DYNAMIC CONTEXT ADAPTATION FOR DIAGNOSING THE HEART DISEASE IN HEALTHCARE ENVIRONMENT USING OPTIMIZED ROUGH SET APPROACH

G.NaliniPriya[1], A.Kannan[2] and P.Ananahakumar[3]

[1] Research scholar ,Department of IST, Anna University, Chennai
nalini.anbu@gmail.com
[2]Professor, Department of IST, Anna University, Chennai
[3]AssociateProfessor, Department of IT, Anna University, Chennai

ABSTRACT

In a smart medical environment, the ability to adapt context is critical. Context adaptation (CA) requires applications to delegate adaptation control to an entity that can receive state information and trigger adaptation in multiple applications. Thus, the idea of CA is to extract general knowledge from each contextualized system or medical dataset and to use it, in adapted form, when facing a similar problem in a different environment. In this paper, we describe a model for providing smart intelligent diagnosing services to the healthcare Environment and present work on our own architecture that has been designed to meet the key requirements of healthcare in a context-aware adaptive applications. The proposed system is capable of providing context intelligence, Decision Making, adaptability and extensible application framework for dynamic remote healthcare environments. The objective of the research is to revolutionize daily human life by making people's surroundings flexible and adaptive.

KEY WORDS

Context adaptations, CAD(coronary artery disease),Heart disease dataset , Context Aware Services, context service discovery, rough set, Fuzzy set.

1. INTRODUCTION

The context [4] is defined as the interrelated conditions in which something exists or occurs. This means that context is the mutual relationship between the many conditions that exist in a given situation in which some actor exists or an event occurs. Context-aware [19] applications look at the who's, where's, when's and what's (that is, what the activities are occurring) of entities and use this information to determine why a situation is occurring. An application does not actually determine why a situation is occurring, but the designer of the application does .The designer uses

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incoming context to determine why a situation is occurring and uses this to encode some action in the application.

1.1 General structure of context

The structure of the context mainly has User, Social environment, Task, Condition, Infrastructure, Location categories. When compare together these two lists of categories resembles each other very much. But there are minor differences such as time which is not apparent in the list given by [6]Schmidt et al. and the more differentiated physical environment which is in the list by Dey[5] et al. is captured in one item e.g. Location.All actions carried out by a human are taking place in context - in a certain situation. All contexts and situations are embedded in the world, but the perception of the world is dictated by the immediate context someone is in. Explicit user interaction with an application is embedded into the context of the user and is also a way of extending the context of the user, e.g. by having access to the [6]network.

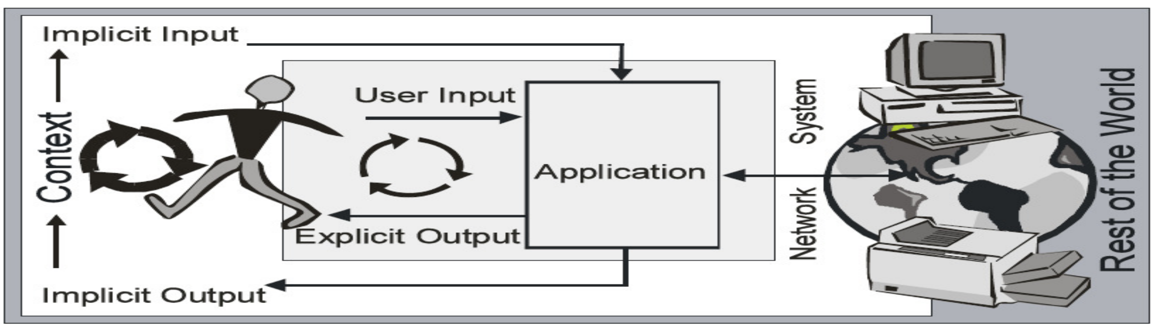

Figure 1.Implicit Human Computer Interaction Model

1.2 About the Heart disease Dataset

Heart disease, which is usually called coronary artery disease (CAD), is a term that can refer to any condition that affects the heart. CAD is a chronic disease [14][15] in which the coronary arteries gradually hardens and narrow. It is the most common form of cardiovascular disease. Moreover, cardiovascular disease is the biggest killer of the world. While many people with heart disease have symptoms such as chest pain , fatigue and breathing discomfort etc.. The data generally used for diagnosing the CAD will be multivalent in nature. Having so many factors to analyse to diagnose the heart diseases, physicians generally make decisions by evaluating the current test results of the patients. The previous decisions made on other patients with the same condition are also examined by the physicians. These complex procedures are not easy when considering the number of factors that the physician has to evaluate. So, diagnosing [16] [17] the heart disease of a patient involves experience and highly skilled physicians. In this paper we have taken few of the major symptoms of Heart disease and trying to give solution through Context awareness and Rough set with our own Architecture.

1.3 Context Adaptation

Context adaptation (CA) is a knowledge engineering technique that deals with the instantiation of a universal model to a context-dependent system [1][2]. While the universal model usually represents versatile knowledge that can be reused in several different environments, the context-dependent system is a specialized version of the model that is properly suited to work in a specific environment. The use of CA is motivated by the observation that many real-world problems are common to different environments, exhibiting independent and similar patterns. Thus, the idea of CA is to extract general knowledge from each contextualized system and to use it, in adapted form, when facing a similar problem in a different environment.

1.4 Basic Rough Set Theory

The main concept of rough set [13] theory is an indiscernibility relation associated with a set of attributes. Cases with the same attribute profile are grouped to form elementary sets. Cases within each elementary set are indiscernible. Any finite union of elementary sets is a definable set. If a set of attributes does not contain any redundant information (no redundant attributes), it is a minimal set or a reduct. Once reducts are established, rules are generated linking the variables to the outcome on a development sample. These rules are then applied to new data and the classification rate is determined and the relative importance of variables to outcomes can be discerned.

Rough Set Theory deals with information represented by a table called an information system, which consists of objects and attributes. An information system is composed of a 4-tuple as following S = (U, A, V; f) where U is the universe, a finite set of N objects where {X1, X2, .., N}, A = C U D is condition attribute V is attribute value. f: U x A - V is the total decision function called the information function. upper and lower approximation is an important concept in Rough Set Theory.

2. PROPOSED WORK

In this paper, we define a new context Architecture model named DYCOD (Dynamic context Adaptation).This Model will provide a dynamic context adaptation for CAD (coronary artery disease) Dataset using Roughest Theory. We divide the entire execution into problem of context adaptation and problem solution through roughset Theory. Here context awareness is combined with the service discovery mechanism to render better adaptive context aware services to the CAD (coronary artery disease) Patients.

2.1 The Dycoad Generic Model Approach

The Proposed work starts with user needs. The context information (value) is detected from the context communication devices. This will be recorded in the administration department and the context values are classified according to the priority of the request. Then the attributes may be checked with validity through reasoning algorithm. The history of the context data is analyzed and stored in the context repository. The information will be retrieved based on the request. The Value of the attribute check for completeness i.e. all the value will be ensuring that it contains full set of value for the each set of contexts. If any of the value is missing in the attribute, it is treated as a partial context. Then it'll be solved with Roughest[5][7] Algorithm. If the value is perfectly match with context data previously stored, then the requested context may be provided to the user.

The objective of the proposed work is to revolutionize the human life by making people flexible and adaptive .In this paper the roughset theory and contexts adaptation is experimented in the guise of healthcare application especially for Heart disease patients. The key goal of the Dycoad architecture is to sense the context, understand the context and retrieve services, which might be useful or relevant to the patient needs, and which are ranked by the relevance for the individual patient's special need.

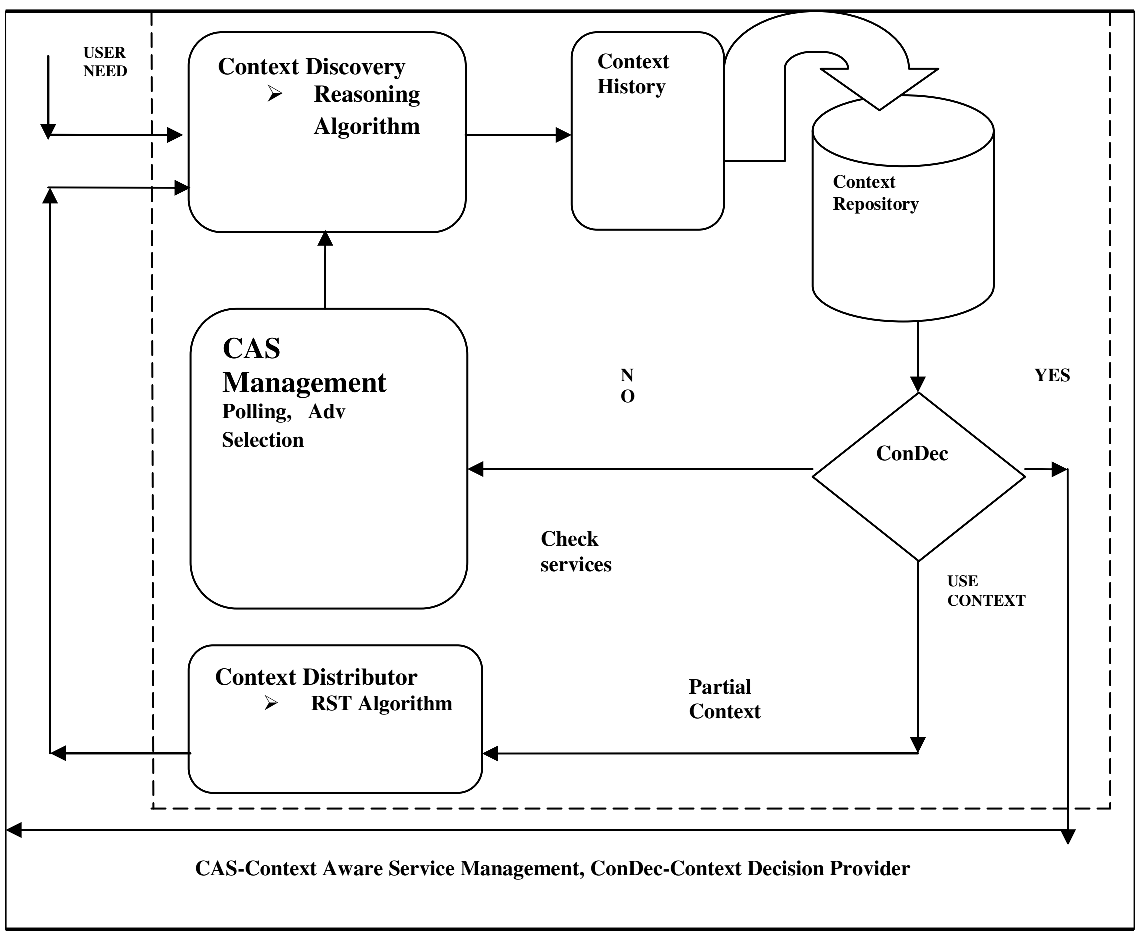

Figure. 2 Simple layout of Dycoad Architecture.

The requested services are provided according to the user need with respect to contexts(eg person context, disease context, place context….) The context aware service [29][30]model Dycoad find the right services when they are needed, either on demand or when new services are provided. This is like an integrated automated information push and pulls cycle.

A successful Dycoad context model of health information is proposed here to achieve the good contextual knowledge over the health domain. The recent convergence of ubiquitous computing and context-aware computing has seen a considerable rise in interest in various context-aware applications especially in medical environment based on the context. Context information gathered from various Context[8][9][10] aware Service directory is the basis for enmeshing ubiquitous computing into our daily lives and exhibiting the autonomy of applications. Storing and acquiring such information in a single smart controller can be easily handled by a centralized context repository. However, handling large-scale context information over multiple smart controllers requires appropriate context lookup architecture. Distributing objects to multiple controllers in a wide-area network does provide a scalable and reliable solution.

2.2 Rough set Theory Based Approach for Context Adaptation

Inconsistent data sets are handled by rough set theory using lower and upper approximations for every concept. These approximations are definable using existing attributes. Furthermore, from the concept lower and upper approximations certain and possible rule sets are induced using one technique of data mining called rule induction. Generally, input data sets are frequently incomplete, i.e., some attribute values are missing. In other words, corresponding decision tables are incomplete.

In general, in data mining two approaches are used to handle incomplete data. The first one is pre-processing of input data and then main processing of data mining such as rule induction. Typically, pre processing deals with replacing the missing attribute values by the most common value, ignoring cases with missing attribute values, etc. The second one is _knowledge is acquired directly from incomplete data sets taking into account that some attribute values are missing. Typical systems using this approach are C4.5 and MLEM2.

In this paper rule induction approach is performed directly from incomplete data. Furthermore, it is assumed that there are two reasons for data to be incomplete. The first reason is that an attribute value, for a specific case, is lost. This may happen when the original value was erased or mistakenly not included into the data set. The second reason for incompleteness is based on the lack of relevance. For example, it was possible to diagnose a patient using only selected results of tests (attributes), while other test results were redundant. Such missing attribute values will be called "do not care" conditions.

2.3 Decision Making Using Rough Set

It is assumed that in the same decision table some attribute values are lost and some are "do not care" conditions [15] from the view point of rough set theory where a method for rule induction was introduced in which each missing attribute value was replaced by all values from the domain of the attribute.

Originally such values were replaced by all values from the entire domain [11][12] of the attribute, selected results of tests (attributes), while other test results were redundant. Such missing attribute values will be called "do not care" conditions.

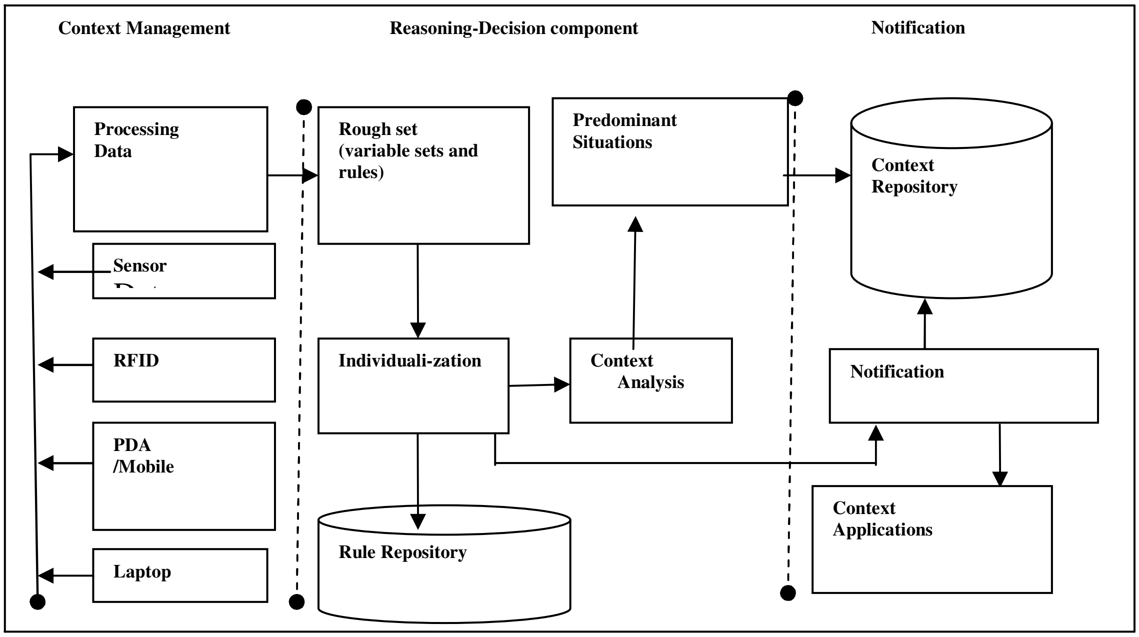

Figure. 3 Decision making using rough set

For incomplete decision tables, for a given characteristic relation and the concept, there are three different possible ways to define lower and upper approximations, called singleton, subset, and concept approximations. As it was observed in singleton lower and upper approximations are not applicable in these Dycoad Architecture blocks of attribute-Value Pairs, Characteristic Sets, and Characteristic Relation: In the sequel it is assumed that all decision values are specified, i.e., they are not missing. Also, it is assumed that all missing attribute values are denoted by "?" and by"*", lost values will be denoted by "?" and "do not care" conditions will be denoted by "*". Additionally, another assumption for each case is at least one attribute value should be specified.

2.4 Case study – Decision making from incomplete data

For incomplete decision tables [12]13][14]1the definition of a block of an attribute-value pair must be modified. For the example of an incomplete data set from Table 1.

· If an attribute a there exists a case x such that (x, a) = ? i.e., the corresponding value is lost, then the case x should not be included in any block [(a, v)] for all values v of attribute a.

·If for an attribute a there exists a case x such that the corresponding value is a "do not care" condition, i.e., (x, a) = *, then the corresponding case x should be included in blocks [(a, v)] for all specified values v of attribute a.

[(Chest Pain, high)] = {1, 4, 5, 8},
[(Chest pain, very high)] = {2, 8},
[(Chest pain, normal)]= {6, 7, 8},

[(Breathing Discomfort, yes)] = {2, 4, 6, 8},

The characteristic set KB(x) is the intersection of blocks of attribute-value pairs (a, v) for all attributes a from B for which_(x, a) is specified and (x,a) = v.

Table 1.Incomplete decision table

Case	Attributes		
	Chest Pain	Breathing Discomfort	Sweating
Patient 1	High	?	No
Patient 2	Very high	Yes	Yes
Patient 3	?	No	No
Patient 4	High	Yes	Yes
Patient 5	High	?	Yes
Patient 6	Tolerable	Yes	No
Patient 7	Tolerable	No	Yes
Patient 8	*	Yes	*

KA(1) = {1, 4, 5, 8} ∩ {1, 3, 6, 8} = {1, 8},
KA(2) = {2, 8} ∩ {2, 4, 6, 8} ∩ {2, 4, 5, 7, 8} = {2, 8},
KA(3) = {3, 7} ∩ {1, 3, 6, 8} = {3},
KA(4) = {1, 4, 5, 8} ∩ {2, 4, 6, 8}∩{2, 4, 5, 7, 8} = {4, 8},
KA(5) = {1, 4, 5, 8} ∩ {2, 4, 5, 7, 8} = {4, 5, 8},
KA(6) = {6, 7, 8} ∩ {2, 4, 6, 8} ∩ {1, 3, 6, 8} = {6, 8},
KA(7) = {6, 7, 8} ∩ {3, 7} ∩ {2, 4, 5, 7, 8} = {7}, and
KA(8) = {2, 4, 6, 8}.

Characteristic set KB(x) may be interpreted as the smallest set of cases that are indistinguishable from x using all attributes from B and using a given interpretation of missing attribute values. Thus, KA(x) is the set of all cases that cannot be distinguished from x using all attributes. The characteristic relation R(B) is a relation on U defined for x, y ϵ U as follows (x, y) ϵ R(B) if and only if y ϵ KB(x).The characteristic relation R(B) is reflexive but—in general—does not need to be symmetric or transitive. Also, the characteristic relation R(B) is known if characteristic sets KB(x) for all x ϵ U are known.

In our example(A) = {(1, 1), (1, 8), (2, 2), (2, 8), (3, 3), (4, 4), (4, 8), (5, 4), (5, 5), (5, 8), (6,6), (6, 8), (7, 7), (8, 2), (8, 4), (8, 6), (8, 8)}.

In our example presented in Table 1 let us say that B = A. Then the singleton A lower and A-upper approximations of the two concepts: {1, 2, 4, 8} and {3, 5, 6,7} are:

A{1, 2, 4, 8} = {1, 2, 4}, A{3, 5, 6, 7} = {3, 7},
A {1, 2, 4, 8} = {1, 2, 4, 5, 6, 8},A {3, 5, 6, 7} = {3, 5, 6, 7, 8}.

Note that A{1, 2, 4, 8} = {1, 2, 4}. But the set {1, 2, 4} is not A-globally definable. Furthermore, the set {1, 2, 4} is not even A-locally-definable, so no set of rules can cover precisely this set. Similarly, A {3, 5, 6, 7} = {3, 5, 6, 7, 8}, and the set {3, 5, 6, 7, 8} is also not A-locally-definable. Therefore, in general, singleton approximations should not be used for data mining. The second method of defining lower and upper approximations for complete decision tables uses another idea: lower and upper approximations are unions of elementary sets, subsets of U (Grzymala-Busse 2003). Therefore lower and upper approximations[15][16] for incomplete decision tables by analogy with the second definition of approximations is defined for completely specified data, using characteristic sets instead of elementary sets.

There are two ways to do this. Using the first way, a subset B-lower approximation of X is defined as follows:

BX=U { KB(X) | XϵU, KB(X)   X }
A subset B-upper approximation of X is
BX=U { KB(X) | XϵU, KB(X)∩X□ }

Since any characteristic relation R(B) is reflexive, for any concept X, singleton B lower and B-upper approximations of X are subsets of subset B-lower and B upper approximations of X, respectively. The second possibility is to modify the subset definition of lower and upper approximation by replacing the universe U from the subset definition by a concept X. A concept B-lower approximation of the concept X is defined as follows:BX=U { KB(X) | XϵU, KB(X) X } Obviously, the subset B-lower approximation of X is the same set as the concept B lower approximation of X. A concept B-upper approximation of the concept X is defined as follows:

BX=U { KB(X) | xϵX, KB(x)∩X□ }= U { KB(X) | xϵX}.

The concept B-upper approximations of X are subsets of the subset B-upper approximations of X. For the decision presented in Table 7.3, the concept A-lower and A-upper approximations are:A{1, 2, 4, 8} = {1, 2, 4, 8}, A{3, 5, 6, 7} = {3, 7}, A {1, 2, 4, 8} = {1, 2, 4, 6, 8},A {3, 5, 6, 7} = {3, 4, 5, 6, 7, 8}.For complete decision tables, all three definitions of lower approximations, singleton, subset and concept, coalesce to the same definition. Also, for complete decision tables, all three definitions of upper approximations coalesce to the same definition. This is not true for incomplete decision tables, as our example shows. Singleton B-lower and B-upper approximations of the set X are subsets of the subset B-lower and B-upper approximations of X, respectively. The subset Blower approximation of X is the same set as the concept B-lower approximation of X. The concept B-upper approximation of X is a subset of the subset B-upper approximation of X. The concept B-upper approximations are the smallest B definable sets containing X. Rules may be framed by using concept approximations which will have an another way of research avenue in the context computing.

The Example rule set

2, 3, 3
(Breathing Discomfort, yes) & (Sweating, yes)-> (Heart Disease, yes)
2, 2, 2
(Chest pain, high) & (Sweating, no) -> (Heart Disease, yes)
1, 3, 4
(Breathing Discomfort, yes) -> (Heart Disease, yes)
2, 1, 3
(Chest pain, high) & (Sweating, yes) -> (Heart Disease, yes)
1, 2, 3
(Chest pain, Tolerable) -> (Heart Disease, no)
1, 2, 2
(Breathing Discomfort, no) -> (Heart Disease, no)

Figure.4 Rule set

3. RESULTS AND DISCUSSION

3.1 Performance Analysis – Fuzzy Vs Rough set Based

This section evaluates the DYCOAD context model approach with the help of both fuzzy sets and rough sets. Previous section completely describes the roughest based approach. Similarly for fuzzy sets, Let Chest pain, Breathing Discomfort and Sweating are the separate fuzzy sets. Here we are making use of CAD (coronary artery disease) Dataset attributes. Then based on the if then rules of fuzzy set, if (Chest pain => high) and (Breathing Discomfort => yes) and (Sweating => yes) then patient => Heart Disease

Table 2. Comparative study Fuzzy Vs Rough set

Parameters	Rough set	fuzzy set
Decision making	95	80
missing data prediction	95	0
context intelligence	94	75
Supportability	88	70

if any one of the data is missing then it is said to be false condition. Hence the comparative study for fuzzy and roughest is shown Table2.All the entries of the Table2 is represented in Percentages.

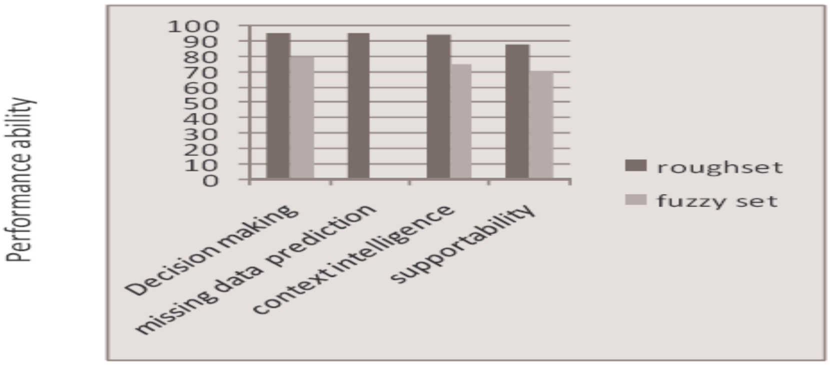

Figure 5 Performance analyses – Fuzzy Vs Rough set theory

4. CONCLUSION

In this paper, the context model is designed for CAD (coronary artery disease) dataset using a context-aware system .Knowledge inference engine is also proposed for context-aware applications. The reasoning performance ability of our approach showed that context modeling and development of inference rules are applicable for the wearable computing environment.

The above DYCOAD architecture improves the quality of the service discovery by providing specific node values and multiple inheritances. The rules are generated using roughest approach and it is proved that roughest will provide a good clarity around 90% over the incomplete data set compared to fuzzy set. Thus, the discussed issues and challenges in context aware service discovery platforms are alleviated with the help of the define DYCOAD approach, Rough set and CAD Dataset.

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