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A Hybrid Scheme for Heart Disease Diagnosis Using Rough Set and Cuckoo Search Technique

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Abstract

Large volumes of raw data are created from the digital world every day. Acquiring useful information from these data is challenging, and it turned into a prime zone of momentum explore. More research is done in this direction. Further, in disease diagnosis, many uncertainties are involved in the information system. To handle such uncertainties, intelligent techniques are employed. In this paper, we present an integrated scheme for heart disease diagnosis. The proposed model integrates cuckoo search and rough set for inferencing decision rules. At the underlying phase, we employ a cuckoo search to discover the main features. Further, these main features are analyzed using rough set generating rules. An empirical analysis is carried out on heart disease. Besides, a comparative study is also presented. The comparative study demonstrates the feasibility of the proposed model.

Keywords Feature selection · Rough set · Rule generation · Indiscernibility · Classification · Reduct · Approximation

Introduction

Growth of communication technology and use of the web is the prime factor for a large amount of data deposited every day. This aggregated data is meaningless if not investigated to get some significant information. Handling of this data to get significant information is known as data investigation. Thus analyzing data is of prime concern in recent years. Besides recognizing features is another challenging issue in data analytics. Machine learning strategies are utilized to customize and supervise information system to find knowledge and main features. The extracted knowledge and rules must be exact, meaningful, comprehensible, and simplicity of comprehension. Moreover, it is a goal and means to find the insignificant subset of the original features. At the same time, it is a vital pre-preparing system helpful for analyzing an information system, where just a subset from the original features is picked to analyze the system. These systems are connected to a wide range of datasets to foresee the main features and are a primary advance utilized in classification, cluster analysis, pattern recognition, and image retrieval [1].

Numerous algorithms about feature selection choice have been proposed by different researchers [2–5]. In medical diagnosis, feature selection is of prime importance. Initially feature was carried out with the help of discretization and implemented over heart disease diagnosis [6] It is further extended to feature subset selection using genetic algorithm and applied to medical diagnosis of heart diseases [7, 8]. Similarly, support vector machine integrated with feature selection is used for breast cancer detection [9]. In addition, a comparative study of feature selection techniques using binary particle swarm optimization and genetic algorithm is also discussed in the literature. The comparison is carried out over coronary heart disease [10]. Similarly neuro fuzzy feature selection is used for medical disease diagnosis [11].

Recently, evolutionary and swarm intelligence algorithms are utilized in feature selection. With a feature selection, it is conceivable to increase good prediction accuracies [12]. An overview on six biologically inspired swarm algorithms, to be specific particle swarm optimization, ant colony optimization, artificial fish swarm algorithms,

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artificial bee colony algorithms, firefly algorithms, and bat algorithm and its application in feature selection is also carried out [13]. Similarly, the cuckoo inspired algorithm for feature selection and classification is carried out [14]. The model accomplished a higher classification accuracy of 94% on diminishing the number of features. Further, it is used for multi-objective optimization for optimizing feature selection, and the outcome demonstrated that it outperforms particle swarm optimization and genetic algorithm [15]. All these models fails to handle uncertainties. Besides these models are restricted to feature selection only and not addressed rule generation.

On the other hand, the rough set [16] of Pawlak set up as a sound hypothesis to determine issues identified with uncertainty, indeterminacy, and imprecise variety of applications. [17]. Further, the rough set has extended to fuzzy rough set [18], rough set on fuzzy approximation space [19], rough set on intuitionistic fuzzy approximation space [20], rough set on two universal sets [21, 22], intuitionistic fuzzy rough set on two universal sets [23] for feature selection and knowledge acquisition. Also, the rough set is hybridized with formal concept analysis [24], rough set on fuzzy approximation space in hybridized with the soft set [25], the rough set is hybridized with genetic algorithm [26], and information retrieval is carried out. The real advantage is that it works well for rule generation. But, rough set has a limitation. The limitation is that the rough set generates an excessive number of rules. Once in a while, it is hard to infer rules that are useful for the issue contemplated [27–29]. These rules are generated due to many number of features available in the information system. Therefore, it is essential to minimize the number of features so as to get minimum number of rules. It, in turn, helps the decision makers to take right decision at the right time.

Considering the above constraints, in this paper, we hybridize cuckoo search and rough set for inferencing knowledge from an information system. The prime target of hybridization is to keep the optimized features while inferencing knowledge from information system using rough set. In the early stage, we utilize the cuckoo search to identify optimized features. Further, these optimized features are utilized to inference knowledge using the rough set. Finally, we compare both the rough set model and the hybridized model that integrates both cuckoo search and rough set (CSRS) regarding rule generation.

The article is enunciated as follows. Section "Foundations of cuckoo search" discusses the foundations of cuckoo search and the ideal strategy of getting the best features. Following Section "Foundations of cuckoo search", the foundations of the rough set are discussed in Section "Fundamentals of rough set". Explanation and clarification of the proposed model are discussed in Section "Proposed research design". An experimental investigation on heart disease is presented in Section "An empirical study on heart disease". Further outcome and analysis of the empirical study and a comparative analysis with the rough set, and decision tree predictive learner model are also carried out. The article is concluded in Section "Conclusion".

Foundations of cuckoo search

Cuckoos are a group of flying creatures with a kind of reproductive strategy that uses brood parasitism method, and it is more aggressive compared with other birds species. Some of parasitic cuckoo birds species lay eggs in other nests and evacuate others eggs to increase the hatching probability of their eggs. The parasitic cuckoos are great in finding a nest where eggs have recently been laid, and their planning of laying eggs is scrupulous. They lay one egg in the host nest which typically hatches quicker than alternate eggs. At the point when this occurs, the foreign cuckoo would expel the non-hatch eggs from the nest by pushing the eggs out of the nest.

Levy flights represent the best strategy in many bird's species using random walks to randomly search for a target with the help of levy distribution in an unknown environment. Animals and bird's species perform these levy flights, and it is described by the arrangement of straight flights pursued by sudden 90 deg turns. Levy flights are more proficient in investigating extensive search areas. That is principally due to levy flights fluctuations expands a lot quicker than that of the ordinary random walk, and it can reduce the number of iterations compared to the usual random walk.

The cuckoo search algorithm (CSA) is a nature-inspired search algorithm in which the cuckoo and levy flight are applied as an optimization tool [30]. According to the algorithm, each cuckoo selects a nest randomly and lays one egg on it. The best nests with high quality of eggs are carried out to the next generation. The number of nests is fixed, and there is a probability that a host can discover a foreign egg. If it happens, then the host can discard the egg or the nest. The cuckoo search algorithm based on the above three principles is outlined below for attribute reduction.

According to the algorithm, every host nest n contain one simple egg q (One dimension). In case of multiple dimension, every host nest may contain more than one egg. The nests are updated at each iteration using random walk via Levy flights. Levy flights is a random step drawn from Levy distribution.

$$q_i^j(t+1) = q_i^j(t) + \alpha \oplus Levy(\lambda) \quad (1)$$

$$Levy \sim u = s^{-\lambda}; (1 < \lambda \leq 3) \quad (2)$$

In the above equations, $q_i^j(t)$ gives the current solution i of iteration j, where $i = 1, 2, 3, \cdots, n$ and $j = 1, 2, 3, \cdots, m$. The step size is denoted as s, and $\alpha > 0$ is the scaling factor of the step size s. The symbol $\oplus$ is a entrywise product. Finally, the new solutions [30] are created by replacing the eggs of lowest quality. The selection of new solution is done in accordance with the probability function $Pr \in [0, 1]$.

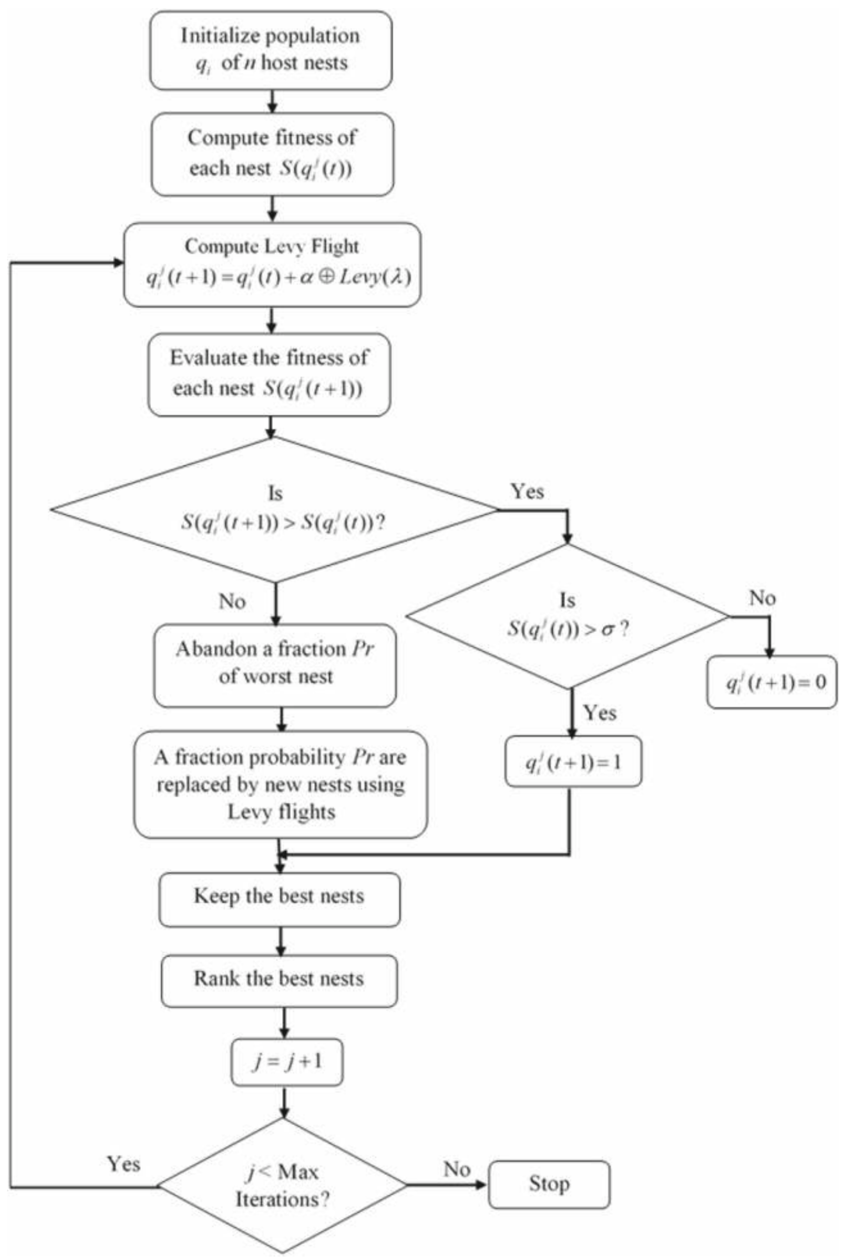
In case of feature selection, the main aim is to select or deselect a given feature. Therefore, there is a necessity of employing a solution binary vector. In such cases 1 corresponds to the selection of feature, whereas 0 corresponds against the selection of feature. The selection of a feature is defined as in Eq. 3, where $S(q_i^j(t))$ is defined in Eq. 4 and $\sigma \sim U(0, 1)$.

$$q_i^j(t+1) = \begin{cases} 1 & \text{if } S(q_i^j(t)) > \sigma \\ 0 & \text{Otherwise} \end{cases} \tag{3}$$

$$S(q_i^j(t)) = \frac{1}{1 + e^{-q_i^j(t)}} \tag{4}$$

For better understanding, the flow diagram of cuckoo search technique is depicted in Fig. 1. The algorithm starts with the generation of initial population of host nests. Further it undergoes several iterations to get the optimal

Fig. 1 Flow diagram of cuckoo search algorithm



solution and terminates after reaching the maximum number of iterations. Finally, the selected features are obtained.

Fundamentals of rough set

An information system is a collection of objects, where each object is associated with some information. It can be expressed in a two-dimensional system. The vertical dimension refers to features of objects, and the horizontal dimension refers to objects. Some feature values characterize each object. Similar feature values characterized by different objects are indiscernible. It means that indiscernibility leads to an equivalence relation and is the basic philosophy of the rough set [16]. On employing this equivalence relation over an information system, the objects are classified into different classes, and we call it a partition of objects.

Now we discuss rough set more formally as follows. Let Q be the set of objects of the universe. Let $R \subseteq (Q \times Q)$ be an indiscernible relation defined over Q such that $R = \{(q_i, q_j) | p(q_i) = p(q_j) \forall p \in P\}$ where P is the set of features. On imposing the indiscernibility, the information system reduces to indiscernible classes Q/R. If $[q] \in Q/R$ be an indiscernible class, then each object belonging to $[q]$ are indiscernible with respect to the given features P. Therefore, (Q, R) is called an approximation space of an information system $I = (Q, P, V, f)$ where $V = \bigcup_{p \in P} V_p$ and $f : (Q \times P) \rightarrow V$ is an information function.

Let $Z \subseteq Q$, be a target set. The set Z can be characterized by a pair of lower and upper approximations $\underline{R}Z$ and $\overline{R}Z$ respectively as below.

$$\underline{R}Z = \cup\{Y \in Q/R : Y \subseteq Z\} \tag{5}$$

$$\overline{R}Z = \cup\{Y \in Q/R : Y \cap Z \neq \phi\} \tag{6}$$

The R-boundary of Z, $BN_R(Z)$ is given by $BN_R(Z) = \underline{R}Z - \overline{R}Z$. We say Z is rough with respect to R if and only if $\underline{R}Z \neq \overline{R}Z$ or equivalently $BN_R(Z) \neq \phi$. Thus, set Z is rough with respect to R if and only if it is not R-definable. The target set Z is R -definable if $BN_R(Z) = \phi$ [31].

For example consider an information system shown in Table 1. The features varices, bilirubin, albumin, protime are referred as p_1, p_2, p_3, p_4 respectively. The object is characterized by varices = yes, bilirubin = high, albumin = medium and protime = high.

Let R be the indiscernibilty relation defined over the features $P = \{p_1, p_2, p_3, p_4\}$ on $Q = \{q_1, q_2, \cdots, q_{10}\}$. Thus we have $Q/R = \{\{q_1, q_3\}, \{q_2, q_5\}, \{q_4, q_8, q_{10}\}, \{q_6\}, \{q_7, q_9\}\}$. On considering $Z = \{q_1, q_4, q_3, q_6\}$, we get $\underline{R}Z = \{q_1, q_3, q_6\}$ and $\overline{R}Z = \{q_1, q_3, q_4, q_6, q_8, q_{10}\}$. The boundary line objects $BN_R(Z) = \{q_4, q_8, q_{10}\}$. For better visualization, Fig. 2 depicts the lower, upper and boundary line objects.

Table 1 Sample information system

Objects	p_1	p_2	p_3	p_4	Hepatitis (d)
q_1	yes	high	medium	high	die
q_2	no	low	high	low	die
q_3	yes	high	medium	high	die
q_4	yes	medium	low	medium	live
q_5	no	low	high	low	die
q_6	yes	medium	high	high	die
q_7	no	high	low	high	live
q_8	yes	medium	low	medium	live
q_9	no	high	low	high	live
q_{10}	yes	medium	low	medium	live

Core and reduct

The major concept of rough set theory is core and reduct. Reduct helps us to remove the superfluous features that do not have any influence in the information system. Besides it also make object classification satisfy the full set of features. The objects that belong to all the reducts is known as core of the information system. We define it as $core(I) = \cap \text{Red}(I)$, where I is the information system.

Let $A \subseteq P$ and $p \in A$. The attribute p is dispensable in A if $Q/A = Q/(A - \{p\})$. Otherwise p is indispensable in A. Set A is independent if all of its attributes are indispensable. Reduct A' of A is a subset of attributes of A such that the equivalence class induced by A is same as the equivalence class induced by A' , i.e., $Q/A = Q/A'$. Thus, we may have many reducts in an information system.

Rule generation

A decision rule in a decision system is of the form $\phi \rightarrow \psi$, where ϕ the set of conditional parameters and ψ is the decision. The various measures of a decision rule are support, strength, and accuracy of the rule. The support is defined as $Supp(\phi, \psi) = card(||\phi \wedge \psi||)$ whereas strength is defined as $\sigma(\phi, \psi) = Supp(\phi, \psi)/card(||\phi||_\psi)$. The accuracy of the rule is defined as in Eq. 7, where $N_{supp}(\phi, \psi)$ denotes the number of non supporting objects of the rule $\phi \rightarrow \psi$.

$$Accuracy = \frac{|Supp(\phi, \psi)|}{|Supp(\phi, \psi) + N_{supp}(\phi, \psi)|} \tag{7}$$

Now we briefly discuss decision rule generation procedure using rough set. The qualitative decision system is given as input, and we get candidacy rules as for output. The

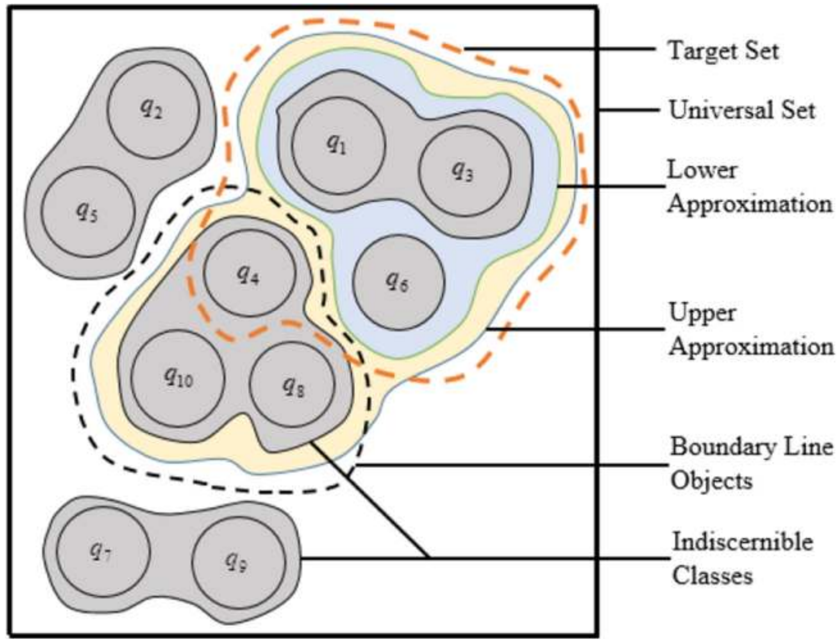


Fig. 2 Lower, upper and boundary region

steps involved in the decision rule generation procedure is given below. The decision rules of Table 1 is presented in Table 2.

Algorithm 1 Decision rule generation.

1. Set decision $d = 1$
2. Compute a set of reducts considering all the condition parameters for each decision.
3. Replace $d = d + 1$. If all the objects have been chosen, then go to step 4. Else go to step 1.
4. Compute the number of supporting objects of the decision rule $\phi \rightarrow \psi$ after combining the identical reducts.
5. Calculate the strength of each decision rule $\sigma(\phi, \psi)$.
6. Obtain the accuracy of each decision rule using Eq. 7.
7. Terminate the process and write the rules.

Proposed research design

The proposed research design depicted in Fig. 3 consists of three stages. In the initial phase, the proposed model of knowledge inferencing uses a cuckoo search algorithm to find the main features of the information system. The second stage of the model employs rough set data analysis for decision rule generation. Finally, the decision rules are validated in the validation stage. The proposed research design starts with the identification of the right problem. Once the problem is identified, data are collected from various sources. Further data cleaning technique is employed to process these data. Data cleaning is carried out to remove, missing attributes values, and incomplete data. After employing data cleaning, the information system becomes suitable for further analysis. In this research work, we employ an integrated data analysis technique that integrates cuckoo search and rough set data analysis (CSRS) technique to inference knowledge. The basic objective of this hybridization is to handle the uncertainties present in the information system. In addition to it, achieving higher accuracy with less number of features is another objective during classification. The proposed integrated, CSRS, technique is applied to heart disease diagnosis to inference knowledge. Before we employ the integrated CSRS data analysis technique, the processed data is partitioned into training dataset of 55% and testing dataset of 45%. The prime objective of data partition is rule generation and validation. The training dataset is used for rule generation whereas using testing dataset we can compute the accuracy of rules generated in training phase. The training data is analyzed using the CSRS technique, whereas testing data is used to validate the results obtained from the CSRS technique.

The partitioned data is executed using cuckoo search algorithm for identifying minimal features without impacting the decisions of the information system. Further on considering these minimum features, the rough set rule generation algorithm is employed to mine knowledge. The support, strength, and accuracy of each rule are obtained. The rules whose accuracy is more than the pre-defined threshold of 65% are selected as candidacy rules. These candidacy rules are further validated with the testing data set. In this stage, the candidacy rules obtained in the training phase are validated using 5 fold cross-validation. The

Table 2 Decision rules of the sample decision system presented in Table 1

Rule No.	Description	Support	Strength (%)	Accuracy (%)
1	If p_2 = low then d = die	2	40	100
2	If p_3 = medium then d = die	2	40	100
3	If p_3 = high then d = die	3	60	100
4	If p_4 = low then d = die	2	40	100
5	If p_1 = yes and p_2 = high then d = die	2	40	100
6	If p_1 = yes and p_4 = high then d = die	3	60	100
7	If p_3 = low then d = live	5	100	100
8	If p_4 = medium then d = live	3	60	100
9	If p_1 = no and p_2 = high then d = live	2	40	100
10	If p_1 = no and p_4 = high then d = live	2	40	100

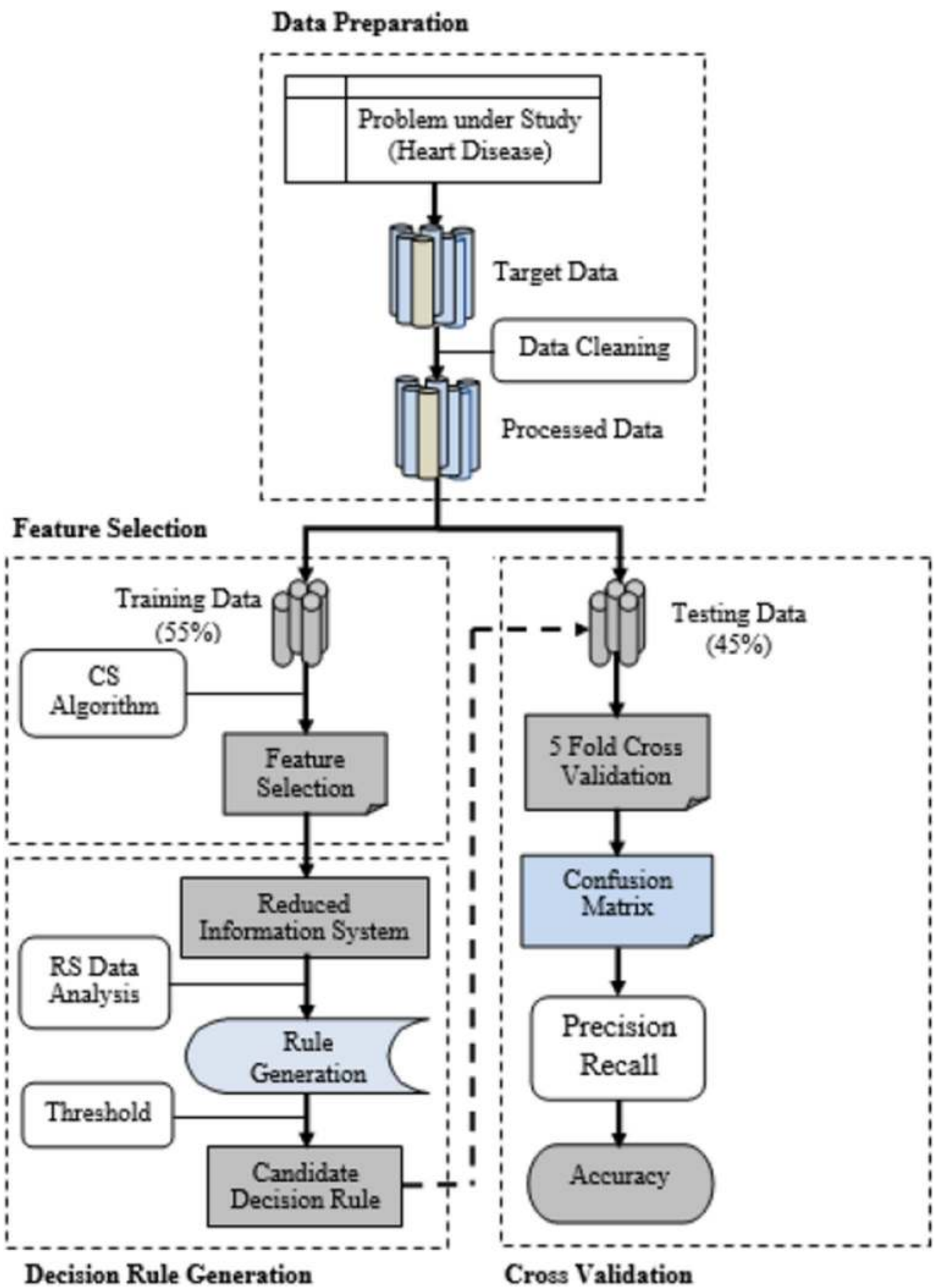


Fig. 3 Proposed research design of CSRS model

confusion matrix is generated for each folder to compute the accuracy. The accuracy of the integrated CSRS technique is computed from true positive (TP), true negative (TN), false positive (FP), and false negative (FN). We also compute precision and recall. The precision, recall, and accuracy are computed using the Eqs. 8, 9, and 10 [32–35]. Additionaly, we also compute F-measure as a function of precision and recall. It is essential to check the balance in between precision and recall. Besides, it is useful in case of uneven class distribution. It is defined in Eq. 11.

$$Precision = \frac{|TP|}{|TP + FP|} \tag{8}$$

$$Recall = \frac{|TP|}{|TP + FN|} \tag{9}$$

$$Accuracy = \frac{|TP + TN|}{|TP + FP + TN + FN|} \tag{10}$$

$$F = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right) \tag{11}$$

An empirical study on heart disease

This section presents an empirical study on heart disease. The most common symptom of heart disease is chest pain. Other symptoms include blood pressure, cholesterol, blood sugar, electrocardiography (ECG), maximum heart rate (MHR), exercise, old peak, thallium scan, sex, and age. With these symptoms, the heart disease is classified according to the physician as hypertensive heart disease, coronary heart disease, heart failure, potential patient, and cardiomyopathy. Further, the attributes that take continuous values are classified according to domain experts. For example, cholesterol is classified into 4 categories such as < 160; $160 - 190$; $191 - 250$; and > 250. We denote these classes as low, medium, high, and very high. We use symbols 1, 2, 3, 4 for low, medium, high, and very high, respectively while analyzing the heart disease information system. These symbols are just indicative and do not affect our analysis. A complete description of these symptoms about heart disease is presented in Table 3. Our objective is to identify the minimum number of symptoms that can classify a heart disease correctly. In general heart disease occurs due to less supply of oxygen and blood to heart, low pumping capacity of heart, increase in blood pressure, and thickness of heart walls. According to the symptoms the disease is categorized.

Depending on various heart conditions, heart diseases are categorized. Most common heart diseases are coronary heart disease, hypertensive heart disease, cardiac arrest, congestive heart failure, arrhythmia, peripheral artery disease, stroke, congenital heart disease, and cardiomyopathy. In this study we analyze coronary heart disease, hypertensive heart disease, congestive heart failure, and cardiomyopathy. Coronary heart disease is generally occured due to damage in hearts major blood vessels. In such cases, arteries find difficult to supply oxygen and blood to the heart. Hypertensive heart disease is generally found when the force of blood against the artery walls is very high. It leads to heart disorders. Similarly, congestive heart failure is a cronic disease in which heart does not have enough strength to pump the blood. In such cases heart works less efficiently than a normal and blood circulation rate is very slow. As a consequence, pressure increases in the heart and cannot pump enough oxygen and nutrients to meet the body's requirement. In cardiomyopathy, heart muscle becomes harder and heart finds difficult to pump blood to the rest of body parts. For better understanding various functionality of heart, components and heart diseases considered in the analysis is depicted in Fig. 4 [36].

In this empirical study, an integrated CSRS technique is applied for inferencing knowledge from heart disease information system. Each patient's treatment depends on different attributes values (symptoms), and it leads to a particular decision class. In some cases, there is a difference in physician opinion observed while having the same attribute values. Thus, it is necessary to generate specific rules using feature selection and rough set data analysis. It, in turn, identify the primary factors and classify the type of heart disease at an early stage. Simultaneously, it helps in reducing the diagnosis time and early detection of heart disease. It, in turn, saves money and time of a patient.

Research methodology

There is a voluminous of electronic medical data available in the healthcare domain. Heart disease dataset from Cleveland, Hungary, and Switzerland are taken into consideration from data mining repository of the University of California, Irvine (UCI) [37]. Besides, we have also collected data from reputed hospitals of Tamilnadu, India. However, the identity of the patients and hospitals are kept confidential due to some official reason. In total, 857 patient's information collected is analyzed for noisy, completeness, and consistency. In order to avoid unnecessary execution and complexity, we removed data based on missing values and the decision that does not have any impact on the diagnosis of the disease. We have removed 151 patient's information from the information system as they do not have heart disease. Also, 103 patient's data are also removed from the dataset because of missing attribute values. In total, 254 patient's information

Table 3 Representation of symptoms of heart disease

Attribute	Range	Classification
Chest pain (p_1)	–	Typical angina (1) Atypical angina (2) Non-anginal pain (3) Asymptotic (4)
Blood pressure (p_2)	120–139/80–90 140–159/91–99 160–179/100–109 $\geq 180/110$	Normal (1) Medium (2) High (3) Very high (4)
Cholesterol (p_3)	$<$ 160 160–190 191–250 $>$ 250	Low (1) Medium (2) High (3) Very high (4)
Fast blood sugar (p_4)	$< 126 \geq 126$	Normal (1) Very high (2)
ECG (p_5)	[-0.5, 0.4] [2.45, 1.8] [1.4, 2.5]	Normal (1) ST-T Abnormal (2) Hypertrophy (3)
MHR (p_6)	$<$ 60 60–100 $>$ 100	Medium (1) Normal (2) High (3)
Exercise (p_7)	–	False (1) True (2)
Old peak (p_8)	$<$ 2 2–3 $>$ 3	Low (1) Risk (2) Terrible (3)
Thallium scan (p_9)	3 6 7	Normal (1) Fixed defect (2) Reversible defect (3)
Sex (p_{10})	–	Male (1) Female (2)
Age (p_{11})	$<$ 35 35–60 61–75 $>$ 75	Young (1) Mild (2) Old (3) Very old (4)
Type of diagnosis (d)	–	Hypertensive (1) Coronary (2) Heart failure (3) Potential patient (4) Cardiomyopathy (5)

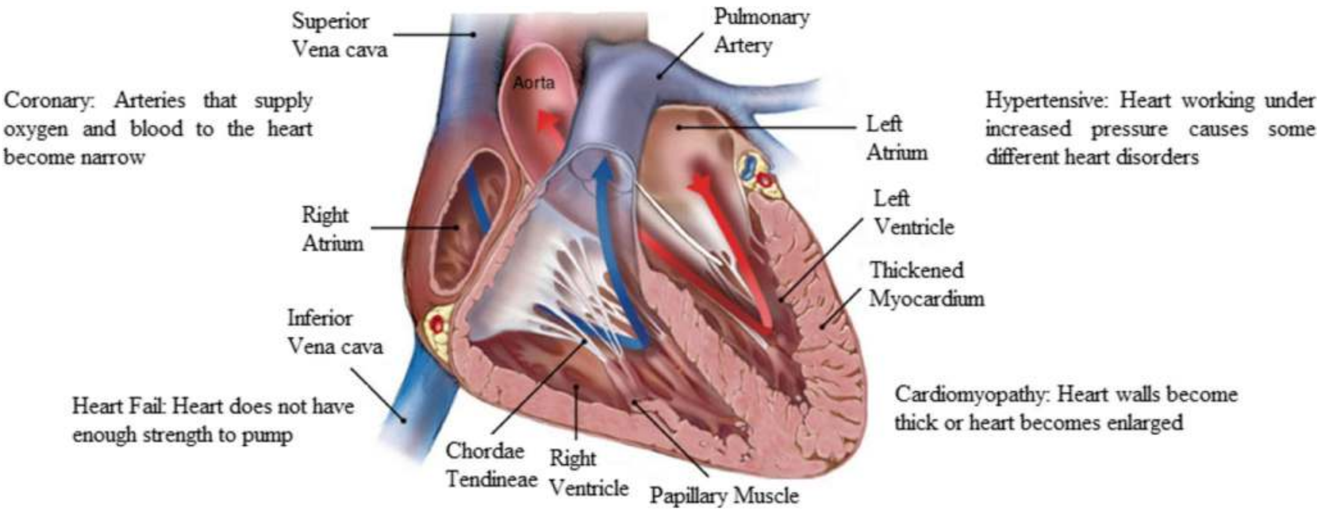


Fig. 4 Components of heart and description of heart diseases

is removed from the information system since it does not have any impact on the decision-making process. Finally, after removal, 603 patient's information is considered for the decision-making process. The prime objective of this research work is to discover the hidden patterns and knowledge from these electronic medical information system to detect heart disease at an early stage. With these analyses, the number of deaths of patients with heart disease can be reduced with early diagnosis and appropriate treatment at an affordable cost.

Besides, we have also consulted with domain experts like cardiologist and attended numerous forums to know about heart disease and its symptoms. This process gave us an understanding of the historical data and knowledge about heart disease. A sample information system of heart disease diagnosis is presented in Table 4. It means that patient q_1 is characterized as hypertensive heart disease.

Experimental result analysis

The experiments were conducted with a laptop having the configuration as Intel Core i5-4200U CPU 1.60 GHz 2.30 GHz, 4 GB RAM, Windows 8 operating system, and Python. The total of 603 patients' data is divided into two parts, such as training data of 332 (55%) and testing data of 271 (45%). The training data is processed for identifying the best features using cuckoo search.

After 1000 iterations of cuckoo search algorithm, it is found that 8 features whose significance values are more than the trend line are selected. For better understanding it is depicted in Fig. 5. The selected features are chest pain (p_1), cholesterol (p_3), fast blood sugar (p_4), ECG (p_5), MHR (p_6), exercise (p_7), old peak (p_8), and age (p_{11}). Further, the other features are eliminated from the training data of the information system.

Table 4 Sample heart disease information system

Objects	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	d
q_1	1	3	4	2	1	3	2	3	1	1	2	1
q_2	3	3	4	2	1	1	2	3	1	1	3	1
q_3	2	2	4	2	1	1	1	1	3	1	2	2
q_4	3	2	4	1	1	1	1	1	3	1	3	2
q_5	1	2	3	1	2	1	2	3	3	2	1	3
q_6	4	4	3	1	2	1	2	3	3	2	1	3
q_7	3	4	1	1	3	1	1	2	1	2	1	4
q_8	2	3	2	1	3	1	1	2	1	2	1	4
q_9	2	2	4	1	3	3	1	2	1	1	4	5
q_{10}	4	2	4	1	3	3	1	1	1	1	4	5

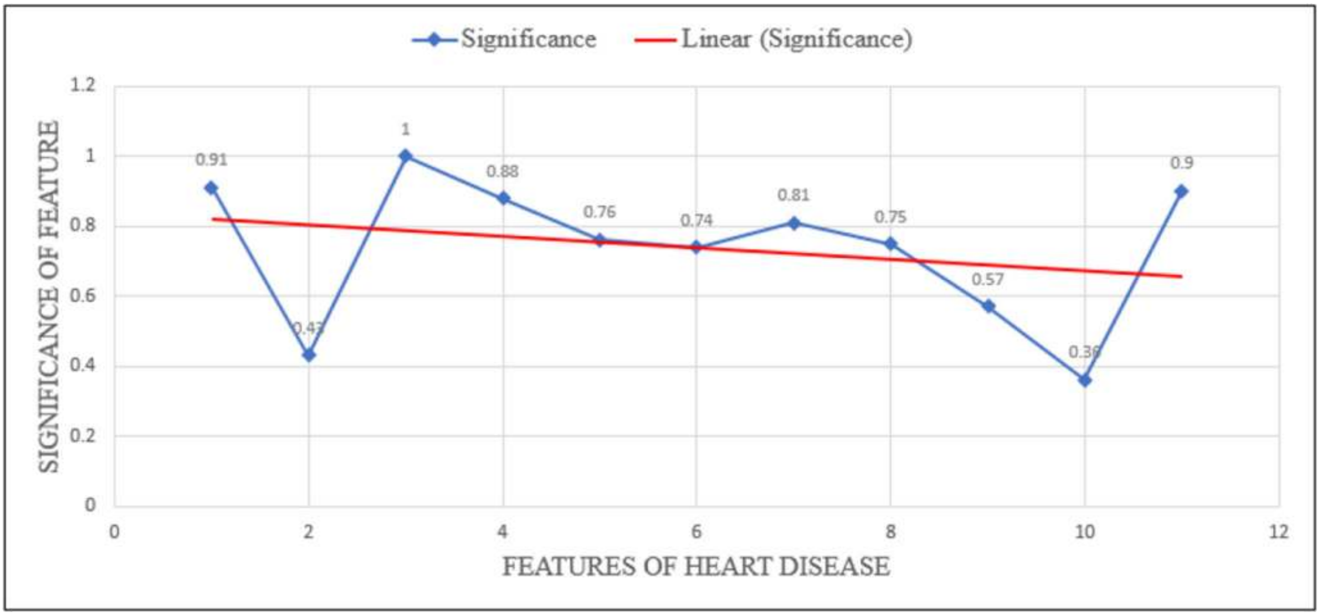


Fig. 5 Significance of features of heart disease and setting of trend line

The reduced information system is analyzed using rough set data analysis. The rules that are generated for hypertensive heart disease are presented in Table 5. From Table 5, it is clear that rule number 6, and 10 are having accuracy less than 65% and hence discarded. Finally, 10 rules are selected from Table 5.

Similarly, the rules that are generated for coronary heart disease are presented in Table 6. Table 7 presents the decision rules of heart failure whereas Table 8 presents decision rules for the decision potential patient. Finally, Table 9 presents decision rules for decision cardiomyopathy.

Similarly, from Table 6, it is clear that rule number 8, and 12 are having accuracy less than 65% and hence discarded. Finally, 10 rules are selected from Table 6. Besides rule number 3, 4, and 8 are discarded from Table 7 as they have an accuracy of less than 65%. Finally, 6 rules are selected from Table 7. Again from Table 8, it is clear that rule number 6, 7, 9, and 13 are having accuracy less than 65% and hence discarded. Finally, 15 rules are selected from Table 8. Also, rule number 10, and 14 are being discarded from Table 9 as they have an accuracy of less than 65%. Finally, 12 rules are selected from Table 9.

According to the analysis, hypertensive and coronary heart disease has each 10 candidacy rules, whereas heart failure has 06 candidacy rules. Similarly, 15 candidacy rules are selected for potential patients, and 12 candidacy rules

Table 5 Decision rules of hypertensive heart disease using proposed CSRS hybridization

Rule No.	Description	Support	Strength (%)	Accuracy (%)
1	If $p_4 = 2$, $p_5 = 1$ & $p_8 = 3$ then $d = 1$	10	18.87	100
2	If $p_1 = 2$ & $p_6 = 2$ then $d = 1$	7	13.21	100
3	If $p_1 = 1$, $p_3 = 4$ & $p_5 = 1$ then $d = 1$	5	9.43	97
4	If $p_4 = 2$ & $p_6 = 2$ then $d = 1$	6	11.32	100
5	If $p_1 = 1$, $p_5 = 1$ & $p_7 = 1$ then $d = 1$	5	9.43	97
6	If $p_3 = 2$, $p_4 = 2$ & $p_8 = 3$ then $d = 1$	1	1.89	63
7	If $p_1 = 3$, $p_3 = 3$, $p_5 = 3$ & $p_8 = 2$ then $d = 1$	1	1.89	67
8	If $p_1 = 3$, $p_4 = 2$, $p_5 = 3$ & $p_{11} = 2$ then $d = 1$	4	7.55	83
9	If $p_1 = 2$, $p_5 = 2$ & $p_6 = 3$ then $d = 1$	9	16.98	100
10	If $p_3 = 3$, $p_4 = 2$ & $p_8 = 3$ then $d = 1$	1	1.89	43
11	If $p_1 = 2$, $p_3 = 4$, $p_4 = 1$, & $p_5 = 1$ then $d = 1$	1	1.89	100
12	If $p_3 = 3$, $p_6 = 3$, $p_7 = 2$, $p_8 = 2$ & $p_{11} = 3$ then $d = 1$	1	1.89	67

Table 6 Decision rules of coronary heart disease using proposed CSRS hybridization

Rule No.	Description	Support	Strength (%)	Accuracy (%)
1	If $p_1 = 4$, $p_3 = 4$, $p_5 = 2$ & $p_7 = 1$ then $d = 2$	12	25.53	100
2	If $p_1 = 4$, $p_3 = 4$, $p_4 = 1$, $p_5 = 1$ & $p_7 = 1$ then $d = 2$	9	19.15	100
3	If $p_3 = 4$, $p_4 = 1$ & $p_6 = 1$ then $d = 2$	11	23.40	100
4	If $p_1 = 2$, $p_6 = 3$, $p_8 = 1$ & $p_{11} = 3$ then $d = 2$	2	4.26	87
5	If $p_1 = 4$, $p_5 = 2$ & $p_8 = 1$ then $d = 2$	8	17.02	100
6	If $p_6 = 2$, & $p_{11} = 1$ then $d = 2$	4	8.51	97
7	If $p_5 = 2$, $p_7 = 1$ & $p_{11} = 1$ then $d = 2$	14	29.79	100
8	If $p_1 = 1$ & $p_3 = 1$ then $d = 2$	1	2.13	37
9	If $p_4 = 2$, $p_5 = 1$, $p_7 = 1$ & $p_{11} = 2$ then $d = 2$	2	4.26	87
10	If $p_3 = 1$, $p_8 = 1$ & $p_{11} = 2$ then $d = 2$	1	2.13	67
11	If $p_3 = 3$, $p_5 = 1$, $p_7 = 2$, $p_8 = 1$ & $p_{11} = 2$ then $d = 2$	1	2.13	67
12	If $p_3 = 2$, $p_7 = 2$ & $p_8 = 2$ then $d = 2$	1	2.13	57

Table 7 Decision rules of heart failure using proposed CSRS hybridization

Rule No.	Description	Support	Strength (%)	Accuracy (%)
1	If $p_3 = 3$, $p_5 = 2$, & $p_7 = 2$ then $d = 3$	22	52.38	100
2	If $p_1 = 4$, $p_3 = 4$, $p_5 = 3$, $p_7 = 1$, $p_8 = 1$ & $p_{11} = 3$ then $d = 3$	2	4.76	87
3	If $p_3 = 2$, $p_4 = 1$, $p_7 = 2$ & $p_8 = 1$ then $d = 3$	1	2.38	57
4	If $p_3 = 3$, $p_5 = 1$ & $p_{11} = 1$ then $d = 3$	1	2.38	57
5	If $p_3 = 4$, $p_4 = 2$, $p_5 = 3$, $p_7 = 1$ & $p_{11} = 2$ then $d = 3$	2	4.76	87
6	If $p_1 = 4$, $p_3 = 3$, $p_5 = 1$, $p_7 = 1$ & $p_8 = 2$ then $d = 3$	1	2.38	87
7	If $p_1 = 4$, $p_5 = 3$, $p_7 = 1$, $p_8 = 2$ & $p_{11} = 2$ then $d = 3$	2	4.76	87
8	If $p_3 = 3$, $p_5 = 1$ & $p_6 = 2$ then $d = 3$	1	2.38	57
9	If $p_1 = 4$, $p_3 = 4$, $p_7 = 2$, $p_8 = 3$ & $p_{11} = 3$ then $d = 3$	1	2.38	100

Table 8 Decision rules of potential heart patient using proposed CSRS hybridization

Rule No.	Description	Support	Strength (%)	Accuracy (%)
1	If $p_1 = 3$ & $p_6 = 1$ then $d = 4$	20	30.77	100
2	If $p_1 = 3$, $p_4 = 1$ & $p_7 = 2$ then $d = 4$	2	3.08	100
3	If $p_1 = 4$, $p_5 = 1$, $p_8 = 3$ & $p_{11} = 2$ then $d = 4$	2	3.08	87
4	If $p_1 = 4$, $p_4 = 2$ & $p_5 = 1$ then $d = 4$	4	6.15	97
5	If $p_6 = 2$, $p_7 = 2$, $p_8 = 1$ & $p_{11} = 3$ then $d = 4$	1	1.54	67
6	If $p_3 = 2$, $p_5 = 1$ & $p_{11} = 3$ then $d = 4$	1	1.54	37
7	If $p_1 = 3$, $p_3 = 3$, $p_5 = 3$ & $p_8 = 3$ then $d = 4$	1	1.54	47
8	If $p_1 = 4$, $p_6 = 2$, $p_7 = 2$ & $p_{11} = 2$ then $d = 4$	2	3.08	77
9	If $p_7 = 2$ & $p_{11} = 4$ then $d = 4$	1	1.54	37
10	If $p_1 = 3$, $p_3 = 2$ & $p_{11} = 2$ then $d = 4$	1	1.54	77
11	If $p_1 = 4$, $p_3 = 3$, $p_5 = 1$, $p_6 = 3$ & $p_{11} = 3$ then $d = 4$	2	3.08	67
12	If $p_1 = 3$, $p_8 = 2$ & $p_{11} = 3$ then $d = 4$	2	3.08	67
13	If $p_1 = 1$, $p_4 = 2$ & $p_8 = 1$ then $d = 4$	1	1.54	57
14	If $p_6 = 2$, $p_8 = 2$ & $p_{11} = 3$ then $d = 4$	1	1.54	77
15	If $p_3 = 3$, $p_5 = 1$ & $p_8 = 3$ then $d = 4$	3	4.62	67
16	If $p_3 = 3$, $p_4 = 2$ & $p_8 = 1$ then $d = 4$	2	3.08	77
17	If $p_3 = 2$, $p_5 = 3$ & $p_8 = 1$ then $d = 4$	5	7.69	87
18	If $p_5 = 2$, $p_6 = 3$, $p_7 = 2$ & $p_8 = 3$ then $d = 4$	1	1.54	67
19	If $p_3 = 3$, $p_5 = 3$, $p_7 = 1$, $p_8 = 2$ & $p_{11} = 3$ then $d = 4$	1	1.54	77

Table 9 Decision rules of cardiomyopathy heart disease using proposed CSRS hybridization

Rule No.	Description	Support	Strength (%)	Accuracy (%)
1	If $p_3 = 3$, $p_5 = 2$ & $p_7 = 1$ then $d = 5$	8	17.02	100
2	If $p_1 = 3$, $p_4 = 1$, $p_8 = 3$ & $p_{11} = 3$ then $d = 5$	2	4.26	100
3	If $p_7 = 1$ & $p_{11} = 4$ then $d = 5$	5	10.64	97
4	If $p_1 = 2$, $p_3 = 3$ & $p_{11} = 2$ then $d = 5$	3	6.38	87
5	If $p_3 = 2$, $p_5 = 3$, $p_8 = 2$ & $p_{11} = 3$ then $d = 5$	1	2.13	100
6	If $p_1 = 3$, $P_3 = 4$, $P_8 = 2$ & $p_{11} = 2$ then $d = 5$	1	2.13	100
7	If $p_3 = 2$, $p_4 = 1$, $p_7 = 1$ & $p_8 = 3$ then $d = 5$	2	4.26	67
8	If $p_3 = 3$, $p_7 = 2$, $P_8 = 2$ & $P_{11} = 2$ then $d = 5$	2	4.26	47
9	If $p_1 = 3$, $p_6 = 3$, $P_7 = 1$, $P_8 = 1$ & $p_{11} = 3$ then $d = 5$	2	4.26	67
10	If $p_3 = 4$, $p_4 = 2$, $P_5 = 3$, $P_7 = 2$ & $p_{11} = 3$ then $d = 5$	2	4.26	47
11	If $p_3 = 2$, $p_5 = 1$, $P_7 = 1$ & $p_8 = 1$ then $d = 5$	1	2.13	100
12	If $p_1 = 3$, $p_3 = 4$ & $p_6 = 2$ then $d = 5$	1	2.13	77
13	If $p_1 = 4$, $p_3 = 3$, $p_4 = 1$, $P_5 = 3$ & $p_8 = 3$ then $d = 5$	1	2.13	87
14	If $p_3 = 4$, $p_5 = 3$, $p_7 = 2$, $P_8 = 2$ & $P_{11} = 3$ then $d = 5$	1	2.13	47

are selected for cardiomyopathy. In total, 53 candidacy rules are further tested with the testing dataset of 271 objects. The testing dataset consists of 59 cases of hypertensive heart disease, 57 cases of coronary heart disease, 43 cases of heart failure, 61 cases of potential patients, and 51 cases of cardiomyopathy heart disease. Further confusion matrix and F-measure are computed. The computation accuracy of CSRS hybridization model is presented in Table 10.

A comparative study

This section compares the results with the rough set (RS) [16] model. The training dataset of 271 objects is analyzed using rough set with all features of the information system. The total number of rules generated using rough set is 86, of which 7 rules are discarded on imposing threshold. The total number of rules finally selected using RS for testing analysis is 79. On the otherhand, the total number of rules finally selected using CSRS for testing analysis is 53. It indicates that the proposed CSRS hybridization technique generates 32.91% fewer rules as compared to RS technique. Keeping view the length of this article, the rules generated through RS technique are waived out.

Further, to compare in terms of accuracy, we have computed the confusion matrix. For computing the accuracy, the testing dataset consisting of 59 cases of hypertensive heart disease, 57 cases of coronary heart disease, 43 cases of heart failure, 61 cases of potential patients, and 51 cases of cardiomyopathy heart disease are considered. The confusion matrix about the rough set technique is presented in Table 11. From the analysis, it is clear that the accuracy of the rough set technique is 92.1% whereas the accuracy of CSRS hybridization is 93.7%. It means the proposed CSRS technique is having 1.6% more accuracy than the rough set technique. For better visualization, precision, recall, and accuracy of both the models are depicted in Fig. 6.

Furthermore, we have compared with cuckoo search integrated with decision tree predictive learner (CSDTPL)

Table 10 Computation of accuracy and F-measure for CSRS hybridization model

Decision	TP	FN	FP	TN	Precision	Recall	Accuracy (%)	F-Measure
Hypertensive heart disease ($d = 1$)	45	6	8	212	0.849	0.882	94.8	0.865
Coronary heart disease ($d = 2$)	47	4	6	214	0.886	0.921	96.3	0.903
Heart failure ($d = 3$)	25	7	11	228	0.694	0.781	93.3	0.734
Potential patient ($d = 4$)	41	9	11	210	0.788	0.820	92.6	0.803
Cardiomyopathy heart disease ($d = 5$)	28	10	13	220	0.682	0.736	91.5	0.707
Total	186	36	49	1084	0.791	0.837	93.7	0.813

Table 11 Computation of accuracy for crisp rough set model

Decision	TP	FN	FP	TN	Precision	Recall	Accuracy (%)	F-Measure
Hypertensive heart disease ($d = 1$)	41	7	11	212	0.788	0.854	93.3	0.818
Coronary heart disease ($d = 2$)	42	6	9	214	0.823	0.875	94.5	0.848
Heart failure ($d = 3$)	23	8	12	228	0.657	0.742	92.6	0.696
Potential patient ($d = 4$)	34	11	16	210	0.680	0.755	90.0	0.715
Cardiomyopathy heart disease ($d = 5$)	25	11	15	220	0.625	0.694	90.4	0.657
Total	165	43	63	1084	0.723	0.793	92.1	0.756

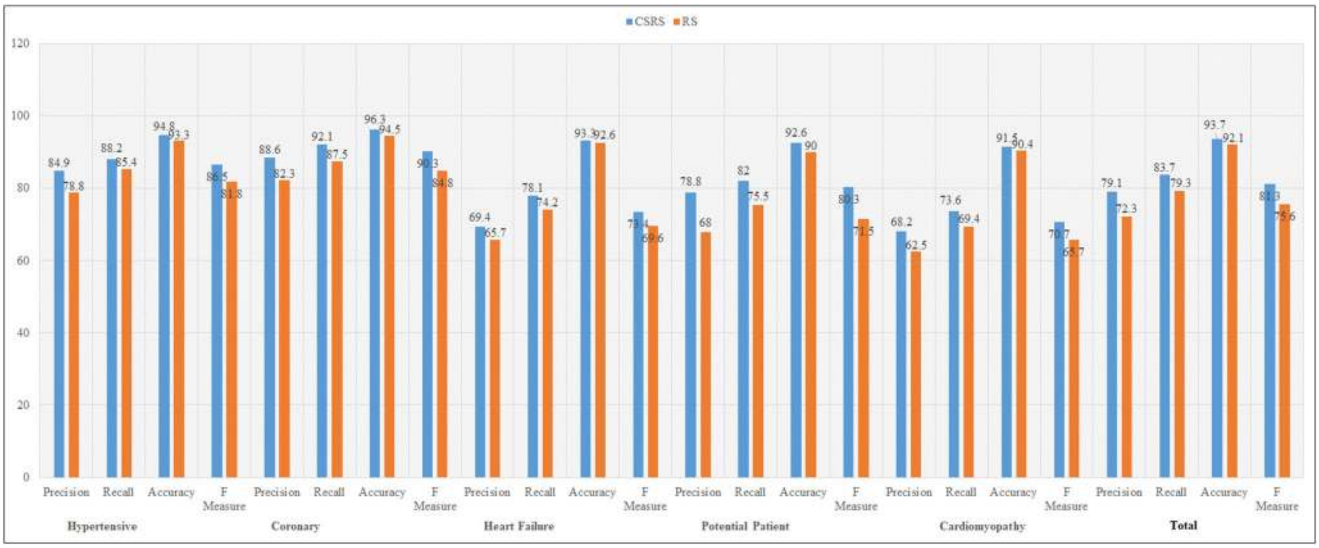


Fig. 6 Precision, recall, accuracy, and F measure of both CSRS and RS model

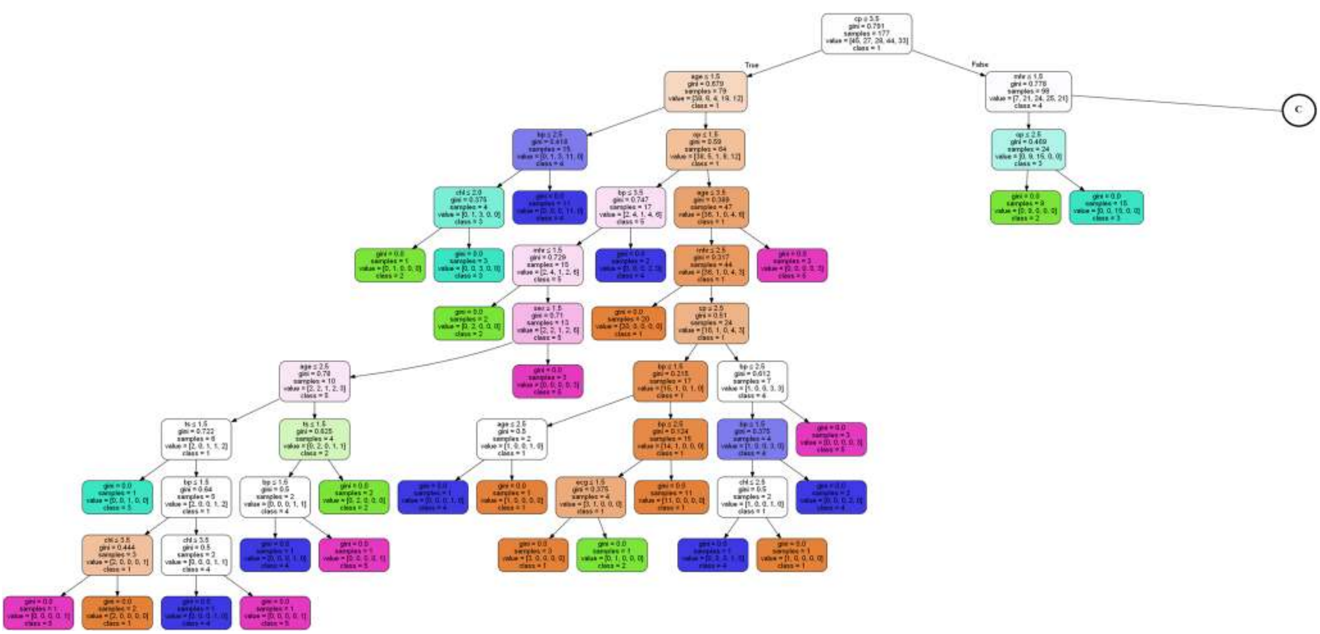


Fig. 7 Decision tree of CSDTPL model (part 1)

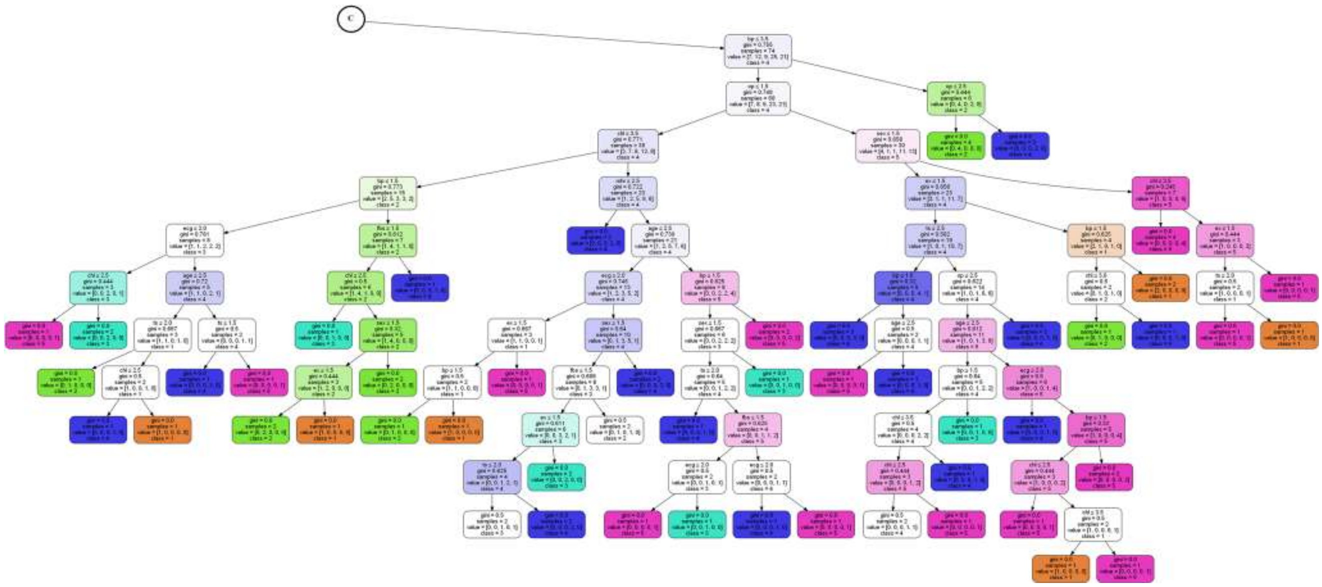


Fig. 8 Decision tree of CSDTPL model (Part 2)

[36] model. Decision tree predictive learner is a popular classification algorithm that enhances the quality of medical data. Additionally, domain knowledge and preprocessing of raw data is not required in decision tree and can handle huge amount of data. This is the prime reason for which we have integrated cuckoo search with decision tree predictive learner for comparative analysis. The results obtained are easily interpreted as association rules and can be read from decision trees. In such cases, given data is summarized in a tree structure where the topmost is considered as root which represents the result into two or more mutually exclusive subsets depends on the results. The top edge of the node is connected to its parent node and the bottom edge is connected to its child nodes or leaf nodes in the internal nodes. Internal nodes represent an association between feature values and decision attributes. Leaf node will give the final classification results. The decision tree obtained is too large and splitted into two decision trees with a connector symbol. The results obtained is presented in Figs. 7 and 8. The accuracy obtained is 90.33%. Hence it is clear that integration of cuckoo search and rough set gives better result as compared to traditional rough set and cuckoo search integration of decision tree predictive learner.

Besides we have computed the precision, recall, F-measure, and accuracy of CSDTPL method and is presented in Table 12. From Table 12 it is clear that the accuracy of the model is 90.33%. It is clear from the analysis that CSDTPL achieves accuracy of 90.33% whereas rough set achieves accuracy of 92.1%. The proposed CSRS model achieves accuracy of 93.7%. It indicates that proposed CSRS model has higher accuracy of 1.6% than rough set model. Similarly proposed CSRS model has better accuracy of 3.37% than CSDTPL model. For better visualization the accuracy of rough set (RS), CSDTPL, and proposed CSRS model is presented in Fig. 9.

Table 12 Computation of accuracy for CSDTPL model

Decision	TP	FN	FP	TN	Precision	Recall	Accuracy (%)	F-Measure
Hypertensive heart disease ($d = 1$)	31	19	9	212	0.775	0.620	89.6	0.688
Coronary heart disease ($d = 2$)	40	8	9	214	0.816	0.833	93.7	0.824
Heart failure ($d = 3$)	21	10	12	228	0.636	0.677	91.8	0.656
Potential patient ($d = 4$)	30	14	17	210	0.638	0.681	88.5	0.659
Cardiomyopathy heart disease ($d = 5$)	18	18	15	220	0.545	0.500	87.8	0.521
Total	140	69	62	1084	0.693	0.669	90.3	0.681

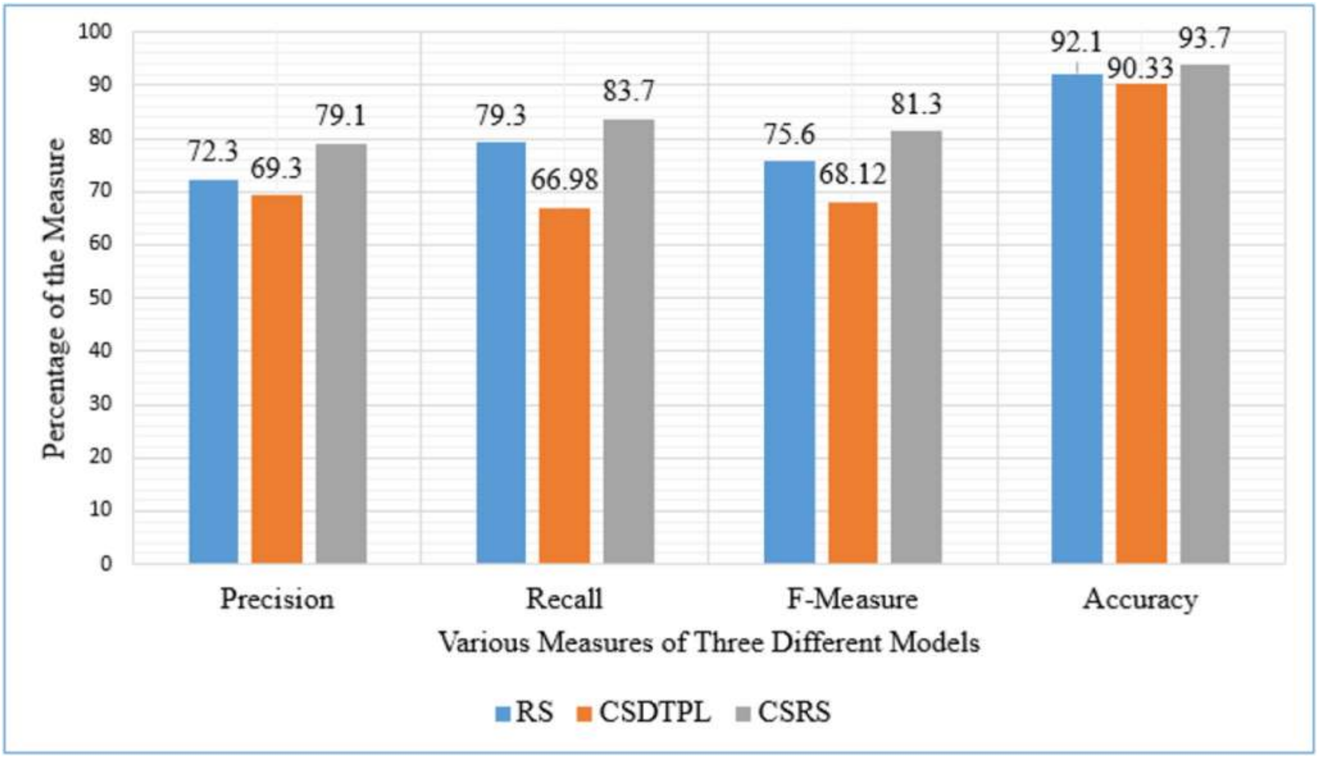


Fig. 9 Graph of comparative analysis

Conclusion

Data are generated from health sector every moment at a higher speed. Additionally, it contains uncertainties. Analyzing this data to get some meaningful information is challenging. To this end in this paper, we have hybridized cuckoo search with the rough set (CSRS) for knowledge inferencing. The proposed model, CSRS, is analyzed over heart dataset and compared with the rough set model. The overall accuracy of the proposed CSRS model is 93.7%, which is 1.6% higher than the rough set model. Additionally, the accuracy of proposed CSRS model is 3.37% higher than the CSDTPL model. Besides the proposed model, CSRS generates only 53 rules during rule generation phase, whereas rough set generated 79 rules during rule generation phase. It indicates that the proposed model, CSRS, minimizes the rule generation procedure. It generates 32.91% fewer rules than the traditional rough set model. Therefore, it is clear that the proposed CSRS model is better as compared to the rough set and CSDTPL model. While analyzing in the real scenario, it is a great help to the physicians to take right decisions. The integration of rough set and cuckoo search approach can be further extended to fuzzy rough set and cuckoo search approach. On introducing the concept of hesitation, it can further be extended to intuitionistic fuzzy rough set and cuckoo search approach for diagnosis of diseases.

Compliance with Ethical Standards

Conflict of interests First Author declares that he has no conflict of interest. Second Author declares that he has no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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