An Intelligent System to Diagnose Chikungunya under Uncertainty

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Abstract

Chikungunya is a virus-related disease, bring about by the virus called CHIKV that spreads through mosquito biting. This virus first found in Tanzania, while blood from patients was isolated. The common signs and symptoms, associated with Chikungunya are considered as fever, joint swelling, joint pain, muscle pain and headache. The examination of these signs and symptoms by the physician constitutes the typical preliminary diagnosis of this disease. However, the physician is unable to measure them with accuracy. Therefore, the preliminary diagnosis in most of the cases could suffer from inaccuracy, which leads to wrong treatment. Hence, this paper introduces the design and implementation of a belief rule based expert system (BRBES) which is capable to represent uncertain knowledge as well as inference under uncertainty. Here, the knowledge is illustrated by employing belief rule base while deduction is carried out by evidential reasoning. The real patient data of 250 have been considered to demonstrate the accuracy and the robustness of the expert system. A comparison has been performed with the results of BRBES and Fuzzy Logic Based Expert System (FLBES) as well as with the expert judgment. Furthermore, the result of BRBES has been contrasted with various data-driven machine learning approaches, including ANN (Artificial Neural networks) and SVM (Support Vector Machine). The reliability of BRBESs was found better than those of data-driven machine learning approaches. Therefore, the BRBES presented in this paper could enable the physician to conduct the analysis of Chikungunya more accurately.

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

1 Introduction

Chikungunya is the virus related disease, which is transmitted into the human body by the biting of Albopictus mosquitoes and Aedes Aegypti. These mosquitoes become poisonous when they bite a person who is already infected by this virus. Chikungunya disease was first detected in Tanzania from the blood of a patient in 1953 [1]. The disease also found repeatedly in many countries of Asia. In 2008, this disease was first identified in Bangladesh and during this time, there was an absence of specific treatment. In the current year (2017) more than 3000 cases were recorded in the country of which 2,700 were in Dhaka [2]. The signs and symptoms are same for both Chikungunya and Dengue. The reason for this

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is that Dengue virus is also carried by the same mosquitos. People who suffer from Chikungunya may notice some signs and symptoms (such as high fever, joint pain and headache) within 3 to 7 days after the time of mosquito biting and its virus can be found in the blood within one week [3][4].

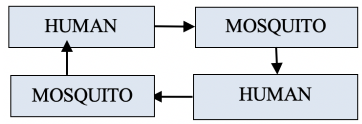

Figure 1: Chikungunya Transmission Cycle

The virus may be spread from one person to another through mosquito biting and hence, other people may be infected. The virus generally spreads through some phase, comprising of transmission from human to mosquito and then from mosquito to human as shown in Fig. 1.

Chikungunya may be severe but it does not cause any death. Most of the patients feel better within 7 days of the disease. However, the symptom such as joint pain may continue for months. The people with Chikungunya, including new born babies, adults over 65 years age as well as persons with heart disease, diabetes and high blood pressure always remain at great risk due to this disease [5]. Different categories of uncertainty including imprecision, vagueness, ignorance, ambiguity and incompleteness hinders the determination of these signs and symptoms with accuracy. Table 1 illustrates the different categories of uncertainty with each of the sign and symptom of this disease. For instance, the categories of uncertainty, linked with the symptom "Headache", include ambiguity, imprecision, incompleteness and vagueness. The reason for this is that the patients cannot express accurately the intensity level of headache, rather they use linguistic expressions for example "severe", "medium" or "low", which are ambiguous, imprecise, vague and incomplete in nature. The uncertainties have been identified while conducting an extensive assessment in discussion with the professional physicians of many hospitals and medical colleges, located in the Metropolitan of Chittagong and Dhaka of Bangladesh.

The physicians normally treat this disease by observing the signs and symptoms of the patients; however, these cannot be measured with 100% accurately. Hence, the diagnosis or the treatment of this disease becomes inaccurate. Expert system, which is used to support the human decision making process can be considered as an alternative to assess this disease by taking account of the signs and symptoms of this disease. In this context, rule-based expert system can be considered to assess the Chikungunya. An expert system based on Fuzzy Logic developed in [6] to assess a chikungunya. The system used 11 variable attributes as input and one output variable attribute in the knowledge base. In the field of medical science, accuracy is of utmost importance. Inaccuracy occurs due to the presence of various categories of uncertainties and erroneous diagnostic results, which may be life threatening. Traditional diagnosis systems may have some problem like improper diagnosis technique, observer bias and faulty equipment. These problems create uncertainties such as imprecision, ambiguity and randomness.

Moreover, it can be argued that the preliminary diagnosis of Chikungunya, which is carried out by the physicians is inherently inaccurate because they are not aware of this uncertainty issue. It is due to the fact that the physicians would like to measure the signs and symptoms by applying Boolean approach, which has been observed during the survey. Consequently, there could be a chance of inappropriate treatment of the patient of this disease. Belief rule based expert systems (BRBES) [6][7][8][9][10] are widely used to diagnose the various diseases, which have the capability to address the categories of uncertainty as illustrated in Table 1.

The objective of this article is to identify the signs and symptoms causing Chikungunya and ascertaining the uncertainties associated with the factors of Chikungunya risk assessment. Another challenge of this research is to develop an expert system by using Belief Rule Base methodology that can handle uncertain clinical data of Chikungunya. This research work studies and reviews the existing systems followed for Chikungunya risk assessment and proposed a web-based Belief Rule Base expert system to assess the Chikungunya risk, taking uncertainties into account. This system has been developed and tested on the samples collected from the survey, carried out for this research. The proposed system will provide an accurate assessment of this disease and delivers a precise output taking into account the various factors involved. Input data has been taken from the patients to assess Chikungunya. It will indicate a value, which will show the level of Chikungunya assessment. The system gives the option to the physician to set the scale of assessment. The BRBES is web-based, enabling the use of this software from any location, when the internet service is available. It is implemented by PHP within MySQL. PHP is used as front end MySQL is used as back end of the system. To show the accuracy the proposed method has been compared with different machine learning techniques, such as Artificial Neural Network and Support Vector Machine.

Table 1: Categories of Uncertainty Signs and Symptoms of Chikungunya

Signs and Symptoms of Chikungunya	Categories of Uncertainty	Discussion
Fever	Randomness	Usually body temperature goes up and down; however data collected randomly by using thermometer may give inaccurate result.
Headache	Incompleteness, Imprecision, Ambiguity, Vagueness	Patients express this by means of linguistic terms and henceforth, it contains ambiguity, imprecision and vagueness.
Joint Pain	Incompleteness, Imprecision	Patients are not able to express their joint pain accurately and hence, expert assessment may be incomplete.
Muscle Pain	Incompleteness, Imprecision	The accurate level of muscle pain is difficult to measure
Joint Swelling	Incompleteness, Ignorance	This abnormal enlargement of part of the body may be due to illness or injury and hence, difficult to assess the causes.

Thus, the present section introduces the problem, addressed in this research. Section 2 demonstrates the literature review. Section 3 details the methodology. The architecture of the expert system and its implementation is narrated in Section 4. The results are described in Section 5, while conclusion is presented in Section 6.

2 Literature Review

An Expert System (ES) is used to simulate human expertise and behavior by employing concepts, methods and tools, used in Artificial Intelligence (AI) [11]. It consists of two core components, namely, knowledge base (KB) which comprises facts and rules, and the other is inference engine (IE). The IE uses algorithms to derive new knowledge and patterns by using facts and rules of KB. Usually, an ES is used in the areas where algorithmic solutions are not available [9]. Medical domain can be considered as one of such areas, where algorithmic solutions cannot be derived to diagnose a disease. Instead, heuristic approaches, which consist of rules and facts, are considered appropriate to disease diagnosis. Therefore, in the medical domain expert systems are extensively used to support the diagnosis of various categories of diseases [8][10][12][13][14][15].

Table 2: Categories of Uncertainty Signs and Symptoms of Chikungunya

Article	Specification	Method	Limitation
[16]	This Fuzzy Expert System is designed to diagnose heart disease by using database of V.A. Medical Center, Long Beach and Cleveland Clinic Foundation. The system considers 13 inputs and one output to diagnose diseases.	Mamdani inference method	The input data have been collected from the patients by using questionnaire. In case, the patients fail to express their feeling accurately, the system will generate inaccurate results. Although fuzzy based expert system presented in this paper is capable to handling uncertainty due to imprecision, vagueness and ambiguity, it is unable to handle uncertainties such as ignorance and randomness.
[15]	This paper presents a diagnostic system, which integrates the Genetic Algorithm (GA) and Fuzzy Logic to determine Chikungunya. The system can diagnose a patient with Chikungunya.	Hybridization of Genetic Algorithm and Fuzzy Logic.	Although the system diagnoses the disease at primary level by considering the initial symptoms, it is unable to determine the type of fever accurately. In addition, GA is sensitive to the initial population and hence, with similar symptom at initial stage, the optimal prediction cannot be achieved.
[17]	This fuzzy based expert system developed by considering a large-scale knowledge base of diabetic patients. The knowledge is fabricated by using the fuzzification, enabling the conversion of crisp values into fuzzy values.	Defuzzification method	Although this system facilitates overcoming of obstruction between the patients and the medical experts by addressing uncertainty due to vagueness arising from symptoms, uncertainties arising from the ignorance and randomness cannot handle.
[3]	This article proposes a 3-dimensional taxonomy that characterizes uncertainty in healthcare system, allowing the identification of relevant sources and issues.	Theoretical concept	Although this paper presents the different sources of uncertainty for medical treatment, it does not present any approaches to handle the uncertainties.
[2]	This paper presents a literature review in clinical decision support systems (CDSSs) with an objective to identify the uncertainty handling capability of the commonly used methods used in knowledge representation and inference procedures.	Theoretical concept	Only future research directions to handle uncertainties of CDSSs are proposed.
[1]	This paper discusses the signs and symptoms of Chikungunya along with commonly used laboratory tests.	Field survey	The uncertainty phenomenon of the signs and symptoms of Chikungunya is not addressed in this paper.

Various fuzzy logic based medical expert systems (FLBESs) were proposed in [13][14][16] to diagnose diseases. Fuzzy based system was also developed to identify diseases such as ADHD, SLP and IBS based on their symptoms [18]. A FLBES developed to diagnose tropical infectious disease [13], enabling the overcoming the limitations of the communication between the patients and the physicians by addressing the uncertainty arising from the vagueness of symptoms. A survey of the applications of

FLBESs to support medical diagnosis presented in [14]. To support diagnosis of Asthma from its various signs and symptoms a FLBES was also developed [19]. Although the above FLBESs are capable of handling uncertainty because of imprecision, vagueness and ambiguity, they are limited in handling other categories of uncertainties, for example ignorance, randomness, incompleteness. However, the uncertainty due to ignorance, incompleteness and randomness are very common with the signs and symptoms of various diseases, which are noticed in case of Chikungunya, as illustrated in Table 1. Therefore, it can be argued that Fuzzy Logic Based Medical Expert System can handle limited types of uncertainty but not all types of uncertainty, especially, ignorance, randomness and incompleteness. Hence, the handling of such uncertainties by these systems remains a great challenge to support the accurate diagnosis of diseases.

Artificial neural networks (ANNs) based system, developed to analyze the diseases [19]. This system used single network for the learning process and also clear connection between input and output cannot be perceived. Moreover, ANN approach is not equipped to handle uncertainty. Bayesian theory to diagnose disease demonstrated in [6] where only randomness can be handled. Hence, both the ANN and Bayesian based approaches have their inherent incapability to address various types of uncertainty.

The diagnosis of Chikungunya is an example of complex phenomenon. Usually, some common laboratory tests are used to diagnose Chikungunya, which are virus isolation, RT-PCR, and serological tests. Virus isolation system involves showing particular cell lines to samples from whole blood and recognizing Chikungunya virus. The RT-PCR uses nested primer pairs to enlarge some Chikungunya-specific genes from whole blood [11]. In the serological test a bigger sample of blood is required, and it uses an ELISA assay to measure Chikungunya-specific IgM levels. However, these conventional diagnostic systems are not capable of assessing the Chikungunya with 100% certainty. The signs and symptoms of Chikungunya is also widely used to diagnosis this disease. Table 2 elaborates the taxonomy of the various research trend and challenges, conducted in the medical domain, by taking into account of their strength and limitations.

The signs and symptoms of Chikungunya in Malaysia are discussed in [20]. This country is heavily dependent on migrant workers from different countries where chikungunya is endemic. To support the diagnosis of this disease, different laboratory tests and serological tests are used. Although serological test is used to diagnosis this disease, it does not give accurate result because of the uncertainty issues related with symptoms are not addressed. In [21] three models namely, vitro cell culture modeling, mouse model and non-human primate are used to diagnose CHIKV virus. Positive predictive value (PPV), and negative predictive value (NPV) are used to identify the presence of CHIKV virus. Since there is an absence of communication gap between the patient and the medical expert, these models cannot identify the Chikungunya with 100% certainty. The survey of the signs and symptoms of Chikungunya is presented in [22][23] but no model is proposed to detect chikungunya.

The use of symptoms of Chikungunya for its analysis is shown in [15]. This system uses an input matrix by taking into account of the response from the patients by asking some questions related to the symptoms of Chikungunya. This input matrix is considered as knowledge base. The output matrix is obtained by multiplying input matrix with the weight matrix. However, the uncertainty issues associated with the symptoms have not covered in this system. Therefore, the output matrix is unable to generate accurate results. Eventually, in case when the patients are unable to express the symptoms exactly, the accurate assessment of the disease is difficult to achieve. Hence, such a system lacks the capability of addressing different categories of uncertainties as illustrated in Table 1. The combination of neural network and certainty factor has also been used to develop an expert system [24] to support diagnosis of Chikungunya. This expert system has three phases, in each phase it uses single network for the learning process. More than 820 cases were used to test the system and also cross-validation tests presented the diagnostic performance rate. This approach works as a black-box system and is unable to handle various categories of uncertainties associated with the signs and symptoms of Chikungunya.

Thus, from the above, it can be argued that in order to handle various categories of uncertainty in a unified way it requires new methodologies and techniques. Belief rule based expert system, which uses belief rule base to represent uncertain knowledge and evidential reasoning as the inference engine can be thought of as the appropriate candidate to diagnosis Chikungunya from the signs and symptoms of this disease. The reason for this is that BRBES can handle all types of uncertainties as shown in Table 1 in an integrated framework, which is not the case with other expert systems which use Fuzzy Logic, Bayesian Approach and ANN. Therefore, the next section will introduce the BRB and ER, which form the methodology of BRBESs.

3 Overview of BRBES Methodology

Knowledge representation schema based on Belief Rule Base (BRB) and the inference mechanisms using Evidential Reasoning are considered as the core components of BRBES's methodology.

3.1 BRB to Represent Domain Knowledge

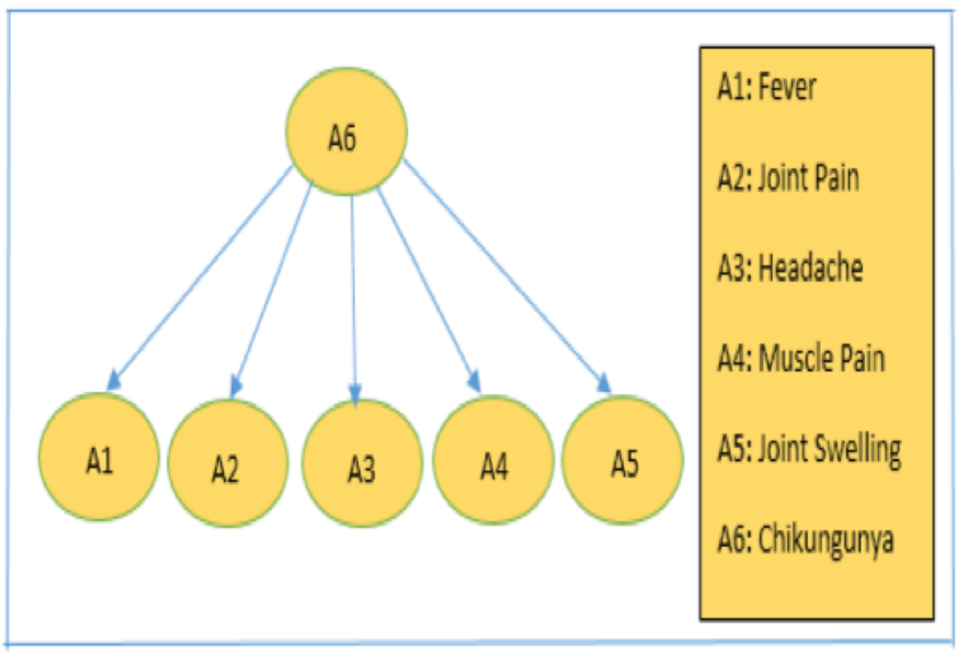

Figure 2: BRB Framework to diagnose Chikungunya

The knowledge representation by taking account the factors indicated in Fig. 2 is narrated in this section. Our BRB framework has been developed by considering the five signs and symptoms of Chikungunya as depicted in Table 1. Basically, a belief rule is the extent of conventional IF-THEN rule, which has two components namely, cause and effect. The root node of BRB tree represents the effect attribute while leaf nodes represent causal attributes. Both the causal attribute and effect attribute are associated with evaluation grade such as "High", "Medium" and "Low". A BRB comprises many rules depends upon the number of the evaluation grades of the causal attributes, which can be computed by using Eq. 1.

$$L = \prod_{i=1}^{T} J_i \tag{1}$$

where L is the total number of rules in a BRB, and J_i is the Evaluation Grade of the ith causal attribute.

Fig. 2 consists of five causal attributes and if three evaluation grades for each causal attribute are considered then the entire rules of this BRB are 243 by using Eq. 1. Each rule of a BRB is linked with the parameters of knowledge representation such as belief degrees, rule weight and causal attribute weights which are entrenched with the evaluation grades of the effect attribute. An example of a belief rule from the field of Chikungunya can be expressed as shown in Eq. 2.

R_k: IF Fever is High AND Joint Pain is Medium AND Headache is Low AND Muscle Pain is Medium AND Joint Swelling is High THEN Chikungunya (High, 0.6), (Medium, 0.4), (Low, 0.0)

(2)

In this rule 'Fever', 'Muscle Pain', 'Joint Pain', 'Headache', 'Joint Swelling', are the causal attribute and 'High', 'Medium', 'Low' are their evaluation grades while Chikungunya is the effect attribute. From this rule (2), it can be observed that the risk of Chikungunya of a patient is high if the degree of belief is 60%, medium if the degree of belief is 40% and low if the degree of belief is 0%.The total degree of belief [0.6+0.4+0.0=1], linked with each evaluation grade of the effect attribute is one and hence, the rule is said to be complete. On the contrary, the rule is said to be incomplete if the summation is less than one. In this technique, uncertainty because of incompleteness is addressed in BRB. It is remarkable to note that a belief rule capture the non-linear relationship which is not the case with the conventional IF-THEN rule.

3.2 Inference Procedures in BRBESs

The inference procedure of the BRBESs is presented in this section.

3.2.1 Input Transformation

The allocation of the input values of a causal attribute among its various evaluation grades constitutes the process of input transformation. For example, if a patient with Chikungunya expresses his muscle pain in term of linguistic term as "low" then this need to be given out over the three evaluation grades of causal attribute "muscle pain". The patient data which is "low" in this case is transformed into a numerical value by taking the opinion of physician in the scale of 0-1 and it is obtained as 0.3. This numerical data 0.3 is then converted by using either Eq. 3 or Eq. 4 and in this case Eq. 4 is used. In this way, by considering various input data of a patient are converted into the evaluation grade of the causal attributes, which are illustrated in Table 3. The acquired evaluation grades linked with each causal attribute is called matching degree. When these matching degrees are assigned with the causal part of the rules then they are called packet causal, meaning the rules are in the active memory.

$$\begin{gathered} IF(Hvalue \geq Inputvalue \geq Mvalue)THEN \\ Medium = \frac{Hvalue - Inputvalue}{Hvalue - Mvalue}, High = 1 - Medium, Low = 0.0 \end{gathered} \tag{3}$$

$$\begin{gathered} IF(Mvalue \geq Inputvalue \geq Lvalue)THEN \\ Low = \frac{Mvalue - Inputvalue}{Mvalue - Lvalue}, Medium = 1 - Low, High = 0.0 \end{gathered} \tag{4}$$

Table 3: Input Transformation

S. No.	Input Causal	Input Data	Expert	High	Medium	Low
I	Fever	Low	0.2	0.0	0.4	0.6
II	Joint Pain	Medium	0.5	0.0	1.0	0.0
III	Headache	High	1.0	1.0	0.0	0.0
IV	Muscle Pain	Low	0.3	0.2	0.6	0.4
V	Joint Swelling	Medium	0.6	0.0	0.8	0.2

3.2.2 Rule Activation Weight calculation

This procedure be made up of two parts namely; the calculation of joint matching degree and the other is rule activation weight calculation. Table 3 illustrates the matching degree which is also demonstrated in Table 4 with one of the rules among the 243 rules of the BRB.

The rule, presented in Table 4, consists of five causal attributes. The evaluation grade of each causal attribute contains its matching degree. These matching degrees need to be combined, which can be obtained by using Eq. 5 [11], which uses the multiplicative aggregation to demonstrate the integrity among the causal attributes. The calculated combined matching degree is shown in column 5 of Table 4. The contribution or importance of each rule in generating ultimate output of the BRBES is required to be carried out. This is achieved by applying Eq. 6 [11] and the degree of activation for the rule, presented in the column 6 of Table 4, is obtained as 0.94.

$$\alpha_{ki} = \prod_{i=1}^{T_k} (\alpha_i^k)^{\delta_{ki}} \tag{5}$$

$$\omega_k = \frac{\theta_k \alpha_k}{\sum_{j=1}^{L} \theta_j \alpha_j} = \frac{\theta_k \prod_{i=1}^{T_k} (\alpha_i^k)^{\delta_\mu}}{\sum_{j=1}^{L} \theta_j [\prod_{i=1}^{T_k} (\alpha_i^j)^{\delta_\mu}]}, \delta_{ki} = \frac{\delta_{ki}}{\max_{i=1,\ldots,T_k}\{d_{ki}\}} \tag{6}$$

Table 4: Rule Activation Weight Calculation

Rule id (1)	Rule Weight (2)	IF Causal Attributes (3) A1∧A2∧A3∧A4∧A5 is	THEN Effect Attribute (4) A6 is	Combined Matching Degree (5)	Activation Weight (6)
5	1	H(0.0)∧M(1.0)∧M(0.0)∧L(0.4)∧L(0.2)	{(H, 0.3), (M, 0.4), (L, 0.3)}	0.08	0.94

3.2.3 Belief Degree Update

There could be a case when it is impossible to obtain the initial value of all five causal attributes, which can be defined as a situation of ignorance. In that case by applying Eq. 7 [25], the initial belief degrees of all the 243 rules should need to be updated. Table 5 illustrates the updated belief degree for rule no. 5, when input data of “joint pain” is missing. In this technique, the uncertainty due to ignorance is addressed by the BRBESs inference procedures.

$$\beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k} (\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj})}{\sum_{t=1}^{T_k} \tau(t,k)} \tag{7}$$

Table 5: Belief Degree Update

Rule Id		High D1	Medium D2	Low D3
5	Initial	0.3	0.4	0.3
	Update	0.056	0.16	0.02

Here, $\overline{\beta_{ik}}$ is the new belief degree, while β_{ik} is the updated belief degree.

3.2.4 Rule Aggregation

The risk of Chikungunya or the output value for the preliminary input data of the five signs and symptoms or the causal attributes can be obtained by aggregating the 243 rules. This can be obtained by using the Evidential Reasoning algorithm as shown in Eq. 8 [25]. There are two forms of this algorithm, one is called recursive and the other is called analytical. However, the analytical evidential reasoning algorithm is considered because it reduces the computational complexity significantly. The belief degrees of effect attribute or the root node of Fig. 2, are obtained as (Severe, 84.08%) (Moderate, 11.99%) and (Normal, 3.93%).

$$\beta_j = \frac{\mu \times [\prod_{k=1}^{L}(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}) - \prod_{k=1}^{L}(1 - \omega_k \sum_{j=1}^{N} \beta_{jk})]}{1 - \mu \times [\prod_{k=1}^{L} 1 - \omega_k]} \tag{8}$$

$$\mu = [\sum_{j=1}^{N} \prod_{k=1}^{L}(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}) - (N-1) \prod_{k=1}^{L}(1 - \omega_k \sum_{j=1}^{N} \beta_{jk})]^{-1} \tag{9}$$

Since the output, obtained using Eq. 8 are fuzzy values; they need to be converted into crisp value. This can be achieved by using preference values, associated with each of the evaluation grades (severe, moderate and normal) of the effect attribute. This can be obtained by using Eq. 9. The crisp value obtained in this case is 74.045. D_n is the preference value while B_n is the degree of belief in Eq. 10. The preference value, considered, for the evaluation grade “Severe” is 80, for the “Medium” is 50, while for the “Low” is 20.

$$y_m = \sum_{n=1}^{N} D_n \times B_{n(m)} \tag{10}$$

4 Belief Rule Based Expert System (BRBES) to Diagnose Chikungunya

This section presents the BRBES’s system architecture as well as its various components.

4.1 Architecture, Design and Development of the BRBES

The BRBES consists of three layers architecture, including interface layer, database management layer and application layer as illustrated in Fig. 3. Hyper Text Markup Language (HTML) and Cascading Style Sheet (CSS) have been used to develop the interface, allowing the user to input and to obtain data from the system. The application layer has been developed by using PHP (Hypertext Preprocessor), enabling the synchronization of interface and data access.

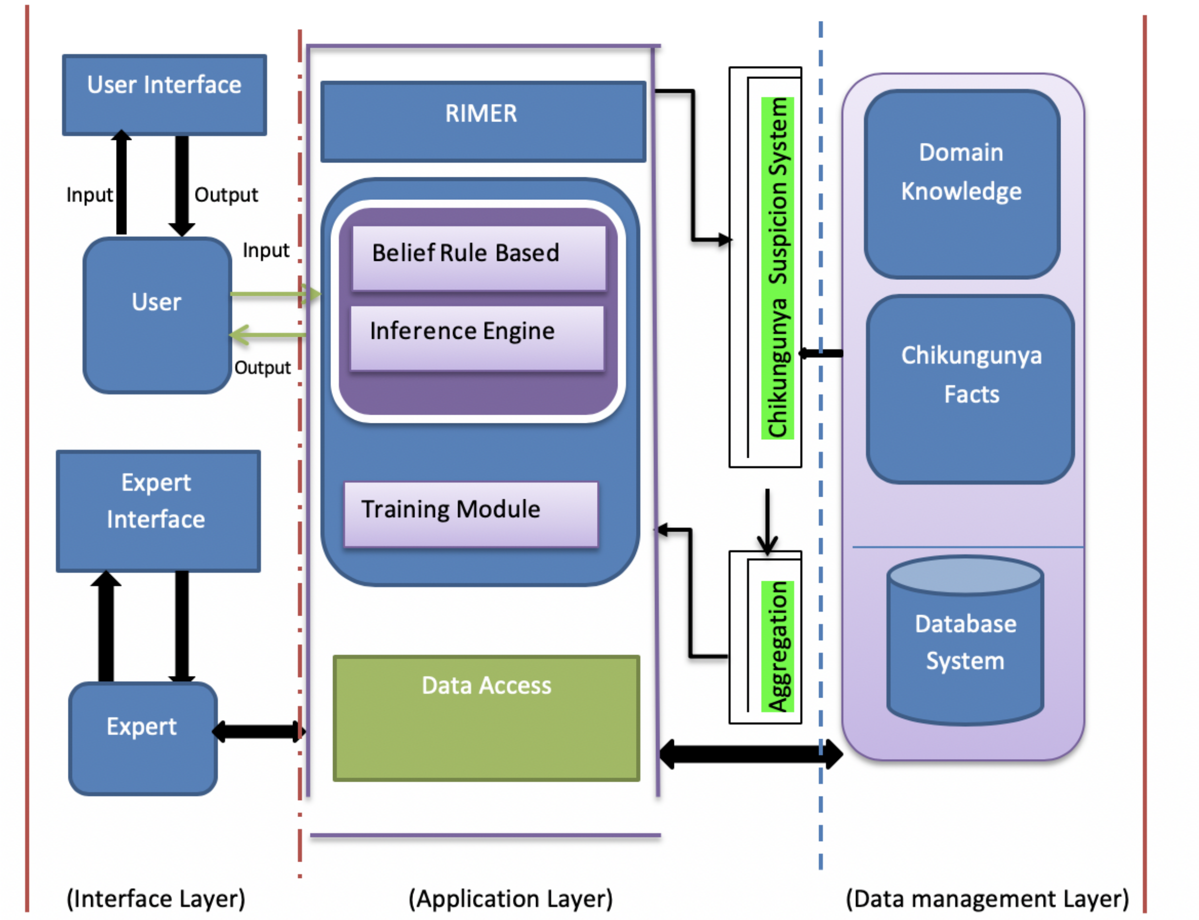

Figure 3: BRBES Architecture

The database management layer has been developed by using MYSQL because of its flexibility, security and it allows faster access as well as retrieving data.

4.2 Knowledge Base Construction

A framework of BRB to diagnose Chikungunya has been developed in consultation with the domain experts, especially with the physicians as illustrated in Fig. 2. This is an important step to develop the BRB for the BRBES as mentioned in Section III. The BRB consists of 243 rules as mentioned earlier, which is illustrated in Table 6. Usually, a BRB is developed by using domain expert opinion, by observing practical data, or by using prior rules if available or by using random method without any earlier information. However, in this research by extracting knowledge from the physicians, the initial BRB has been built and each rule is assigned the weight of 1 while each causal attribute is also assigned same weight.

Table 6: Preliminary BRB for all Rule Base

Rule Id	Rule Weight	IF Causal Attribute A1∧A2∧A3∧A4∧A5 is	THEN Effect Attribute A6 is
1	1	H∧H∧H∧H∧H	(H, 1.00), (M, 0.0), (L, 0.0)
2	1	H∧H∧M∧M∧L	(H, 1.00), (M, 0.0), (L, 0.0)
3	1	H∧H∧M∧M∧L	(H, 0.9), (M, 0.1), (L, 0.0)
4	1	H∧M∧M∧M∧L	(H, 0.4), (M, 0.5), (L, 0.1)
5	1	H∧M∧M∧L∧L	(H, 0.3), (M, 0.4), (L, 0.3)
6	1	H∧L∧M∧L∧M	(H, 0.0), (M, 0.5), (L, 0.5)
...	...	...	...
241	1	L∧H∧L∧L∧M	(H, 0.0), (M, 0.0), (L, 1.0)
242	1	L∧M∧L∧L∧L	(H, 0.0), (M, 0.0), (L, 1.0)
243	1	L∧M∧L∧L∧L	(H, 0.0), (M, 0.0), (L, 1.0)

4.3 BRB Interface

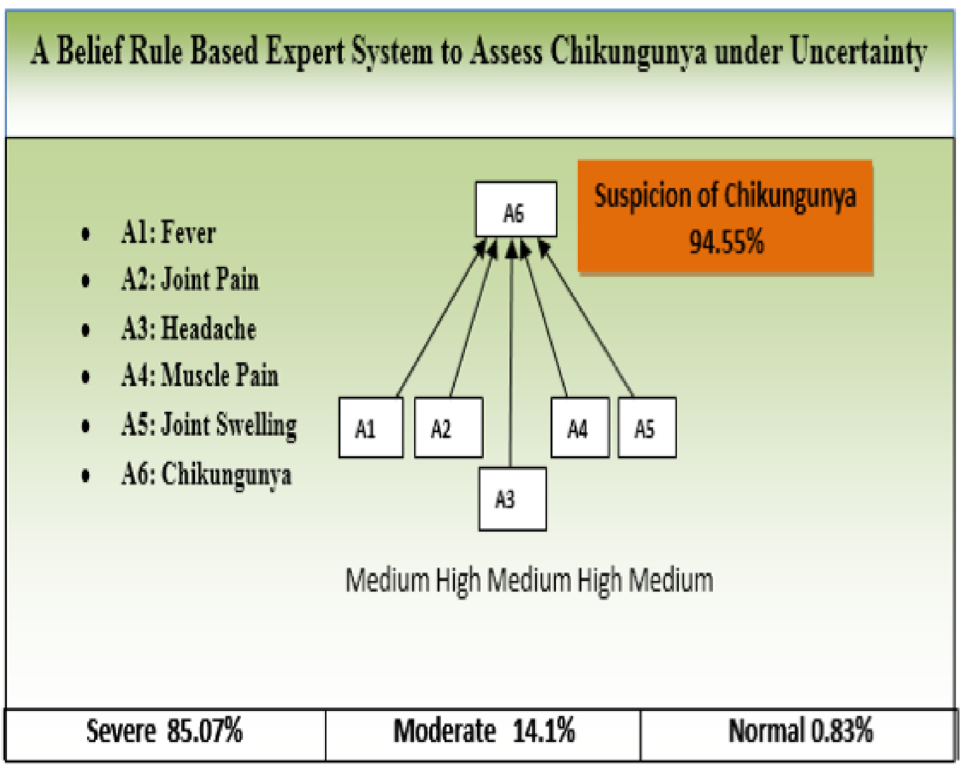

Figure 4: BRBES Interface to Diagnose Chikungunya

An interface acts as an intermediary between the system and the users. Fig. 4 demonstrates the main module of the BRBES to diagnose Chikungunya. This interface illustrates the results of the risk of Chikungunya both in terms of fuzzy values [(Severe, 85.07%), (Moderate, 14.1%), (Normal, 0.83%)] and crisp value (94.55%) for specific input data of the causal attribute, consisting of signs and symptoms of Chikungunya. The same input data as illustrated in Table 3 have been used to obtain this result. The subsequent interfaces also allow users to add the value of the causal attributes in linguistic terms, which

Table 7: Dataset for System Testing

Sl No (1)	A1 (2)	A2 (3)	A3 (4)	A4 (5)	A5 (6)	BRBES Result (%) (7)	Expert Opinion (%) (8)	Bench-mark (9)
1	High	High	Medium	Medium	High	75.4430	75	1
2	Medium	High	Medium	High	High	83.7135	86	1
3	Low	Low	Low	Low	Low	27.8756	29	0
4	High	Medium	High	High	Medium	70.8900	73	1
5	High	Medium	Medium	High	High	58.2996	54	1
6	High	Low	High	Medium	High	61.3430	60	1
7	High	Medium	High	Medium	High	74.6747	71	1
8	Medium	Low	Low	Medium	Low	34.9860	32	0
9	Low	Low	High	Low	Low	27.3110	26	0
10	Low	High	Low	High	Medium	61.3026	65	1

are then converted into matching degree as illustrated in Table 3. In addition, the combined matching degree and rule activation weight can also be calculated as shown in Table 4.

To validate the BRBES, the collected data are partitioned into a training data set and a test dataset. The training data set is used for training the system parameters. The BRB system is then used to generate outputs for the test input data. Data for the leaf nodes of the BRB framework has been collected from the interviews in the case study area. Expert opinions have also been collected in the same way. BRBES has been applied by considering collected patients data to evaluate its performance.

The evaluation of the performance of our proposed solution is depicted in Fig. 4.

5 Results and Discussion

To demonstrate the application as well as the reliability of the results, made by the BRBES, data of Chikungunya patients were collected from various hospitals in Dhaka and Chittagong, Bangladesh.

The signs and symptoms data (A1 = Fever, A2 = Joint Pain, A3 = Headache, A4 = Muscle Pain and A5 = Joint Swelling) of Chikungunya of 250 patients were collected which is shown in Table 7. However, for the simplicity, Table 7 contains the data of ten patients. Column 7 of Table 7 shows the level of risk of Chikungunya of each patient which is obtained by using the BRBES in term of crisp value, while column 8 shows the level of risk of Chikungunya, obtained from the physician, which is considered as human expert opinion. Column 9 of Table 7 shows the benchmark data, which is considered as 1 when the patient is confirmed with the disease of Chikungunya after laboratory test and 0 when the patient is without the disease.

To investigate the efficiency of diagnostic tests which have ordinal or continuous outputs [26] the Receiver Operating Characteristic (ROC) curves are widely used. The Area under curve (AUC) is considered as one of the important metrics of this method. When the value of AUC becomes one then it can be concluded that the result generated by a system is 100% accurate. In addition to the BRBES's results as well as expert opinion as shown in Table 7, the results of fuzzy logic based expert system (FLBES) for the same number of patients are also generated, which is established in Matlab. Table 8 shows the results of all the three systems, including, BRBES, human expert and FLBES.

The BRBES has the capability to process the uncertain clinical data related to the signs and symptoms of Chikungunya. This BREBS will be effective tool to carry out the preliminary investigations of this disease. This system has been tested and tried using the data of 250 real patients collected from various parts of Bangladesh, giving the credibility to be used on a larger mass. The results generated by this system were found reliable than that of human experts as proved in this research. It has been proved that this BRBES results were more accurate and reliable than the Fuzzy Rule based expert systems.

Table 8: Chikungunya Assessment by BRBES, FLBES, and Expert

Case Study	BRBES	Expert Opinion	FLBES	ANN	SVM	Benchmark
1	66.4440	66	64.9	41.00	43.00	1
2	85.6215	86	77.8	62.8	54.0	1
3	38.9265	40	43.9	34.5	41.5	0
4	82.9800	84	76.3	60.0	53	1
5	60.3295	54	60.4	46.8	38.5	0
6	72.4330	71	69	58.5	60	1
7	76.5745	71	75.5	68	65.5	1
8	45.8850	43	38	26.5	30	0
9	30.3610	26	30	27.0	28.5	0
10	52.2925	56	50.6	48.5	33	0

Table 9: Comparison of AUC Values for Various Systems

Expert System	AUC	Asymptotic 90% Confidence Interval
BRBES	0.837	0.803-0.942
ANN	0.811	0.727-0.896
SVM	0.808	0.722-0.893
FLBES	0.797	0.708-0.886
Expert's opinion	0.763	0.666-0.860

ROC curves for the BRBES and judgment are depicted in Fig. 5. ROC curves for BRBES, expert opinion and FLBES are depicted in Fig. 6. From Fig. 5, it can be noticed that the AUC value of ROC curve for Expert opinion is less than that of AUC of BRBES. This is also evident from Table 9, where it can be noticed that the value of AUC for BRBES is 0.837, while AUC is 0.797 for Expert Opinion. The reason for the better performance of BRBES is that it considers different categories of uncertainty linked with the signs and symptoms of Chikungunya. On the contrary, the physicians, who are considered as human experts, cannot consider uncertainty phenomenon, while assessing Chikungunya rather their minds inherit a Boolean approach, which observed during our conversation with them. From Fig. 6, it can be examined that AUC of ROC curve for FLBES is less than the BRBBES. However, AUC of ROC curve for FLBES is fine than that of Expert judgment. The above is also evident from Table 9, where AUC for FLBES is 0.808 which is less than BRBES but greater than human expert which is 0.797. The reason of less value of AUC for FLBES than from BRBES is that FLBES can manage linguistic uncertainty such as ambiguity, imprecision and vagueness but not due to incompleteness and ignorance. Moreover, such as Mamdani FLBES's inference procedures and Takagi- Sugeno are not well equipped to process all categories of uncertain information [10]. However BRBES can tackle all categories of uncertainty and its inference procedures made up of input transformation, belief degree update, rule activation weight calculation and rule aggregation using ER algorithms can address all categories of uncertainties as demonstrated in Section III. However, FLBES performs better than human expert because it considers uncertainty due to linguistic terms which is not the case with the physicians mentioned earlier.

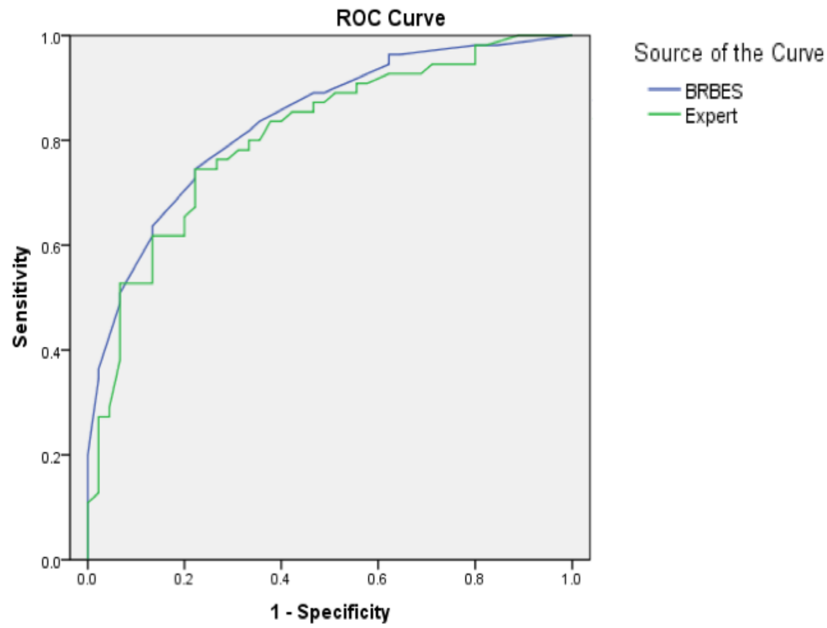

Figure 5: ROC curves comparing BRBES's result and Human Expert

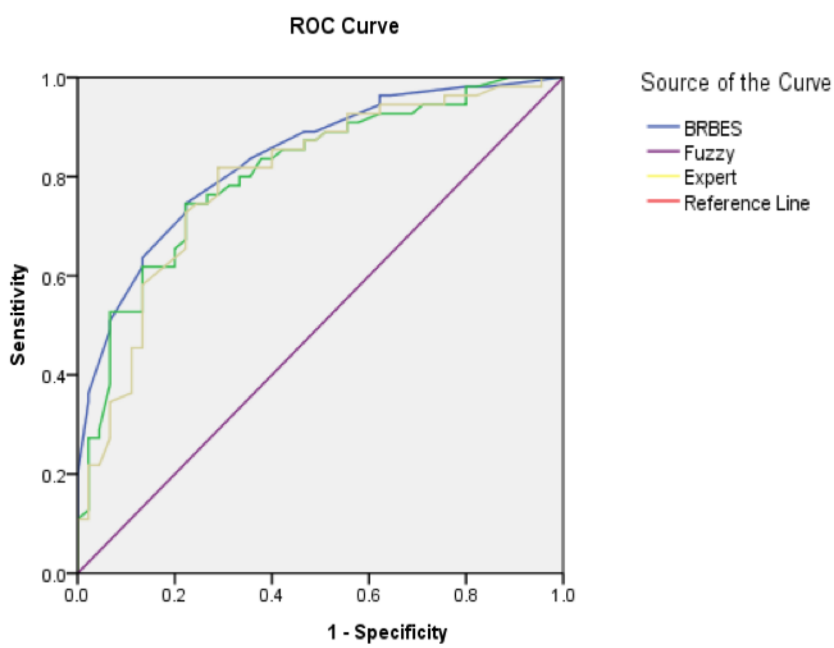

Figure 6: ROC curves comparing BRBES's result, FLBES and Human Expert

The proposed learning and inference procedure has been compared with different machine learning techniques, such as Artificial Neural Network and Support Vector Machine. The ANN approach adjusts only one parameter which is the weight for training process and the ultimate target is to reduce the error. BRBES can adjust more learning parameters such as rule weight, attribute weight, belief degree update and so on. Hence the result of BRBES is more accurate as compared to ANN. SVM algorithm is based on finding the hyperplane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of margin within SVM's theory. Therefore, the optimal separating hyperplane maximizes the margin of the training data [27][28]. However, the algorithm uses input data directly for prediction, instead of distributing the data over belief degrees to address various categories of uncertainty. Therefore, it does not address any categories of uncertainty. A comparison has been made between the results of BRBES and different machine learning techniques, such as ANN and SVM [29][30][31][32]. Fig. 7 shows ROC curves for BRBES, Human Expert, FLBES, ANN and SVM. Table VIII illuminates the AUC's of BRBES, Human Expert, FLBES, ANN, SVM are 0.920, 0.851, 0.811, 0.808 and 0.644 respectively. By considering 95% CI, the lower and upper limits of AUC for BRBES, ANN and SVM are found respectively 0.823-0.955, 0.775-0.927, 0.727-0.896, 0.722-0.893, 0.536-0.852. Hence, it can be said that BRBES gives better output than other machine learning techniques.

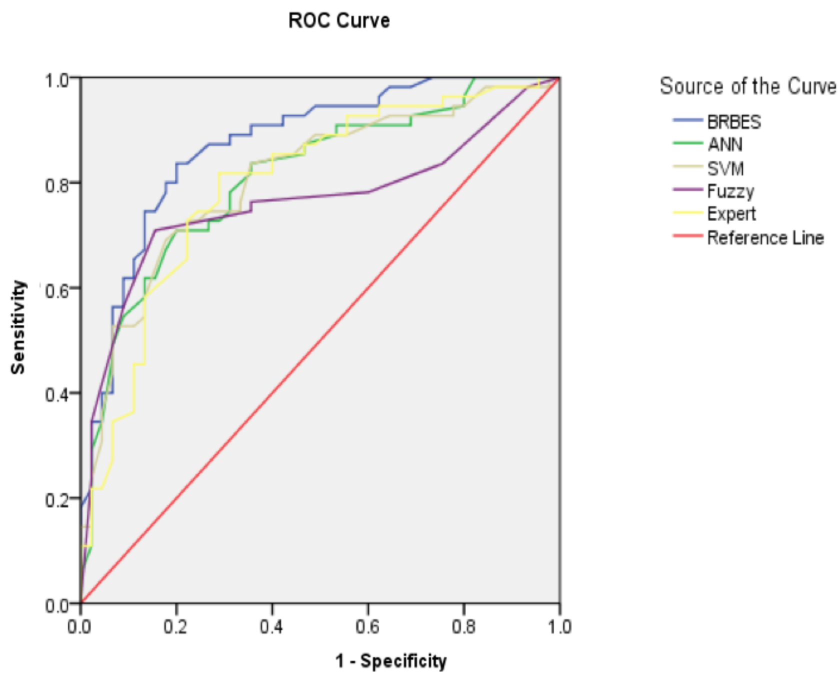

Figure 7: ROC curves comparing BRBES, FLBES, ANN, SVM and Human Expert

6 Conclusion

One of the significant achievements of this research has been to develop a system which can accurately and timely assess the risk of Chikungunya .This paper presents the design and implementation of a belief rule based expert system (BRBES), which has the capability to process uncertain clinical data linked to the signs and symptoms of Chikungunya. Therefore, the BRBES can be considered as an effective tool to carry out the primary investigation of the Chikungunya. It has been exhibited that the performance of the BRBES is fine than that of FLBES, human experts and other machine learning techniques such as ANN and SVM. Nowadays, especially in Bangladesh, the risk of Chikungunya increases significantly and this system can be used in a cost effective way to get the primary idea on the suspicion of this disease. As this system is very user friendly and cost effective it will help faster diagnosis of this deadly disease and give faster and timely treatment to the affected people. This BREBS will be a great help to medical fraternity and save many human lives who today die due to late or no diagnosis of this disease.

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