A Belief Rule Based Expert System to Assess Hypertension under Uncertainty

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Abstract

Hypertension (HPT) plays an important role, especially for stroke and heart diseases. Therefore, the accurate assessment of hypertension is becoming a challenge. However, the presence of uncertainties, associated with the signs and symptoms of HPT are becoming crucial to conduct the precise assessment. This article presents a web-based expert system (web BRBES) by employing belief rule based (BRB) methodology to assess HPT, allowing the generation of reliable results. In order to check the reliability of the system, a comparison has been performed among various approaches such as decision tree, random forest, artificial neural networks, fuzzy rule based expert system and experts' opinion. Different performance metrics such as confusion matrix, accuracy, root mean square error, area under curve have been used to contrast the reliability of the approaches. The BRBES produces a more reliable result than from the other approaches. Moreover, the user friendliness of the web BRBES found high as obtained by using the PACT (People, Activities, Contexts, Technologies) approach over 200 people.

Keywords: Expert System, Belief Rule Base, Hypertension, Uncertainty, Knowledge Base

1 Introduction

Hypertension (HPT) is also known as high blood pressure. It indicates a situation where persistent force of blood against arteries is high enough to cause different cardiovascular complexities [28]. When blood is circulated, it creates a force against the vessel walls, known as blood pressure (BP). Systolic and diastolic are the two types of blood pressures, which are to be considered while measuring BP. The systolic represents the maximum pressure, which is observed during the contraction of heart muscles, while diastolic blood pressure means minimum pressure which is noticed during the expansion of heart muscle. Usually, the normal range of blood pressure is considered in between 120/80 mm Hg (millimeters of mercury) in an adult. The presence of systolic blood pressure is noticed when mercury level appears 120 mm. On the contrary, diastolic blood pressure is noticed when mercury level appears 80 mm. However, Hypertension (HPT) is noticed when the mercury level is in between 80 mm to 140 mm [28][2].

HPT becomes a global public health concern because it is the source of most of the life-threatening diseases such as cardiovascular, brain stroke and kidney failure.

Approximately, each year, one billion people are affected by HPT worldwide [23][29]. Consequently, HPT is creating severe sufferings to the people, especially by increasing their financial burden. The reason for this is that costly treatment involves with the diseases which are the by-product of HPT. HPT is the source of 7.5 million deaths [23][29], constituting 12.8% of all death worldwide. In addition, HPT

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is accountable for 45% of death occurred by cardiovascular disease. This is also responsible for 51% death happened by brain-stroke [29]. An estimated 26.4% of adult population worldwide is suffering from HPT in 2000, which could increase to 29.2% by the year 2025 [5]. At least 20% of adult people and 40-65% of the elderly people of Bangladesh are suffering from HPT [14].

Table 1: Patterns of Uncertainties Related to HPT

Signs and Symptoms	Patterns of Uncertainty	Description
BMI (Body Mass Index)	Ignorance	BMI calculates the amount of body fat of a person by taking account of weight which is related to height. However, most people are generally unfamiliar with this term and do not know their exact weight or height.
BP (Blood Pressure)	Imprecision	Daily routine activities can interfere with the accuracy of blood pressure measurement. Moreover, almost 20% of patients show "white coat" effect that is, they show a false hypertensive blood pressure in a clinical setting due to nervousness [21].
Headache	Vagueness, ignorance	Most of the times patients consider it as a common event and consume medicine without consultation with doctors.
Fatigue	Imprecision, vagueness, ignorance	People ignore the symptom as they consider that overworking, warm weather and excessive physical activities are liable for it.

Usually, HPT is preliminary diagnosed by looking at its various signs and symptoms such as body mass index (BMI), BP, heart rate, headache, chest pain, fatigue, breathlessness and vision disturbance [28]. Some of these signs and symptoms such as BMI, BP and heart rate are measured in a quantitative way while others such as headache, chest pain, fatigue, breathlessness, vision disturbance are measured in a qualitative way. Various types of uncertainties can be noticed during measurement of both categories. However, the types of uncertainty such as vagueness, imprecision and ambiguity are caused during the measurement of fatigue, chest pain and breathlessness.

There exist various types of uncertainties while assessing the signs and symptoms of HPT and these are described in Table 1. It is interesting to note that in middle and low-income countries, only half of the hypertensive patients are aware of these signs and symptoms due to their illiteracy as well as poor socio-economic conditions [30].

In this context, an expert system having the capability of dealing with different patterns of uncertainties can be considered as an appropriate candidate to assist the preliminary investigation of HPT. The reason for this is that expert systems can be used in such an area where it is difficult to find an algorithmic solution of a problem where human knowledge or heuristic dominates the decision-making process. Belief rule based expert systems (BRBES) are commonly used to diagnose various diseases, which has the capability of representing uncertain knowledge as well as inference under uncertainty.

Since it is necessary to make available the proposed BRBES to the wider audience, the system should be portable; meaning can be used from anywhere where there is an access of internet connectivity. Therefore, the main goal of this research is to proceed with the development of a web BRBES to assess HPT under uncertainty.

Moreover, an approach is presented here for the determination of optimal value of the various learning parameters such as attribute weight, rule weight and belief degrees of the BRB. Yang et al. [16] proposed a method for learning and inference for BRBES. By training the learning parameters, an improvement in accuracy has been achieved in this paper. Results generated from the BRBES after learning the parameters have been compared with different machine learning algorithms. This article shows the efficiency of BRB over all the machine learning algorithms as it handles all the uncertainties presented in Table 1.

The rest of the article is organized in the following way. The literature review is presented in Section 2. An overview of RIMER methodology is given in Section 3, while Section 4 describes the implementation along with architecture of the proposed BRBES. Section 5 elaborates the experimental results and Section 6 concludes the article.

2 Literature Review

Several artificial intelligence-based techniques proposed to assess HPT [24][26]. Artificial neural networks (ANN) based system developed to predict HPT, which used multi-layer feed-forward architecture along with Levenberg-Marquardt back propagation algorithm to support training [24]. This system considered 13 signs and symptoms as inputs and the measurement of level of HPT considered as the output. However, it fails to show the explicit relationship between inputs and outputs and as a result it is unable to handle the uncertainties illustrated in Table I. Moreover, it is a black box approach. SVM (Support Vector Machine) based procedures are also used to diagnose HPT [26]. In this procedure four kernels namely polynomial, RBF, multi-plication and summation were used to develop L-J approach to select features. However, the limitation of SVM comprises in its inability to demonstrate transparency [4][13]. It is due to the fact that an association among the diagnosis and the signs and symptoms of HPT cannot be recognized understandably. Different classification techniques to predict HPT by considering its signs and symptoms were compared in [27] by using Hierarchical Cluster Analysis (HCA) approach. The classification techniques considered consist of decision trees, statistical approaches and ANNs. Among them neural network based approaches found better than the other. Fuzzy logic based expert systems (FLBESs) were also used to diagnose HPT [17][1][25][8]. A comparative study carried out in [6] to demonstrate the effectiveness of neuro fuzzy system (NFS) with respect to fuzzy expert system (FES) to diagnose hypertension. As NFS is able to overcome the black box behavior of neural networks but it lacks the procedures of finding suitable memebership values for fuzzy systems [19]. In [22], Adaptive Neuro-fuzzy inference system (ANFIS) technique was proposed to diagnose hypertension and a comparative study between FES and ANFIS was given. The performance of hybrid approaches such as NFS (neuro fuzzy system), ANFIS (Adaptive Neuro-fuzzy inference system) to diagnose HPT found better than that of FLBESs or ANN [19][22]. However, the uncertainties related to the signs and symptoms of HPT are not considered. Thus, from the above it can be argued that none of the approaches can handle all categories of uncertainties related to both qualitative and quantitative data of signs and symptoms of HPT as illustrated in Table 1. On the contrary, Belief Rule Based Expert Systems (BRBESs) can handle both types of data and their associated uncertainties in an integrated framework, which will be presented in the next section.

A relative comparison among different artificial intelligence techniques has been given in Table 2. In this table, different dimensions like architecture, uncertainty handling capacity and data type are considered in order to find out the suitable model for HPT detection. For example, from this table, it can be shown that as SVM is black box in nature and unable to handle the qualitative data. As a result, it fails to detect any type of uncertainty while BRBES denotes all types of uncertainties.

Different learning models has been proposed for single level BRB framework. In [31] a learning methodology has been proposed so that pipeline leak can be accurately detected to minimize the environmental damage and economic loss. For increasing the efficiency of BRB, a number of optimization models were developed in [20]. The models considered single or multiple-objective nonlinear optimization problems and further extended to trained hierarchical BRB system.

In [11], for predicting datacenter PUE under uncertainty a system has been developed by collecting the real world data from UK data center. In this paper, an optimal learning model has been developed for the BRBES and compared with ANN and Genetic algorithm.

Table 2: Patterns of Uncetainties Related to HPT

Model	Network Architecture	Uncertainty handling capacity	Data types
ANN	Black box in nature as the intermediate layers are not visible [33].	Unable to handle any type of uncertainty.	Can't handle both qualitative and quantitative data.
Fuzzy	Consists of membership functions, however it is difficult to find suitable membership values [19].	Addresses uncertainty due to vagueness, imprecision and ambiguity [10].	Deals with both qualitative and quantitative data expressed in the form of linguistic if-then rules [19].
Adaptive Neuro Fuzzy Inference system	Composed of two stage processes i.e. forward and backward stages [33].	Competent to work with uncertainties due to vagueness, imprecision and ambiguity.	Able to work with qualitative and quantitative data.
BRBES	Consists of knowledge base and learning module [10].	Capable of handling all categories of uncertainties because of vagueness, imprecision, ambiguity, ignorance and randomness [10].	Capable to work with qualitative and quantitative data [10].
SVM	Black box in nature [33].	Unable to handle any type of uncertainty.	Handles only quantitative data.

3 Belief Rule-Based Expert System

A Belief Rule Based Expert System mainly composed of domain specific knowledge base and inference engine [32][10] as will be described in this section.

3.1 Modeling Domain Knowledge using BRB

A belief rule can be formed by incorporating a belief structure in the consequent part of the IF-THEN rule as well as by considering referential values with each antecedent attribute. In addition, a belief rule is also associated with different learning parameters such as rule weight, antecedent attribute weight and belief degrees [33]. A belief rule is represented by Eq. 1.

$$R_k : \begin{cases} \text{IF} \\ (X_1 \text{ is } X_1^k) \wedge (X_2 \text{ is } X_2^k) \wedge ... \wedge (X_{T_k} \text{ is } X_{T_k}^k) \\ \text{THEN} \\ \begin{cases} \{(P_1, \overline{\beta}_{k_1}), (P_2, \overline{\beta}_{k_2}), ..., (P_N, \overline{\beta}_{k_N})\}, ((\sum_{n=1}^{N} \overline{\beta}_{k_n} \leq 1)), \\ \text{with rule weight } 0 \leq \theta_k \leq 1, \\ \text{and attribute weight } \delta_1^k, \delta_2^k, ..., \delta_T^k \geq 0 \\ \text{satisfying } \sum_{i=1}^{T_k} \delta_i^k = 1 \end{cases} \end{cases} \tag{1}$$

where $X_1, X_2, ..., X_{T_k}^k, T_k \in \{1, 2, ..., T\}$, represents the antecedent attributes used in the kth rule and P_1, P_2, ...,P_N are the referential values of the consequent attribute X_i where $(\overline{\beta}_k i$ is the belief degree. Fig. 1 shows the multilevel BRB framework to assess HPT, which has been developed by taking signs and symptoms as illustrated in Table 1. A belief rule in this domain can be written in the following way.

IF (A1 is High) and (A2 is High) and (A3 is Medium) THEN HPT Symptom (A9) is (High, 0.8), (Medium,0.2), (Low, 0).

In this example; A1, A2 and A3 are the antecedent attributes, while A9 is the consequent attribute.

The referential values associated with the antecedent attributes comprise high, medium and low. The illustrated rule is complete since the total sum of the degree of beliefs stands at 1. A9 BRB consists of three antecedent attributes, each with three referential values, namely high, medium and low. As a result, the A9 BRB consists of 27 rules according to Eq. 2 [32][10][12][15][16].

$$L = \prod_{i=1}^{T} J_i \tag{2}$$

where

L = The number of rules in a BRB

J_i = Referential values of the ith antecedent attribute

Table 3: Distribution of Input Data

No	Antecedent Name	Antecedent Value	Expert belief	High	Medium	Low
1	Headache	High	85%	0.7	0.3	0
2	Chest pain	Low	15%	0	0.3	0.7
3	Fatigue	High	80%	0.6	0.4	0
4	Breathlessness	Medium	30%	0	0.6	0.4
5	Vision problem	Medium	50%	0	1	0

The inference mechanisms of BRBES consist of four steps including distribution of input data, the calculation of rule weight, the update of belief degrees and the synthesis of rules by employing ER as indicated before [20].

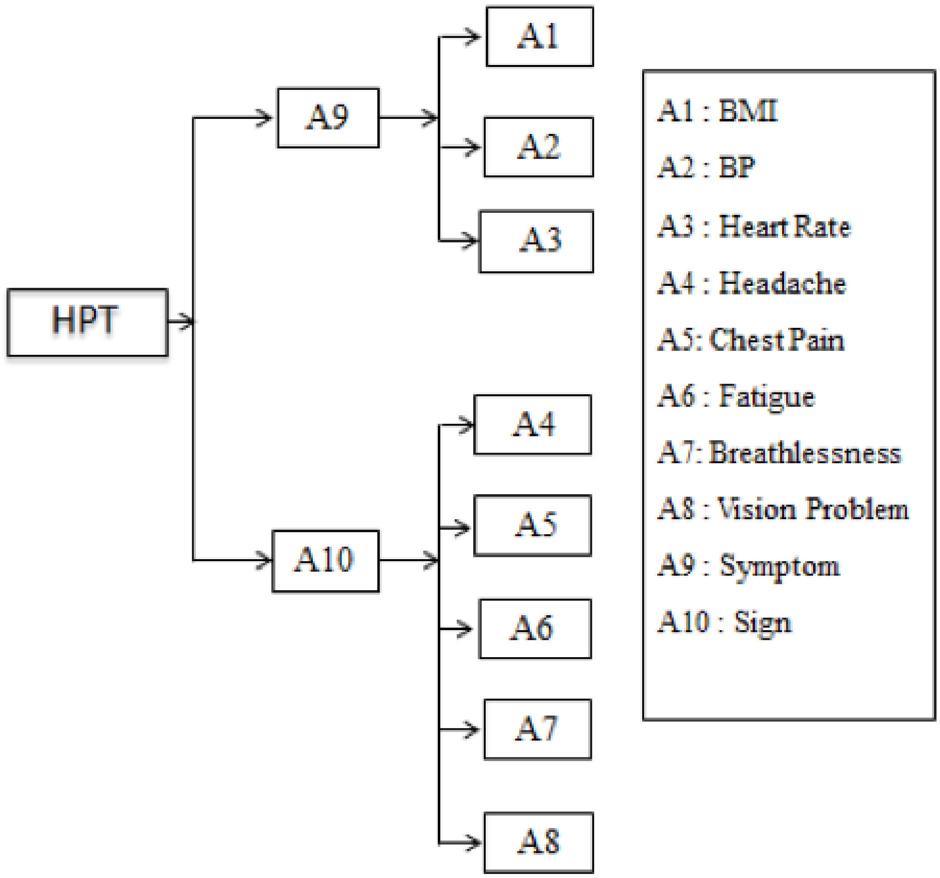

Figure 1: HPT structure of BRB

Usually, the input data of HPT are collected from the patients by the physicians in linguistic terms such as High, Medium, and Low. However, the physicians allocate some numerical values to these linguistic terms as shown in Table 3.

For example, when a patient expresses the input of Breathlessness as Medium then the physician's belief for this input is acquired as 30%. This numerical value is transformed to assign referential values to the antecedent attribute Breathlessness by applying (3) and (4). Different utility values can be assigned to these referential values, such as for High = 1.0, for Medium = 0.5, and for Low = 0.

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

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

The matching degrees of the A10 BRB's attributes' referential values are illustrated in Table 4. A10 BRB consists of 243 rules obtained by using (2). For simplicity the matching degrees of only one rule

Table 4: Matching Degree Calculation

Rule Id	IF	THEN
13	Headache (A4) is High (0.7) ∧ Chest pain (A5) is Low (0.7) ∧ Fatigue (A6) is High (0.6) ∧ Breathlessness (A7) is Medium (0.6) ∧ Vision Problem (A8) is Medium (1)	SIGN (A10) is (High, 0.3), (Medium, 0.6), (Low, 0.1)

is demonstrated here. A rule is said to be active when the referential values of its antecedent attributes are assigned matching degrees. Hence, this rule becomes packet antecedent. The rule 13 of A10 BRB consists of five antecedent attributes with individual matching degrees of their associated referential values.

These individual matching degrees should need to be combined and this can be obtained by using (5).

$$\alpha_k = \prod_{i=1}^{T_k} (\alpha_i^k)^{\overline{\delta}_{ki}}, \overline{\delta}_{ki} = \frac{\delta_{ki}}{\max_{i=1,\ldots,T_k} \delta_{ki}} \quad \text{so that } 0 \leq \overline{\delta}_{ki} \leq 1 \tag{5}$$

where $\delta_I^k (i = 1, ..., T_k)$ is the relative weight of the ith antecedent attribute in the kth belief rule.

The combined matching degree for the rule of 13 of A10 BRB is obtained as shown in Table 4.

Having individual matching degrees being combined, its activation weight needs to be determined. This provides an idea on the importance of each rule. By using (6) the activation weight of rule 13 of A10 BRB has been calculated and shown in Table 4.

$$W_k = \{\theta_k \alpha_k\}\{\sum_{i=1}^{L} \theta_i \alpha_i\} \tag{6}$$

where θ_k denotes the importance of the rule, L denotes the number of rules in a BRB, and α_k is the combined matching degree.

Table 5: Rule Activation and Weight Calculation

Rule id (1)	Rule Weight (2)	IF Antecedent (3)	THEN Consequent (4)	Combined Matching Degree (5)	Activation Weight (6)
13	1	A1∧A2∧A3 is H(0.0)∧M(1.0)∧L(0.4)	A9 is (H, 0.5), (M, 0.4), (L, 0.1)	0.07	0.84

In some cases input data of one or many of the antecedent attributes of A9 BRB or A10 BRB could not be available. Such a phenomenon depicts the ignorance. In such a situation, the degrees of belief, which were assigned to the initial belief rule of A9 BRB or A10 BRBB need to be updated, which can be obtained by using (7) [22].

$$\beta_{ki} = \overline{\beta}_{ki} \frac{\sum_{t=1}^{Tk} (\tau(k,t) \sum_{j=1}^{J_i} \alpha t_j)}{\sum_{t=1}^{T_k} \tau(k,t)} \tag{7}$$

where $\tau(k,t) = \begin{cases} 1, \text{ if used in defining } R_k (t = 1, ..., T_k) \\ \text{or} \\ 0, \text{ otherwise} \end{cases}$

Here, $\overline{\beta}_{ki}$ represents the original belief degree, while is the belief degree, which is updated. Table 6 illustrates the belief degree update for rule 7 of A10 BRB.

Table 6: Belief Degree Update

Rule Id		High	Medium	Low
7	Initial	0.5	0.62	0.3
	Update	0.22	0.01	0.02

For certain inputs of the antecedent attributes of the A9 BRB or A10 BRB the output or the value of the consequent attribute can be obtained by aggregating the 27 rules of A9 BRB or 243 rules of A10 BRB. This aggregation of the rules can be obtained by using evidential reasoning algorithm. There are two forms of ER namely recursive and analytical. The analytical form of evidential reasoning algorithm (as shown in (8)) considered to reduce the computational complexity [22][10].

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

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

The calculated values of the consequent attribute are in fuzzy format, obtained against the input data. These fuzzy values need to be converted into crisp values where utility value with each consequent attribute's referential value is considered.

Table 7: Initial Rule Base

Rule Id	Rule Weight	Antecedent IF			Consequent THEN A9		
		A1	A2	A3	High	Medium	Low
1	1	H	H	H	1.0	0.0	0.0
2	1	H	H	M	0.0	0.7	0.3
3	1	L	H	L	0.0	0.3	0.7
4	1	L	L	L	0.0	0.0	1.0
...	...	...	...	...	...	...	...
279	1	H	M	H	0.1	0.5	0.4

The final combined result or output generated by ER is represented by (C_1, β_1), (C_2, β_2), ..., (C_N, β_N), where β_j is the final belief degree attached to the jth referential value C_j of the consequent attribute C, which is obtained after all activated rules in the BRB are combined by using ER.

3.2 Optimal Learning Methods to Train the BRBES

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

BRB basically consists of three learning parameters namely rule weights, attribute weights and belief degrees. For achieving accurate result, these parameters play an important role as attribute weights and rule weights determine the importance of antecedent attributes. However, these parameters cannot assure the 100% accuracy as these can be generated randomly or collected from domain experts.

In order to minimize the difference between the BRBES results and the real output that is to minimize error E_p an optimal set of parameters have to be obtained by using (9) [11].

$$E_p = \frac{1}{M}\sum_{m=1}^{M}(Z_m - \overline{Z}_m)^2 \tag{9}$$

Here, M denotes the number of training samples, $\overline{Z}_m$ the observed output, and Z_m the simulated output.

The BRBES Training Module for HPT prediction consists of three steps:
1) Identification of the objective function;
2) Setting constraints for the learning parameters; and
3) Optimizing the learning parameters based on the training dataset.

Three different sets of training parameters as given below have been used to construct the trained BRBES.
R1: Training with referential values of the rule weight, antecedent attribute weight ,consequent belief degre.
R2: Training with different sets of rule weight
R3: Training with different sets of attribute weight

Consequently, the trained belief rule base is developed as shown in Table 8.

Table 8: Trained Rule Base

Rule Id	Rule Weight	Antecedent IF			Consequent THEN A9		
		A1	A2	A3	High	Medium	Low
1	1	H	H	H	1.0	0.0	0.0
2	1	H	H	M	0.0	0.75	0.25
3	1	L	H	L	0.0	0.4	0.6
4	1	L	L	L	0.0	0.0	1.0
...	...	...	...	...	...	...	...
279	1	H	M	H	0.1	0.5	0.4

4 System Architecture

This section describes the architecture and implementation techniques of the proposed system for depicting HPT. Here, Model-View-Controller (MVC) design pattern has been used to ensure efficient and faster development. The system consists of different layers, namely the Interface, Application, API, and

Data Management layers as illustrated in Fig. 2.

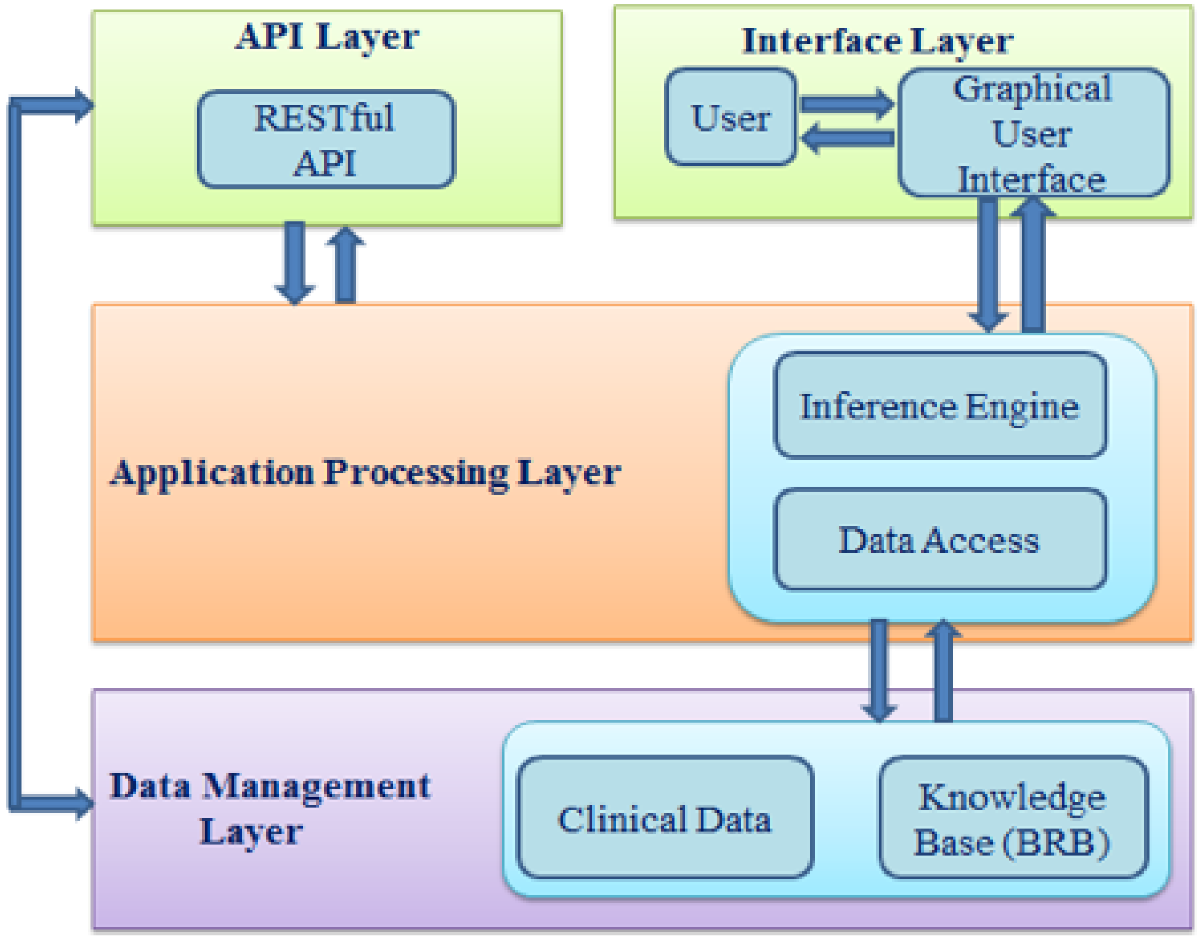

Figure 2: System architecture

4.1 Data Management Layer

Knowledge base construction by using the clinical dataset is the main task of data management layer. By using expert knowledge, historical data, previous rule base or by gener-ating random rules without any prior knowledge a BRB can be constituted. Here, rule base has been generated by consulting with the physicians. An example of the initial rule base A9 BRB is presented in Table 6. JavaScript Object Notation (JSON) has been used for managing this layer as the syntax and parsing procedure of JSON is comparatively easy than that of Extensible Markup Language (XML) and Comma-Separated Values (CSV). Fig. 3 shows the JSON format for the node A1 of the BRB tree as illustrated in Fig. 1.

```
{
  "A1": {
    "antecedent_id": "A1",
    "antecedent_name": "BMI",
    "attribute_weight": "1",
    "ref_val": [
      "1",
      "0.5",
      "0"
    ],
    "ref_title": [
      "high",
      "medium",
      "low"
    ],
    "consequent_values": [
      "[]"
    ],
    "crisp_val": "",
    "parent": "Symptom",
    "input_val": "0",
    "is_input": "false"
  },
  "A2": {
    "antecedent_id": "A2",
    "antecedent_name": "BP",
    "attribute_weight": "1",
```


Figure 3: JSON data format in BRB framework

4.2 Application Layer

This layer consists of data access procedures as well as inference procedures of BRB as discussed in the previous section. The procedures developed using PHP Hypertext Preprocessor (PHP). As a server side scripting language, PHP is easy to implement, efficient and supports all the major web browsers.

4.3 API Layer

RESTful Application Programming Interfaces (APIs) share or exchange information between data management layer and application layer by breaking down the transaction into small modules and communicate with Hypertext Transfer Protocol (HTTP) verbs such as POST, GET, PUT and DELETE [7]. In case of the proposed system, the input JSON file is taken with a POST request and the output can be achieved by using the GET request. The usage of RESTful API in this system has offered ease of access to multiple users by providing a layer of abstraction, which is flexible and computationally efficiency.

4.4 Interface Layer

The interface layer is the junction between the user and the system, which facilitates the interaction by manipulating data. Fig. 4 shows the Graphical User Interface (GUI) of the proposed system which has been developed by using Hypertext Markup Language (HTML) and Cascading Style Sheets (CSS). There are two mid-level nodes namely symptom (A9) and sign (A10). When, the user clicks one of the mid-level nodes, a new window will appear where he can give the referential values, attribute and rule weights. Fig. 4 demonstrates the procedures of obtaining the values of consequent nodes based on the values of the antecedent attribute. For example, the fuzzy values of the A9 con-sequent attribute obtained for the input values of the A1, A2, and A3 antecedent attributes. In the same way, the fuzzy values of the root node consequent attribute i.e. for HPT has been obtained by using the mid-level antecedent attributes A9 and A10 respectively. These fuzzy values have also converted into numerical or crisp value i.e. 92.78% risk of the hypertension (HPT) of the patient for whom input data of the leaf nodes collected as can be seen from Fig. 4.

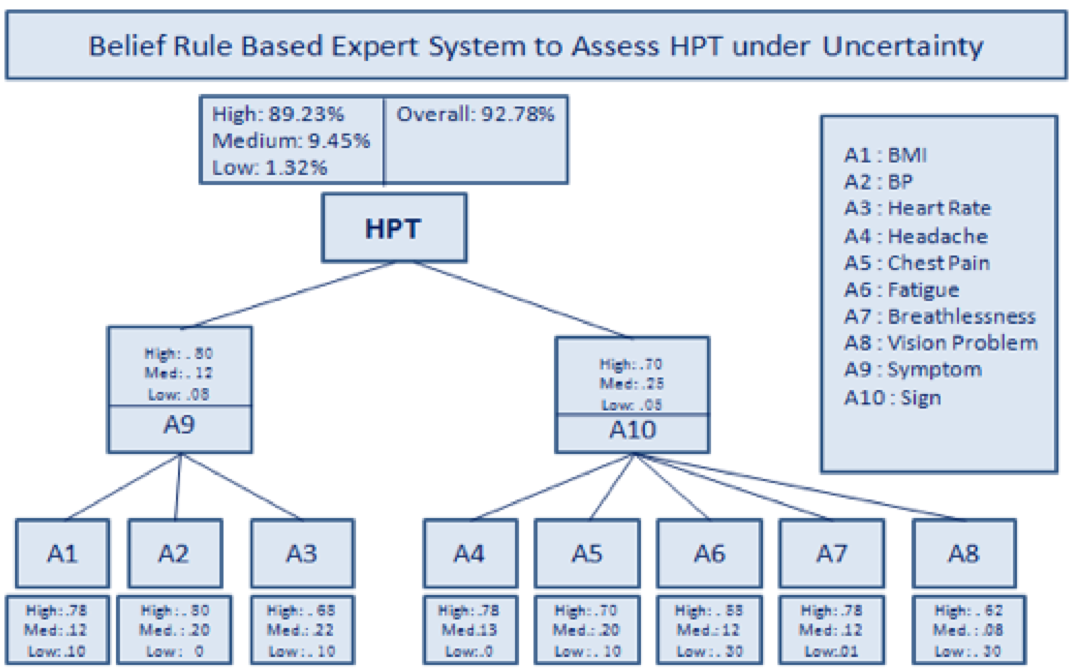

Figure 4: BRBES interface to assess HPT

5 Results and Discussion

In order to check the accuracy and the dependability of the system's results to assess HPT, data was collected from the cardiology departments of Chittagong General Hospital and Chittagong Medical College Hospital of Bangladesh by interviewing the patients and by consulting with the doctors. The signs and symptoms of eight factors of HPT were considered to collect the data from 87 patients. The actual diagnostic reports of the patients have been considered as the benchmark data. The benchmark data has been counted as 1 when HPT is confirmed and 0 when it is not confirmed.

The results of the BRBES have been compared with a Fuzzy Rule Based Expert System (FRBES) as well as with the machine learning tools such as Artificial Neural Networks (ANN), Decision Tree and Random Forest.

This table also illustrates the expert opinion in column 15 and benchmark data in column 16. To compare and evaluate the performance of a predictive model like BRBES, Receiver Operating Characteristics Curves (ROC) [9] are widely employed. In addition, different performance matrices including True Positive (TP), False Positive (FP), False Negative (FN), Sensitivity, Specificity, Accuracy, FRBES developed in the MatLab 2017a environment while the machine learning tools were constructed in the R 3.4.1 environment. Table 9 presents the signs and symptoms data of 87 patients (columns 2 through 9) as well as BRBES, FRBES and the mentioned machine learning tool's produced results (columns 10 through 14).

Area Under Curve (AUC), Confidence Interval, and Root Mean Square Error (RMSE) are also frequently employed.

The results of the mentioned matrices associated with the BRBES, FRBES and various machine learning tools are illustrated in Table 10. Fig. 5 illustrates the ROC of the six methods. ROC graphs are useful and widely popular for organizing and selecting classifiers by visualizing their performance [15]. AUC is associated with the ROC and the greater its value indicates the more accuracy and the relia-bility of the predictive models. From an investigation of the AUC values of column 10 of Table 8, it can be observed that BRBES is enjoying the highest value and hence, its generated results are better than that of other methods. Further, it can also be observed that the range of confidence interval of BRBES as shown in column 11 is the highest among all the methods.

Table 9: HPT Suspicion by BRBES, ANN, Fuzzy Logic, Random Forest, Decision Tree, and Expert Opinion

SL. No. (1)	A_1 (2)	A_2 (3)	A_3 (4)	A_4 (5)	A_5 (6)	A_6 (7)	A_7 (8)	A_8 (9)	Non-Trained BRBES Result (%) (10)	ANN Result (%) (11)	Fuzzy Logic Result (%) (12)	Random Forest Result (%) (13)	Decision Tree Result (%) (14)	Expert Opinion (%) (15)	Bench mark (16)
1	31.34	130/85	70	High	High	Medium	High	High	85.25	81.23	70.41	64.13	62.16	60	1
2	29.3	135/90	65	Low	High	Low	High	Medium	91.41	87.57	74.42	46.23	40.32	70	1
3	20	120/85	75	Medium	High	Low	Low	Low	22.33	34.11	23.12	34.78	30.12	65	0
4	24	110/70	77	Low	Low	Low	Low	Low	39.34	44.89	32.22	23.67	27.39	25	0
5	28.76	140/90	87	Low	Medium	High	High	Medium	63.28	45.27	48.12	84.05	77.34	91	1

Table 10: Comparison of Reliability among Five Systems

Model (1)	TP (2)	TN (3)	FP (4)	FN (5)	Sensitivity (6)	Specificity (7)	Accuracy (8)	RMSE (9)	AUC (10)	95% CI (11)
Decision Tree	32	31	16	8	80 %	65.96 %	72.41 %	0.5102	0.791	0.698–0.866
Random Forest	35	31	14	7	83.33 %	68.89 %	75.86 %	0.4023	0.803	0.711–0.875
FRBES	41	35	6	5	89.13 %	85.37 %	87.36 %	0.3001	0.817	0.727–0.887
ANN	40	34	6	7	85.11 %	85 %	85.06 %	0.3657	0.807	0.714–0.878
BRBES	42	38	3	4	91.31 %	92.68 %	91.96 %	0.2891	0.890	0.812–0.944

Column 9 of Table 10 also illustrates that the RMSE value of BRBES is the lowest among other methods. This means that BRBES's results produce less error than that of other methods. Column 8 of Table 10 illustrates that the accuracy of the BRBES in correctly identifying persons with HPT is the highest among all the methods.

Hence, a correlation among the matrices such as AUC, CI, RMSE and accuracy can easily be observed; and hence, BRBES is performing better than that of other methods. BRBES is also enjoying the highest sensitivity and specificity values in comparison to other methods as can be seen from columns 7 and 8 of Table 10. This means that BRBES can correctly identify both the HPT patients and the healthy persons.

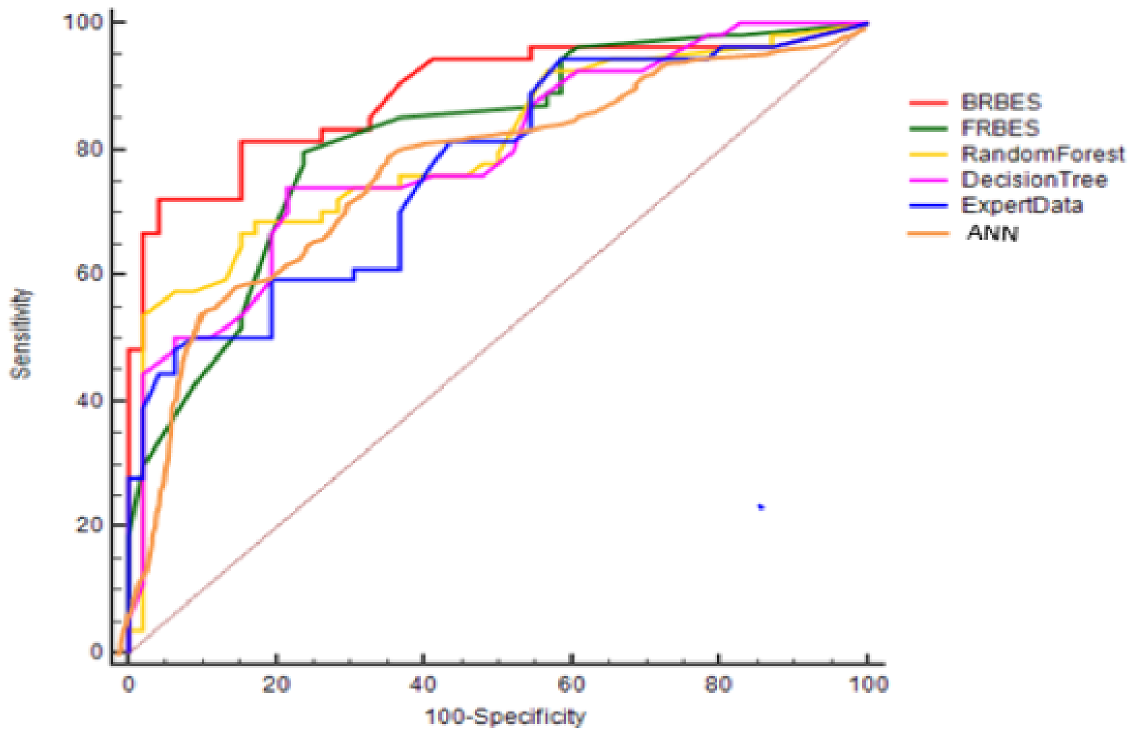

Figure 5: Comparison of results of BRBES, FRBES, Random Forest, Decision Tree, ANN and Expert Data by ROC curves

From column 2 of Table 10, it can be observed that the value of true positive (TP) is the highest in case of BRBES, meaning that this system correctly identifies more HPT patients than from the other methods. It is interesting to note that 45 persons have been found with HPT disease when all the 87 persons gone for the diagnostic investigation. The TP value was found 42 in case of BRBES, which is much closer to 45. This is also true for true negative (TN) value (column 3 of Table 10), meaning that BRBES can identify more healthy patients than from other methods. It is interesting to note that the value of false positive (FP) (column 4 of Table 10) is less in case of BRBES, meaning that in identification of the incorrectness of HPT patients by the system is the lowest among all the methods. In addition, the value of false negative (FN) (column 5 of Table 10) is also lowest in case of BRBES. This means that the number of HPT patients, which are incorrectly identified as healthy is the lowest among all the methods.

From an analysis of AUC values (column 10 of Table 10) of the other methods than from BRBES, it can be observed that the AUC value of Decision Tree is the lowest (0.791). The AUC values of other methods such as Random Forest and ANN a bit higher than Decision Tree i.e. 0.803 and 0.807 respectively. However, AUC value of BRBES, which is 0.890 is much higher than those of Decision Tree, Random forest and ANN. The reason for this is that these methods do not consider all categories of uncertainty related to the HPT's signs and symptoms as illustrated in Table 1.

On the contrary, the AUC value of FRBES is a bit better than those of Decision Tree, Random Forest and ANN but not that of BRBES. Since FRBES is concerned with uncertainties becauseof imprecision, ambiguity and vagueness. The BRBES outperforms FRBES in term of AUC because it considers all categories of uncertainty related to the HPT's signs and symptoms.The BRBES outperforms FRBES in term of AUC because it considers all types of uncertainty associated with the signs and symptoms of HPT. Likewise the above analysis of AUC value, the other values of the evaluation and performance matrices as illustrated in Table 9 can also be understood in the context of uncertainty phenomenon.

Table 11 and Fig. 6 indicate the comparison of ROC values and AUC for the training parameters (R1, R2 and R3).

Here, R1 indicates the trained values of the rule weight, antecedent attribute weight,consequent belief degrees, where R2 describes the trained rule weight and R3 indicates trained attribute weight. Table 10 and Table 11 indicate that the AUC of trained BRB is greater than the AUC of non-trained BRB and other systems.

In case of trained BRB, the AUC value of R1 is 0.964 which is greater than the AUC of R2 and R3. The AUC of R3 is higher than R2 i.e. 0.925 and 0.918 respectively.

From Table 7 and Table 8, it can be shown that the rule base has been updated. Fig. 7 and Fig. 8 shows the ROC curves for intermediary nodes A9 and A10 respectively for the updated rule base for different learning parameters namely R1, R2, and R3. The generated AUC of intermediary nodes for R1, R2, and R3 is given in Table 12. From the analysis AUC, it can be derived that R1 shows higher AUC value than R2 and R3 in case of both intermediary nodes A9 and A10. R1 shows greater AUC as it considers the trained value of attribute weight, rule weight and belief degrees whereas R2 and R3 only works with rule weight and attribute weight respectively.

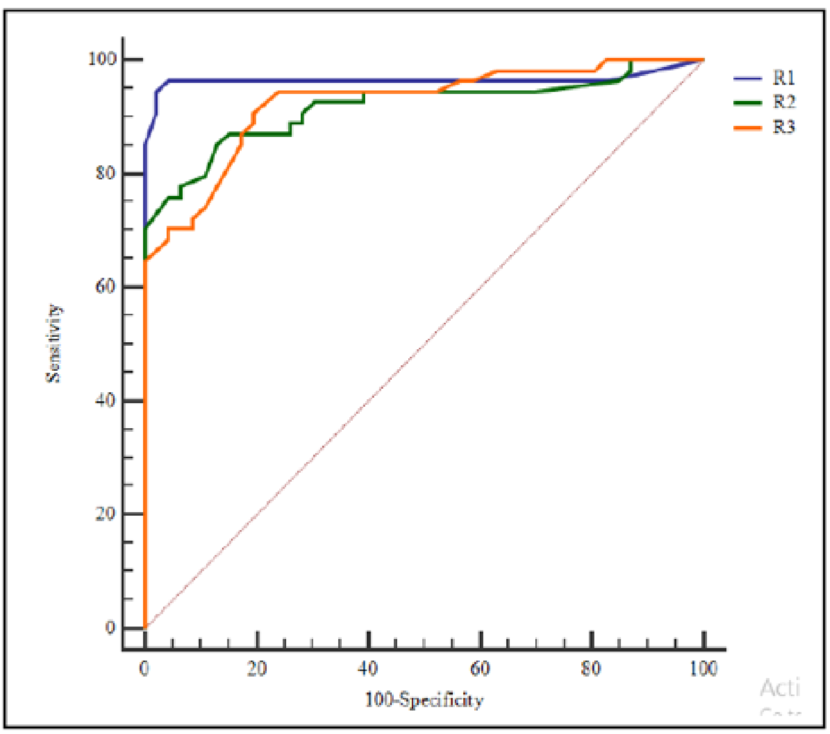

Figure 6: Comparison of results of R1, R2, and R3

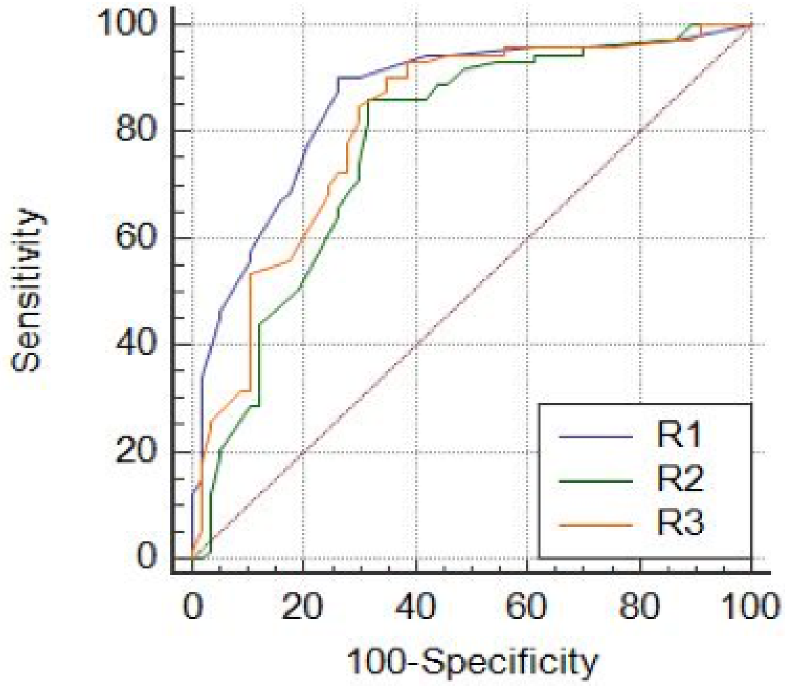

Figure 7: Comparisons of R1, R2 and R3 for intermediary node A9

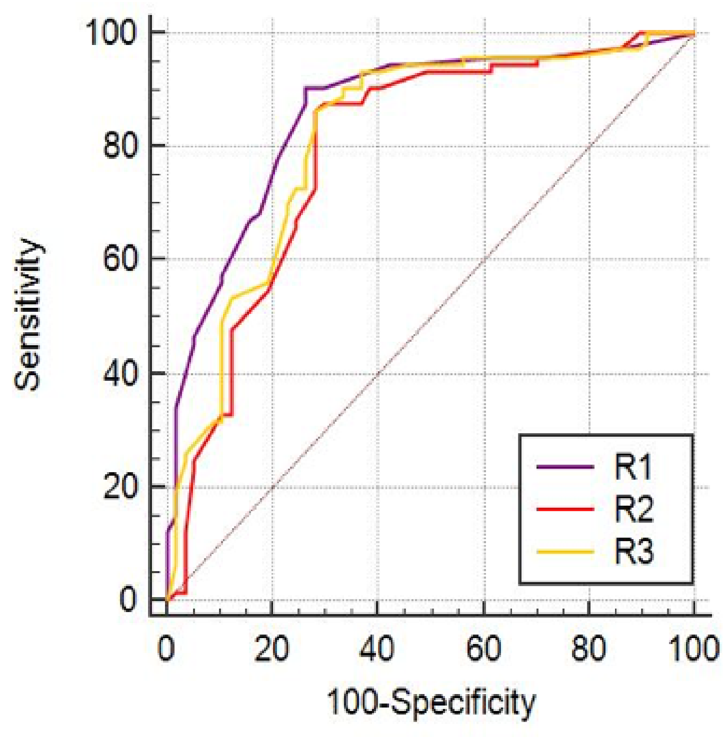

Figure 8: Comparisons of R1, R2 and R3 for intermediary node A10

Table 11: Comparison of AUC for Different Learning Parameters for Intermediary Nodes A9 and A10

Test Result Variables	AUC	Area Asymptotic 95% Confidence Interval
R1	0.964	0.907-0.991
R2	0.918	0.846-0.963
R3	0.925	0.854-0.968

Table 12: Comparison of AUC of Sub Rule Base

Sub Rule Base	R1	R2	R3
A9	0.925	0.774	0.754
A10	0.857	0.775	0.801

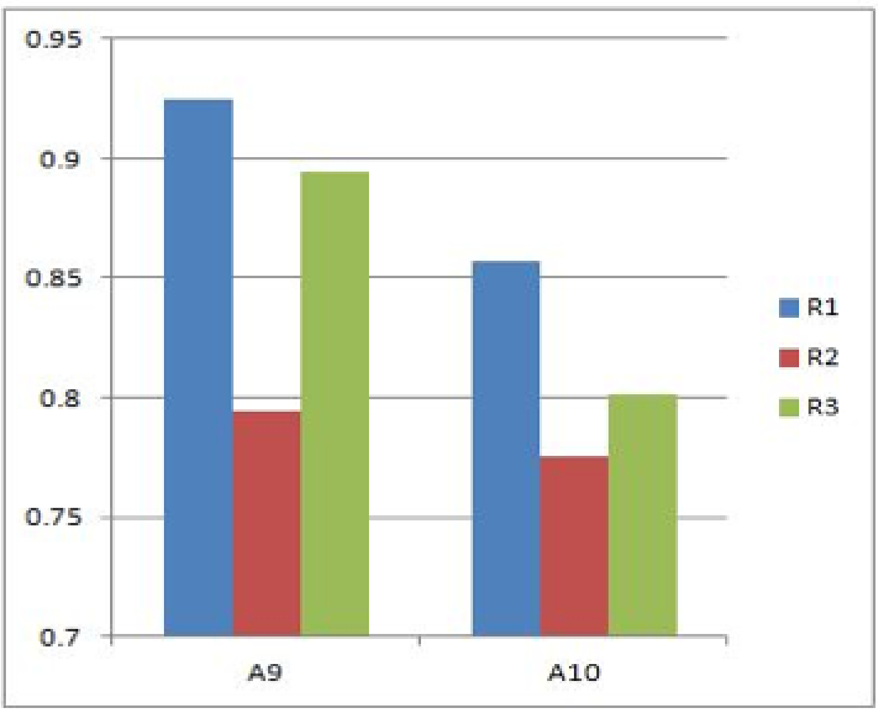

Figure 9: Comparisons of AUC for different learning parameters for intermediary nodes

Since the BRBES is web-based, to check its efficiency over desktop based system, a survey has been carried out among 150 users by using PACT (People, Activities, Contexts, Technologies) framework [18]. PACT analysis framework is developed by analyzing the respective users, their activities and technologies [18][3]. The observations and interviews of the survey outcomes are illustrated in Table 13.

Table 13: Overview of the Experience and Suggestions

Methods and Activities	Participants	Experience	Suggestions
Interview with physicians: Physicians' experience and suggestions	12 Physicians	Reliable, compatible and easy to deploy	A brief suggestion like maintaining a healthy diet, importance of regular exercise may be added in order to prevent HPT.
Interview with patients: Patients' expectations and experience	28 patients	User friendly interface and easy to access	A brief description of some symptoms like BMI may be added as most of the people do not know about the term.
Discussion with IT experts and physicians: Suggestions for security improvement	3 physicians, 2 IT experts	Cost efficient and accessibility for a range of devices.	Security of the system or restriction of unauthorized usage may be taken into account.
Meeting with IT experts: Clarifying the issue of using REST-ful API	4 IT experts	Usage of RESTful API has made the system computationally more efficient.	A trained BRBES may be developed so that the difference between the BRBES result and real system output can be minimized.

From the data presented in Table 9 it can be observed that the web-based BRBES is capable of assessing the feedback of the physicians in geographically different places at any time. User friendly interface has been developed so that people can easily access the system. In addition, users can access the system from any device like computers, mobile phones, PDAs, those are connected with the Internet.

6 Conclusions

To increase the life span of people, the accurate detection of diseases by handling all types of uncertainty is essential. To do so, there is a strong need of the BRBES presented in this paper by both the government and the physicians. The comparative results, generated in Table 8 demonstrate the efficiency and robustness of the BRBES over manual system, FRBES, random forest decision tree and artificial neural networks. The system also offers easy accessibility and portability since it is web-based. Moreover, the usage of RESTful API helps the users to interact with the system without having earlier knowledge about BRBES. In future, the wireless sensor network technologies could be integrated with the BRBES to collect data to support the assessment of HPT of the people in real time. Further, a training module for the BRBES to support optimal learning will be attempted.

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