BRBES and Expert Opinion

5.2. Comparison of BRBES with Fuzzy Logic based System

The BRBES has been compared with a fuzzy rule based expert system. The main difference between fuzzy rule and the belief rule can be understood from the representation of R1 by using these two knowledge representation schemas.

\[
R1: \text{IF Koplik's Spot is High AND Rash is high AND Fever is High AND 'Three C Symptoms' is High THEN Measles}([\text{High},1),(\text{Medium},0),(\text{Low},0)]. \text{[Belief Rule]}
\]

\[
R1: \text{IF Koplik's Spot is High AND Rash is high AND Fever is High AND 'Three C Symptoms' is High THEN Measles is High} \text{[Fuzzy Rule]}
\]

From the above, it can be seen that in case of fuzzy logic degree of belief is not embedded with the consequent part of the rule. The same patients data (which were used with both BRBES and expert) are used to obtain the results of measles diagnosis by using fuzzy logic based expert system (FLBES). Table 3 illustrates the comparison of measles diagnosis results among BRBES, FLBES and expert opinion.

TABLE III COMPARISION AMONG BRBES, FLBES AND EXPERT OPINION

<table>
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<tr>
<th>S.N.</th>
<th>BRBES (%)</th>
<th>Expert opinion (%)</th>
<th>FLBES (%)</th>
<th>Benchmark Data</th>
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<td>67.50</td>
<td>60.00</td>
<td>80.09</td>
<td>1</td>
</tr>
</tbody>
</table>

The ROC curve plotted by red line in fig 5 is obtained by using FLBES, which AUC is 0.824 (95% confidence intervals 0.693 - 0.956). The ROC curve plotted by the blue line is obtained by using result generated by the BRBES, and its AUC is 0.849 (95% confidence intervals 0.729 - 0.970). The ROC curve plotted by the green line is obtained from the result set manually produced based on the expert opinion, which AUC is 0.811 (95% confidence intervals 0.675 - 0.947). The results demonstrate that the AUC of BRBES is greater than that of fuzzy rule based expert system as well as than that of expert opinion. This implies that, under clinical uncertainties, the diagnostic performance of the BRBES is better than that of FLBES.

Figure 5. ROC curves of Measles Diagnosis among BRBES, Fuzzy Logic Based Expert System and Expert Opinion

6 Conclusion

The development and application of a BRBES to diagnose measles under uncertainty presented in this paper. The system employed RIMER methodology, which is capable of handling of various types of uncertainties found in the clinical domain knowledge as well as in the signs and symptoms. The results of the BRBES compared against expert opinion and found more reliable and robust. The reason for this is that expert is unable to consider various types of uncertainties such as vagueness, imprecision, ambiguity, randomness and ignorance, those are associated with the signs and symptoms of the measles during the diagnostic process. In addition, the performance of the BRBES has been compared against fuzzy logic based expert system. It is observed that the results generated from BRBES are better than fuzzy based expert system (fig 5). The reason for this is that fuzzy logic only considers uncertainties due to vagueness, imprecision and ambiguity while BRBES in addition to these uncertainties considers uncertainty due to randomness and ignorance. In addition, the inference procedures of BRBES consists of input transformation, rule activation weight calculation, belief update and rule aggregation using evidential reasoning approach. Evidential reasoning is capable of process various types of uncertainties, which is not the case with the fuzzy based inference engine such as Mandni and Takagi–Sugeno (TS).
7 References


