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Intelligent decision support system for dementia care through smart home

K.S.Gayathri[a,*], K.S.Easwarakumar[b]

[a]*Associate Professor, Department of Computer Science & Engineering, Sri Venkateswara College of Engineering, Sriperumbudur, 602 117, India*
[b]*Professor, Department of Computer Science & Engineering, Anna University, Chennai, 600 025, India.*

Abstract

As per the statistics of WHO (World Health Organization), major percentages of aged society across the globe are affected with memory related disease - dementia. The percentage of dement people would be doubled in future and hence assistive health care systems have become predominant. Smart home, an ubiquitous environment offers ambient assisted living to its occupant through activity recognition and decision making process. This research work proposes an assistive dementia care environment through smart home that aid mentally disabled people with many different types of assistance during emergency. The proposed system models "Intelligent Decision Support System" that identifies deviation of the occupant from their regular activities of daily routines and decides on appropriate alerts to handle these situations. Significant criterion to model dementia care is to handle incomplete event sequences (produced due to memory loss) and to model occupant specific knowledge (provided by the care taker / doctors). Markov Logic Network (MLN), an approach of statistical relational learning models uncertain data and domain knowledge within a single framework. Thus, the proposed approach of decision support system for dementia care effectively utilizes MLN for its modeling. The experimental study made with smart home dataset showcased the competence of MLN approach of decision making has higher F-measure than existing approaches.

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Keywords: Dementia care; Smart homes; Reasoning system; Activity recognition; Decision support system; Markov Logic Network;

1. Introduction

Dementia, an age related memory loss has affected an estimated 35 million people across the globe and is anticipated to be doubled by 2030[1]. Due to memory loss, dement occupant forget to complete their Activities of Daily Living (ADL) thereby require the intervention of care taker[2]. As time progresses, continuous monitoring and assisting dement occupant creates an overhead to the care taker. Therefore, an automated system for assistive care is essential for independent living and is possible through smart homes[3,4,5,6].

* K.S.Gayathri.
E-mail address: gayasuku@svce.ac.in

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Design of smart home has evolved into a significant research area with the development of sensor technology, wireless communications and machine learning strategies[3,7]. Sensing, reasoning and acting are the primary tasks involved in modeling smart home. Amongst all tasks, reasoning is one of central component that facilitate the integration of ambient intelligence into the environment through activity recognition and decision making[8,9,10]. Smart home modeled for dementia care requires extending activity recognition system to detect abnormality in occupant behavior to provide safe and secured living environment[4,11]. The design of intelligent decision support system is also crucial in dementia care as the system needs to decide on an action instantaneously to handle abnormalities in occupant behavior[12].

Uncertainty modeling and domain knowledge modeling are the two specific criteria that need to be addressed in the design of dementia care system[2]. Activities executed by the dement occupant are usually incomplete in nature and hence uncertainty modeling is required. Likewise, representation of personalized knowledge related to occupant's lifestyle together with his medical history can enhance the process of activity recognition and decision making in dementia care. Thus, the modeling strategy employed for the design of dementia care through smart home necessitates uncertainty and domain knowledge modeling. Probabilistic machine learning algorithms and knowledge engineering techniques can effectively model uncertain and domain specific knowledge respectively. Markov Logic Network (MLN)[13], a statistical relational learning approach integrates probabilistic machine learning algorithms and knowledge engineering techniques within a single framework and is innovately used in the proposed design of dementia care. Major contextual factors to cause abnormality in dementia care are identified as object, time, space and duration[14]. The MLN based activity recognition framework presented in this work[15] detects abnormality together with the contextual factors. The function of decision support system is to make quick decision on suitable action for the abnormality detected in a way to enhance the safety of the occupant in the environment.

Alerts are acceptable class of action preferred in dementia care for the reason that the dement occupant tend to forget to complete his activity in appropriate context of the environment. The alerts chosen for decision making process are rated as low alarm, high alarm and emergency alarm based on the direct attention required for secured living of the occupant. Low alarms are simple alarms where the occupant is alerted about certain task that he had forgotten to complete during his routine activity. For e.g. If the occupant executes 'Make Tea' in bedroom then an alert can be given to occupant about the performing activity in wrong location. High alarms are alarms that require attention of the care taker of the occupant to bring back the occupant to the normal state. For e.g. Occupant may be in lying position in kitchen for longer duration that requires intervention of the care taker. Emergency alarms are alerts that necessitate the need of doctors to make the occupant recover from critical state. Low, high and emergency alerts are the actions considered in modeling the proposed decision support system of dementia care.

The proposed research work provides a framework for modeling intelligent decision support system for dementia care through smart homes that chooses suitable alerts to handle abnormal activities using Markov Logic Network. The paper is organized as follows: Section 2 discusses the various existing approaches for modeling activity recognition and decision support system in smart homes. A detailed study of proposed MLN based decision support system for dementia care is presented in section 3. Experimental analysis of the proposed system in comparison with the existing system is summarized in section 4. The need for dementia care system and the distinctive characteristics of the proposed system is concluded in section 5.

2. Literature survey

Various data mining, machine learning and artificial intelligence strategies are employed for modeling activity recognition and decision support system in smart homes. This section provides a brief overview on each of these techniques in modeling smart home[16].

Occupants' are observed constantly in smart home through sensors owing to which enormous collection of sensor dataset is generated. To offer ambient assisted living, habitual patterns or ADL activities of the occupant are to be mined from sensor dataset. Such repeated patterns can be extracted through data mining techniques and later utilized to design recognition and decision making system. Frequent pattern mining and clustering[17] are the commonly used data mining approach. Apriori, FP-growth, Episode Discovery (ED) are the generally used frequent pattern mining approaches that extracts ADLs from dataset[8,18,19]. Clustering, unsupervised machine learning is another class of data mining algorithms that are employed to mine useful information from unlabelled datasets. Clustering discovers inherent characteristics of activities that are later assembled together to form clusters. K-means, fuzzy-C-means, pattern clustering are some of the commonly used clustering algorithms[20,19,21]. The other data modeling approaches in designing reasoning system are Artificial Neural Network (ANN), Decision Tree, Support Vector machine[19,22]. Many smart homes have been modeled using these approaches but they a limitation in modeling unambiguous and incomplete data. The issue of uncertainty modeling is addressed better through probabilistic machine learning approaches. Bayesian and Markov network are commonly used probabilistic graphical model to handle uncertainty. Smart homes are modeled either through Bayesian network or Markov network[19]. The probabilistic model learns the conditional dependencies among random variables to recognize activity with uncertain sensor data. Though it efficiently handles uncertainty through probabilistic reasoning, it has a limitation to represent additional contextual information about the occupant and the environment. Therefore knowledge engineering techniques are required to incorporate context based reasoning.

The knowledge representational approaches that is preferably engaged in smart home modeling are propositional, first order and description logic[19]. Domain knowledge through various logical formalisms is characterized in the form of rules. Resolution, subsumption, abduction and deduction are the inference mechanisms executed over the represented knowledge to carry out activity recognition[17]. Though, context based reasoning are better enabled through symbolic approaches, it has a constraint in modeling temporal and uncertain data.

Therefore, the activity recognition and decision support system in smart home requires a combined approach of data mining, statistical machine learning and symbolic approaches for its design. The existing approaches employ either data driven or knowledge driven approaches for the construction of activity recognition and decision support system. But none of these approaches integrate domain knowledge modeling and probabilistic modeling into a single framework. And more over dementia care is a use case to handle incomplete event sequence and representation of domain specific information. Markov Logic Network (MLN)[13,23] is preferred in the proposed design of intelligent decision support system to incorporate domain knowledge modeling and probabilistic modeling within a single framework.

3. Proposed MLN based decision support system for dementia care

The overall framework to model reasoning system in dementia care is shown in the Figure 1. The design of dementia care system is to perceive the environment and occupant's event through sensors and carry out reasoning through activity recognition and decision making. Markov Logic Network, a statistical relation learning approach is preferred for the design of dementia care as it enables context and probabilistic based recognition within a single framework. As shown in Figure 1, the MLN based reasoning system is subdivided into MLN based activity recognition system and MLN based decision support system. The role of the MLN based activity recognition system is to recognize the ongoing activity of the occupant and detect abnormal factors in occupant behavior. While, the role of MLN based decision support system is to decide on a rational action for the recognized abnormal activity. The case study on dementia exposes that the major contributing factors to abnormality in occupant behavior are location, time, duration and objects used in executing an activity. Thus, the sensed information from the environment is given to the MLN based activity recognition system to detect abnormality factors as shown in Figure 1 through a hierarchical approach[15]. The function of decision support system in dementia care is to make quick decision on suitable action for the abnormality detected in a way to enhance the safety of the occupant in the environment.

The proposed framework to model MLN based intelligent decision support system is shown in the Figure 2. The decision making process is made intelligent by employing MLN for its modeling. The construction of MLN based decision support system involves two steps namely: Representation of MLN structure and weight learning of MLN.

3.1. Markov Logic Network

Markov Logic Network is a statistical relational machine learning approach that integrates logical reasoning and symbolic reasoning within a single structure. MLN is described as a set of weighted first order rule where the first order rule enables domain knowledge modeling and weights of the rule enable probabilistic based reasoning[13]. First order rule comprises of soft and hard rules that differ in the way the output probability is calculated. Hard rules are infinite weighted first order rule that produces output only if all the predicates of the antecedent are satisfied. Whereas,

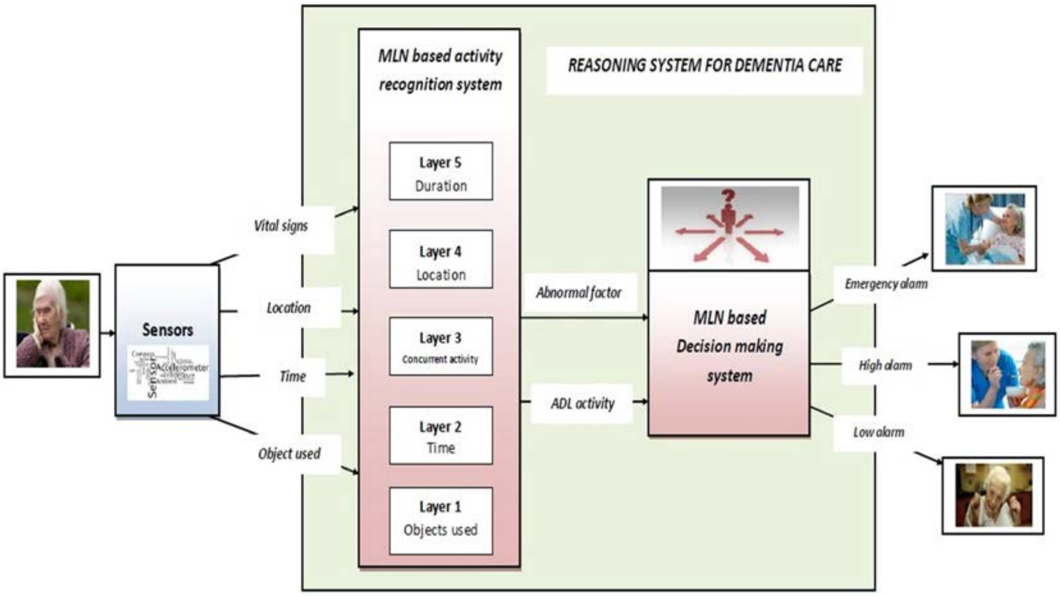

Fig. 1. Overall framework for dementia care through smart home

soft rules produce a probability value for its output that is computed based on the number of predicates satisfied in the antecedent together with the weight. The weighted first order rule is represented as F_i , where w_i represents the weights and f_i represents the predicates in rules. Markov network is constructed during run time from MLN with grounded atom. A joint probability distribution using equation 1 is calculated for the Markov network constructed that outputs the most probable action for abnormality detected. Since the approach of MLN provides the incorporation domain information through hard rules and probabilistic inference through soft rules, it is the optimal approach in the design of decision support system of dementia care.

$$P(X = x) = \frac{1}{Z} \exp(\sum_i w_i f_i(x_i)) \tag{1}$$

3.2. Representation of MLN structure

Representation of MLN structure is critical in the design of decision support system as it establishes an association between abnormality factors (object, location, time and duration) and actions (low, high and emergency alert). First order logic is the knowledge representational approach used to represent MLN structure. MLN is described as a set of weighted first order rule where first order rule comprises of soft and hard rules [13]. Both soft rules and hard rules are utilized in modeling MLN, where soft rules models from data while hard rules models from domain knowledge. Hard rules are essential to capture domain specific information of the occupant provided through care taker / doctors. The Table 1 depicts the structure of MLN (soft and hard rules) designed for modeling the proposed decision support system of dementia care.

From the study of dementia care, it is found that the most influencing factors for abnormality are objects used, location, time and duration of the activity [14]. Therefore it is essential for the soft rule to model these influencing abnormality factors for decision making. The *DMSR1* soft rule of the proposed MLN describes the influence of abnormality factors towards an action. While, the second soft rule *DMSR2* reveals that abnormality factors combined

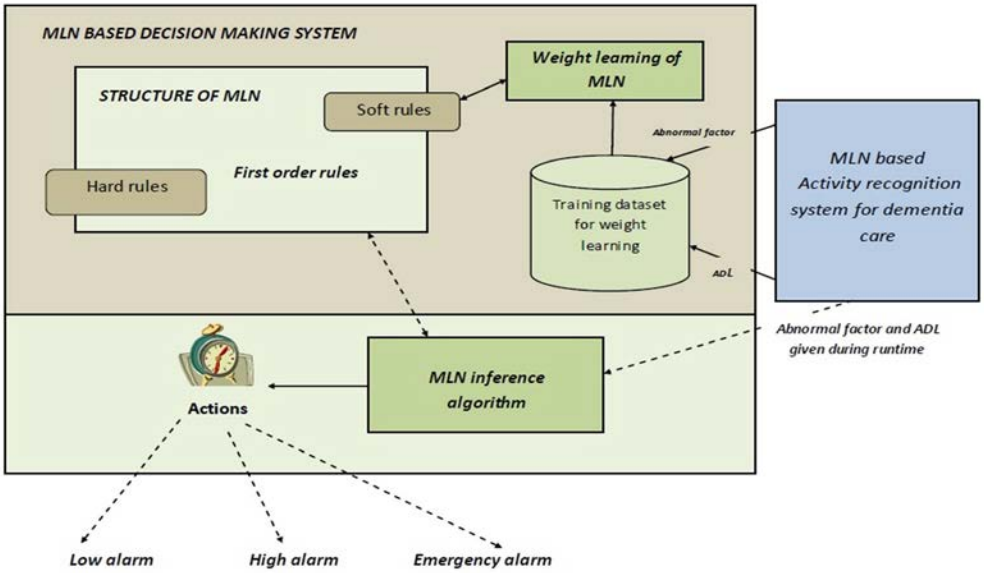

Fig. 2. Proposed MLN based decision support system for dementia care

Table 1. Soft and hard rule for MLN based decision support system

Rule number	Description
DMSR1	∀ ab ∈ Abnormal factor, ∀ ac ∈ Action: abnfactor(ab) → action(ac)
DMSR2	∀ ab ∈ Abnormal factor,∀ a ∈ ADL , ∀ ac ∈ Action: abnfactor(ab) ∧ ADL(a) → action(ac)
DMHR1	∀ a ∈ ADL : BP(high) ∧ ADL(a) → action(high alarm)
DMHR2	∀ ab ∈ Abnormal factor,∀ a ∈ ADL : BP(high) ∧ abnfactor(ab) ∧ ADL(a) → action(emergency alarm)

with ADL has more impact towards decision making. Decision support system will be able to provide better alerts if abnormality is combined with ADL. For e.g. if duration abnormality combined with 'Watching TV' ADL and 'Sleeping' ADL are dissimilar in terms of criticality and hence different alert are required for these situations. Low alert will be raised for 'Watching TV' and high alert will be raised 'Sleeping' ADL. The *DMSR2* is proficient to model these factors into decision support system.

The hard rules in dementia care precise information about the occupant and the environment. Any health care application requires modeling of human vital signals like glucose monitoring, oral, rectal, skin temperature, heart rate and blood pressure for decision making. The influence of these vital parameters towards decision making is better provided through the care taker or the doctors. Thus the proposed system represents hard rules to model the vital parameters in dementia care. Blood pressure is one of the vital parameter considered in the proposed design and the corresponding rules are given in the Table 1. *DMHR1* hard rule, maps high BP with ADL activity to raise high alarm whereas *DMHR2*, maps high BP together with abnormal factors require emergency alarm. There is no restriction on the number of hard rules to be implemented and it varies according to the requirement of doctors / care taker. This could be extended to model the other vital parameters by just including additional hard rules. The explicit specification of hard rule aids the reasoning system to become scalable model to model complex health care applications.

3.3. Weight learning of MLN

To enable probabilistic inference in decision making it is necessary that weights are learnt for the soft rules structured within the system. MLN based activity recognition system as shown in Figure 1 records ADLs and associated abnormality factors, if any. This recorded dataset are utilized by the weight learning algorithm of MLN to model facts about the influence of abnormality factor in decision making. The weights are learnt either through discriminative or generative learning algorithms and choice of the learning approach depends on the application considered for modeling. The proposed system prefers discriminative approach as it is suitable to model decision making process where weights are iteratively optimized to reflect the precision of data. The produced weighted first order rules represents the MLN based decision support system for dementia care.

3.4. Probabilistic inference over MLN based decision support system

During run time, probabilistic inference is done on the MLN based decision support system to decide on an appropriate alert for the given abnormality and ADL activity. A Markov network is constructed from MLN by grounding the predicates of abnormality and ADL. The joint probability distribution is calculated using equation 1 over the Markov Network constructed to enable probabilistic reasoning over the represented knowledge. Maximum-A-Posterior (MAP) query calculates the most probable action for the given abnormality using the equation 1.

4. Experimental study

Experimental analysis for the MLN based decision support system is conducted to evaluate the proficiency of the proposed system with respect to decision making process for dementia care. The events of the occupant obtained from smart home [24] is given as the input to the MLN based activity recognition system [15]. The primary function of the MLN based activity recognition system is to recognize the ongoing activity together with abnormality for the various sensor events [15]. The hierarchical approach of MLN based activity recognition system perform chronological detection over the dataset to recognize abnormal factors and modeled in a way that high priority factors are designed at lower layers of the system to enable quick decision. The abnormal activity identified is passed on to the intelligent decision support system to decide on the precised action to be taken for the recognized abnormality. Several runs of experiments were conducted with various test cases including abnormal and normal ADL of dement occupant obtained from smart home dataset [24] over MLN based activity recognition system and the corresponding abnormality factors were recorded. This dataset was labeled manually by the annotator to recommend suitable alert for the abnormal situation.

4.1. Experimental setup

Modeling MLN based decision support system is performed by utilizing 66% of the recorded data as training dataset and the remaining 34% of data as test dataset. The effectiveness of the proposed system to make an appropriate decision is measured by recording the number of True Positive, True Negative, False Positive and False Negative during the experimentation for various test cases. Precision, Recall and F-measure are the evaluation metrics used to measure the efficiency of the proposed system. The equation 2, 3 and 4 are formula to calculate Precision, Recall and F-measure.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F - Measure = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Alchemy [25], open source software for modeling MLN was utilized in the design of proposed decision support system as it facilitates straightforward framework for weight learning and representation of knowledge. Different types of inferences are possible over the MLN namely Conditional Probability Query, Most Probable Explanation (MPE), Maximum A Posteriori (MAP). The proposed design utilizes MAP query to find the most probable action that could be done for given the situation. Belief Propagation (BP), Lifted Belief Propagation, Gibbs, MCSAT - ms, Simulated Tempering (simtp) are some the inference algorithms available to carry out the process of recognition. All the above mentioned inferences algorithms are available in Alchemy and choice is made based on the execution time of inference mechanism. The Table 2 summarizes the result of the inference algorithms in terms of its execution time and shows that Lifted belief propagation is better in process of decision making. The execution time for Lifted belief propagation is less as it efficiently utilizes the memory and time for its inference. Thus, the proposed decision support system utilizes Lifted belief propagation algorithm for its inference.

Table 2. Comparison between MLN inference algorithms in terms of response time

Run	BP	Lifted BP	MCSAT-ms	Gibbs	simtp
Run 1	0.24	0.2	0.31	0.93	3.31
Run 2	0.26	0.21	0.32	0.96	3.34
Run 3	0.28	0.23	0.35	0.98	3.37

4.2. Experimental analysis

Table 3. F-measure for proposed MLN based decision support system

Run / Action	*Low alarm*	*High alarm*	*Emergency alarm*
Run 1	0.95	0.96	0.97
Run 2	0.94	0.95	0.96
Run 3	0.95	0.94	0.97

The experiments were carried for different runs for various test cases and the results are tabulated as shown in Table 3. It is observed that the F-measures for the proposed MLN based system is high. The reason for the high F-measure is that the system performs probabilistic inference over the represented domain knowledge and is thus able to efficiently handle the uncertain and incomplete sensor information. More over the hard rules included in the structure of MLN enhances the process of recognition through context based reasoning. The weights of the soft rules correlate the truth of the data and simulating action required for abnormal situation.

The literature on decision making shows that the most commonly used approach to model decision support system is Artificial Neural Network (ANN)[22]. Thus, ANN is used for comparative study and modeled with 66% of recorded dataset. The ANN based decision support system is designed with input, hidden and output layer that includes five neurons in input layer accepting abnormality factor and ADL as its input and one neuron at output layer to produce a required action. The ANN system was implemented with 'R' language with back propagation learning algorithm to train the decision support system. The learning process of ANN adjusts the weights in a way they to minimize the error rate.

Table 4. F-measure for ANN based decision making system

Run / Action	*Low alarm*	*High alarm*	*Emergency alarm*
Run 1	0.84	0.86	0.85
Run 2	0.83	0.85	0.86
Run 3	0.84	0.83	0.87

The experiments were carried with various test cases and the F-measure are shown in the Table 4. In comparing with the proposed MLN based system, the F-measure are low because the ANN produce absolute output without stating the probabilistic value for every action. ANN cannot generate output for incomplete inputs and therefore has a restriction to execute inferences over incomplete and uncertain inputs. Furthermore, ANN is a data modeling approach and does not facilitate domain knowledge modeling which is essential for the design of dementia care system.

Another frequently used decision support system is the rule based system where different rules are maintained to decide on appropriate actions. Prolog[26], is used to model the rule based system where the decision rules are hard rules provided by the domain expert. These rules are triggered only if all the predicates in the antecedent are true. The F-measure is shown in Table 5 for rule based system and is lower than ANN based system. The reason for such low F-measure is that there is no learning involved to train the system to reflect the behavior of real world environment. Furthermore, hard rules do not provide any means of probabilistic reasoning and can infer only if complete information is provided and thereby reducing the F-measure.

Table 5. F-measure for rule based decision making system

Run / Action	*Low alarm*	*High alarm*	*Emergency alarm*
Run 1	0.73	0.76	0.74
Run 2	0.74	0.76	0.77
Run 3	0.74	0.75	0.75

The Figure 7 compares the F-measure of the proposed MLN, ANN and rule based systems and illustrates the proposed MLN based decision support system is better than the existing approaches. The reason for the high measure for the MLN based decision support system is that the structure of MLN contains both soft and hard rules that help the modeling of dementia care better than the existing approaches. The ANN structure is equivalent to only soft rules that correlate with the training data. But the limitation of ANN in producing probabilistic output and representing hard rules has reduced its F- measure in recognition. On the other hand, rule based system is able to only represent hard rules and has no provision to model soft rules that is required for probabilistic inferences. As a result, MLN based decision support system with a structure of soft and hard rule is able to perform efficient probabilistic and context based inferences than the existing approaches for decision making in dementia care.

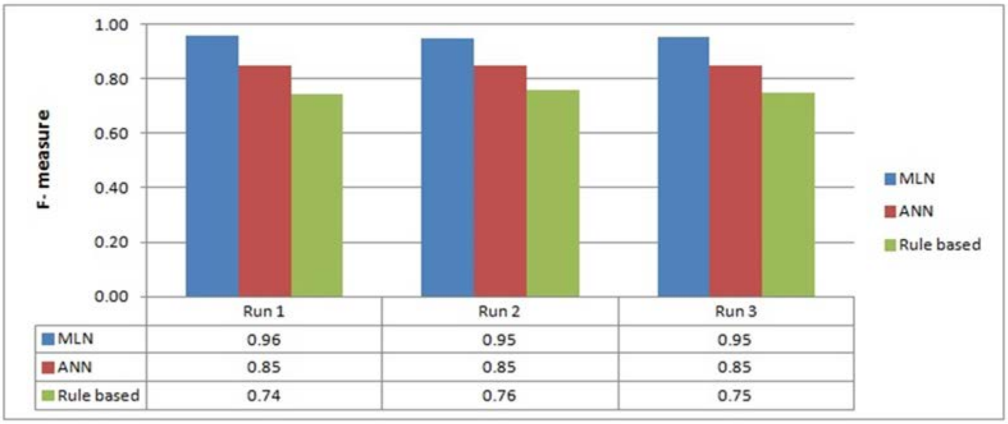

Fig. 3. Comparison of proposed with existing approaches of decision support system

5. Conclusion

The increase in dementia people across the globe requiring help to complete their daily routines has made assistive health care indispensable. Ambient intelligence within smart home aids its integration towards the design of dementia care system. The proposed intelligent decision support system provides assistance to the dement occupant to complete his routine activities without the intervention of the care taker. Markov Logic Network (MLN) is employed in the modeling decision support system to handle uncertainty and domain knowledge. The action (alerts) to be executed back to environment is dependent on the factors that induced abnormality. The proposed system considers abnormality in ADL and abnormality in human vital signs as significant criteria for decision making process. Experiments study shows that the proposed MLN based decision support system has high F-score compared to existing approaches due to the integration uncertainty and domain knowledge modeling within single framework. One of the key concerns of the doctors / care taker is to realize occupant's developmental stage of dementia, that are usually done through manual questionnaire sessions. The future work is to extend the proposed system to automate the process of measuring developmental stage of dementia through smart home.

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