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A Model for Identifying the Behavior of Alzheimer's Disease Patients in Smart Homes

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Abstract
In recent years, Smart Cities and Smart Homes have been studied as an important field of research. The design and construction of smart homes have flourished so that this technology is used for more comfort of people and helping their health. This technology is very useful for single and elderly people especially for Alzheimer's disease patients who are alone at home and need permanent care. A lot of research has been done to detect the activity of users in smart homes. They gather raw data of sensors and use the usual classification algorithms for activity detection. The essence of the time dependency of sensors' data has been ignored in most research, while considering this is very important, especially in the case of Alzheimer's patients. In this study, a Nonlinear AutoRegressive Network (NARX) is employed to detect the patient's activity in a smart home. NARX is a recurrent dynamic network, which is commonly used in time-series modeling. The results show that the proposed model detects user activity, with an accuracy of 0.98. Since the high-risk behavior of the Alzheimer's patient is very unknown; a fuzzy inference system is implemented based on the experience of the Alzheimer's sub-specialist and nurses. The main parameters were extracted and a 3-layers hierarchical fuzzy inference system was developed to detect and alarm the patient's high-risk behavior without wearable sensors. The results show 98% accuracy in detecting the patient's activity and 84% accuracy in determining its abnormality.

Keywords Smart home · Alzheimer's disease patient · Fuzzy inference system · Time series neural network · Hierarchical framework · Activity detection

1 Introduction

We all know that a large number of people live alone and independently. Based on statistics, the number of alone people has increased from 153 million in 1996 to 277 million in 2011 and is expected to double in 2050. Elderly and disabled patients constantly live without a nurse, since the cost of nurses is high and there are not enough nurses for care [1, 2].

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Here the new technologies such as smart homes will improve the quality of the elderly's life who want to live alone at home. These technologies, along with artificial intelligence methods, help them in a dangerous situation [3]. The common illnesses in the elderly include arthritis, heart disease, cancer, respiratory diseases, and Alzheimer's disease. Alzheimer's disease requires permanent care, and therefore the cost of elderly caring increases. Also, with the onset of dementia in the elderly, they become very dependent on others. They need permanent care and there are not enough people for caring for these patients. With the increasing elderly population, the number of Alzheimer's patients has also increased and care of them has become more important [4, 5].

In a smart home covered by embedded sensors, along with artificial intelligence technologies, patient caring will be easier. The patient's behavior is constantly monitored by the intelligent system, as a caregiver, and his activities are detected. In case of any risky behavior by the patient, his relatives were immediately informed. One problem for the elderly is their fall. The falling usually causes physical disabilities and even death; so that death in people over the age of 65 has increased 31% from 2007 to 2016 [6, 7]. Another problem is the patient's disturbances and malfunctioning in daily activities, such as doing activities at an inappropriate time or prolonging them [8, 9].

The main contribution of the study is developing an intelligent hierarchical system, which monitors the behavior of Alzheimer patients and informs their caregivers, in case of risky activity detection. The detailed objectives are:

- Preprocessing raw sensors data, such as normalization, cleaning, remove noises, and … to increase the robustness of the model.
- Developing an accurate activity detection model using Nonlinear Autoregressive Network with concern to time dependency of user activities.
- Implementing a hierarchical fuzzy inference system based on Alzheimer's sub-specialist and nurses' experiences to estimate the abnormality of the patient activity.
- Inform the patient's caregiver in case of risky behaviors.

The rest of the paper is organized as following sections; Sect. 2 highlights the related works; in Sect. 3, the proposed system is fully described. The section is divided into two parts, first the NARX model for activity detection, and then the fuzzy inference system for estimating the behavior abnormality. Then, in section 4, the results of implemented system is discussed, and finally, the last section is dedicated to the conclusion.

2 Related Works

In recent years, there has been a great deal of research on various aspects of smart homes, such as security, energy management, and user behavior [2, 3, 10]. Some studies focus on detecting unusual behavior such as fall detection. These models are applicable for different groups of people, such as Alzheimer's patients and the Parkinson's disease inflicted, people with heart disease, children, and people with paralysis [11].

Activity detection from sensor data in a smart home is one of the key tasks in intelligent healthcare systems. Researchers consider different algorithms to improve the detection accuracy; for example, in [12, 13], Bouchard used the Flocking algorithm for detecting user behavior. This algorithm does not need to define several clusters and it is their advantage. But it has done nothing about the estimation of the activity risk level. In [14], a hybrid algorithm called AR-CBC (Activity recognition approach by clustering and classification) is used. In this method, the number of features is selected using the PCA algorithm, then clustering is done using K-means and finally, for each cluster, the K-NN algorithm is used. This method has low accuracy in detecting some activities such as leaving home and washing dishes and also it has not reviewed the level of risk.

Sukanya and Gayathri [3] state that clustering alone is not suitable for modeling user behavior because users perform a hierarchy of actions for doing an activity. Therefore, a new clustering method called K-pattern clustering is used. In this method, after an initial preprocessing of raw data, data is given to FP-Growth algorithm to identify frequent patterns among the data; in the next step, the obtained patterns are given to clustering algorithm to be clustered and in the final step, the neural network algorithm is used to predict the next user behavior. In line with the objectives of the study, the advantage of this method is the detection of concurrent and interleaving activities, also it has been able to interpret the activity in different time frames, but no results were reported and the final accuracy of tests have not been obtained.

Suryadevara et al. [15] used the text segmentation method presented in [16] to identify user behavior. In this method, each of the sensors and activities is mapped to the letters, and after obtaining a text, the most probable part of the text that has the most repetition is selected as a sequence of that activity, the name of this method is SAPM (Sensor Activity Pattern Matching). To detect the abnormality of activity, the sequences obtained from the previous step, which represent the type of each activity, are placed in a tree, and abnormality is detected with the Apriori algorithm.

Fleury et al. [17] used the SVM (Support Vector Machine) algorithm to classify data; first, several attributes are selected using the PCA algorithm, and after that SVM is applied to these data. Medjahed et al. [18] provided another method with the fuzzy logic, in which each activity is assigned to one of the various periods and then is defined as a series of rules. The type of activity is also predicted using these rules.

Gayathri et al. [8, 9] used a hierarchical approach to detect activities and their abnormalities. Their hierarchical framework locates the higher priority factors in the lower layers and if the lower layer does not report the abnormality of that activity, the layer is executed. Each layer uses one of the artificial intelligence algorithms called MLN (Markov Logic Network); the advantage of this algorithm is that each layer can use both of the soft rules (the rules that the system gains from the data) and the hard rules (the rules defined by experts) but this method cannot identify complex activities. Kim [19] also used the HMM (Hidden Markov model) but if HMM is employed in place of MLN, it won't be satisfactory because the HMM does not use the hard rules.

Casagrande and Zougandeli used the binary sensors and compared the accuracy of predicting the next binary sensor event using probabilistic methods and LSTM networks. LSTM achieved the best accuracy of 83% [20].

Dr. Bashar Barmada and et al. [21] introduce machine learning techniques with ultrasonic sensors to predict the activities of one and two people in the smart home environment. The proposed system is capable of recognizing the activities and identifying the residents without the need to manually label the prior activities; of course, the accuracy of some activities for two persons was low.

Lotfi et al. [22] predicted the activity using ESN (Echo State Network); the advantage of this method is that input data can be logged at any time while in the previous approaches, the data should have been logged simultaneously. Hsueh et al. [23] examined the possibility of living more than one person in a home and posited the cameras on three dimensions of each space to solve the problems. The videos were preprocessed and required information was extracted, such as speed and other features of each user. Various Bayesian networks were applied to these features and the best model was selected with the hill-climbing algorithm; finally, the probabilities of occurrence of different events were calculated using an obtained model of Bayesian network. The disadvantage of this approach is low security in privacy and no strategy for risk identification.

Rebeen Ali Hamad et al. [30] uses delayed fuzzy temporal windows on binary sensors to make a more accurate decision, in case of high-risk behavior of patients engaged with dementia. They extract needed features with multiple incremental fuzzy temporal windows. They appraise their method with two temporal deep learning models (convolutional neural network and long short-term memory). The result shows significantly better achievements than the real-time approaches.

In [31], Deep et al. surveyed dense-sensing networks and their application in anomalous behavior detection. The major advantage of using dense sensing network-based activities and anomaly detection is its robustness to environmental change. They also claimed that it does not require the occupant to wear any devices. They also present the sensor fusion technology and the relation between sensor fusion and dense sensor networks. The result shows that the efficiency and robustness of anomalous detection systems will increase. The disadvantage of the sensing network-based method is variation in sensor data and high false alarm rate.

What has received less attention from researchers is the fact that patient's behavior should be considered as a set of sequential activities, in order to more accurately detect their high-risk behaviors. Although LSTM has been used in some papers, their accuracy is either low, or behavioral risk is not estimated. In this paper, the NARX model applies to sensor data to detect patient activity. The NARX model is commonly used in time-series modeling. NARX model can track the patient's sequential behavior and provide a more accurate prediction of the patient's activity. In the following, a fuzzy inference system is proposed, to estimate the risk level of the patient detected activity. Our fuzzy inference system is based on the rules extracted from the Alzheimer sub-specialist experiences.

3 The Architecture of the Proposed System

The major objective of the intelligent smart home for Alzheimer's patients is to detect their activity with high accuracy. In the next step, it should estimate the level of abnormality regarding that activity. In case of high-risk behaviors, the system should inform the caregiver. Our proposed hierarchical framework of an intelligent smart home for Alzheimer's patients is shown in Fig. 1.

The proposed framework consists of one activity recognition model and three fuzzy abnormality detection layers. In the first step, raw data is accumulated from all sensors around the home in a processing node. If necessary, the data is pre-processed for cleaning, normalization, removing noises, etc. The preprocessing step is very important in practice because the sensors are exposed to environmental noises. Our trained NARX model uses the data to detect patient activity. It also tracks the previous activities to detect current activity more accurately. After determining the activity, the fuzzy inference system tries to estimate the level of abnormality. The system is composed of three different layers. Based on the Alzheimer sub-specialist experiences, three major factors are selected: Activity start time for layer 1, the "ON" interval time of sensors for layer 2, and the "OFF" interval time of sensors for layer 3. Inputs of layer 1 are the

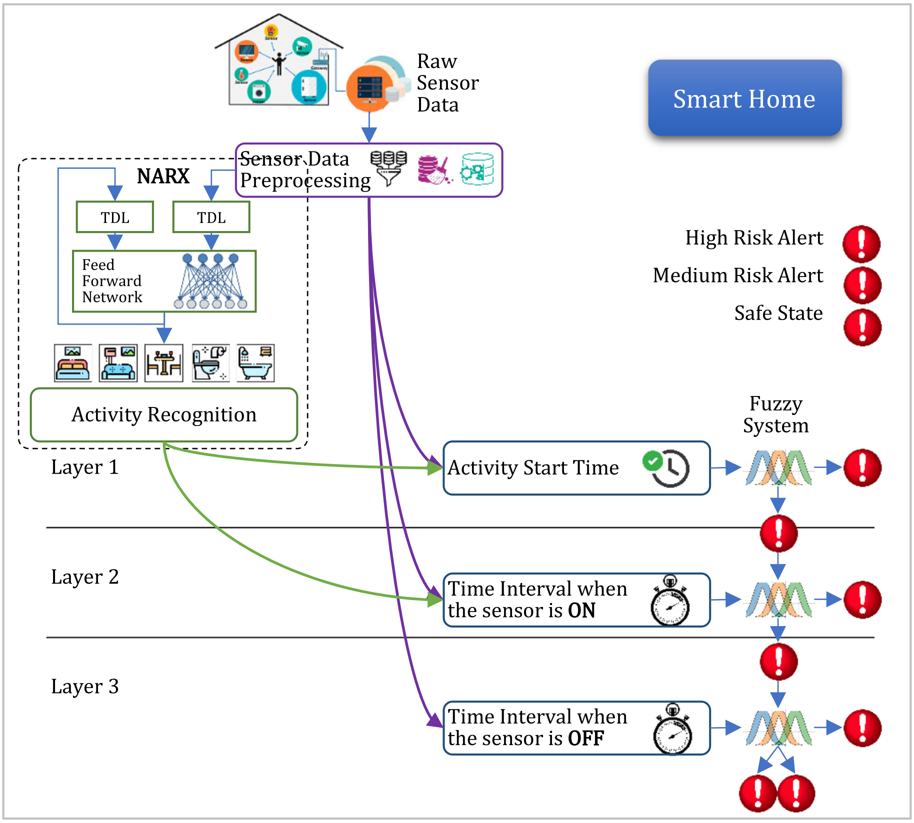

Fig. 1 The hierarchical architecture of the proposed system

activity and its start time. Based on extracted rules, our fuzzy inference system computes the risk level of activity as "Safe", "Medium", and "High". When the output is "High", it will not continue and send the high alert to the caregiver, immediately; otherwise, the output will be sent to the next layer. In the next layer, the current activity, "ON" interval time of the sensor, and the output of the previous layer will be analyzed and the risk level calculates. If the output is "High", the caregiver is announced; otherwise, if the output is "Medium" and the risk level sent from the previous layer is also "Medium", again the high alert is sent to the caregiver. In another state, when none of the previous actions occurs, the last layer computes the final risk level of activity, using the "OFF" interval time of the sensor and the output of the previous layer. The caregiver will be informed if required.

These three parameters have been selected based on Alzheimer's sub-specialist and nurses' interviews. The system could be extended with more important factors in real practice. But, in this research, the most important factors have been chosen to reduce complexity. In the following section, each part of the proposed framework is explained in more detail.

3.1 NARX Model for Activity Detection

In this section, the proposed NARX model for accurate activity detection is fully described. NARX model provided by MATLAB is a common model for time-series analysis. Time-series analysis uses previous events to predict output more precisely. The prediction strongly depends on previous events which happened before.

Note that raw sensor data should be preprocessed before analyzing by the NARX model. This process is more important in real practice because ambient noise strongly affects sensor data. More precise preprocessing leads to a more robust system, especially when unpredictable or rare events occur, such as neighborhood party noise. Common preprocessing tasks are cleaning, reformatting, removing noises, and normalization.

After preprocessing, all sensor data converts to the desired format and numerical range, if necessary. The NARX model has two separate inputs: the sensor data in a specific time period $S\left(t : t - d_s\right)$, and the previous activities $A\left(t : t - d_a\right)$. t is a discrete-time interval when data is received from the sensors. The NARX model tries to approximate a nonlinear function f, to map the input signals to the desired activity $A(t)$. NARX equation model is shown in Eq. 1.

$$A(t) = f\left(A(t-1), A(t-2), \ldots, A\left(t-d_a\right), S(t-1), S(t-2), \ldots, S\left(t-d_s\right)\right) \tag{1}$$

where d_a, d_s are the number of previous activities and the number of previous values of sensor signals, respectively. The architecture of NARX is shown in Fig. 2.

NARX has a feedback connection from activity output to the input of the network. The task of the TDL layer is accumulating the required previous signals and their corresponding activities. NARX model uses the recurrent dynamic network and backpropagation can be used for training.

High accuracy in this layer is very important because:

- This is the base component and its detected activity is applied in all next layers of the fuzzy inference system. If the activity does not recognize carefully, the initial assumption of the fuzzy inference system will not be valid.
- The caregiver who receives the alert is away from home or is in a remote location and the false alarms strongly decrease the system reliability and make it useless.

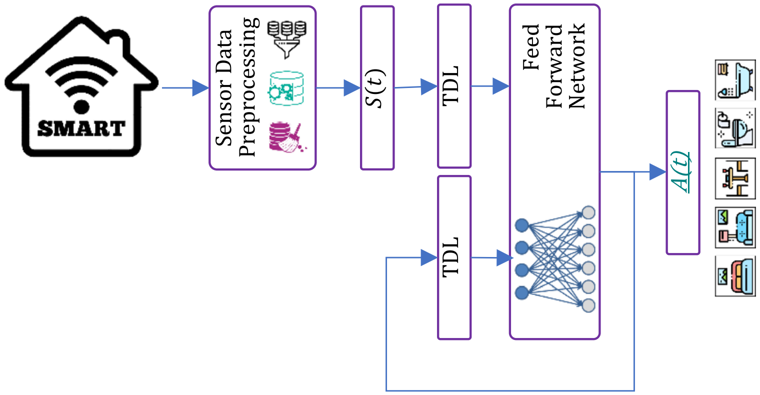

Fig. 2 The general architecture of the NARX model

The major objective of this model is to track patient activities. For example, every person has a clear routine in everyday life; he sleeps around 10 to 12 p.m.; he wakes up at 6 AM to 8 AM, makes meals three times, and follows a relatively specific pattern. The sensors are switched on and off in a special order in each case and the NARX model approximates the patient activity. The NARX model output is the input to the fuzzy inference system. More details of the proposed fuzzy inference system are fully described separately for each layer in the following sections.

3.2 Layer 1-Abnormality Detection by "Start Time"

Some activities are inherently high-risk, such as falling patients, and should be reported to a caregiver as soon as they occur. With other normal activities, when we add some context, such as time, location, and disease, then their normality changes. People with Alzheimer's disease may lose time or may not be aware of it and do their work at an unusual time [24]. Based on Alzheimer's sub-specialist experiences, the major feature that makes an activity abnormal is its "Start Time". But there are no certain rules that can be used to determine the abnormality of an activity. Here, the best system that can simulate these uncertain rules and experiences is the fuzzy inference system. All we have is a collection of linguistic statements derived from interviews with sub-specialists, nurses, and patient caregivers. A fuzzy inference system (FIS) can accurately map the current activity and its related contexts such as time, to desired abnormality level based on the extracted fuzzy rules. Implemented MATLAB FIS in layer 1 composes two inputs: start time of activity and detected activity by NARX model.

The 24 h of the day are divided into 5 zones:

- Midnight, which is about 12 am to 6 am.
- Daytime, which includes from morning to afternoon.
- Sunset, which is the depression time and the behavior of the patient should be under control, sunset is an important and decisive time.
- Night, which may cause depression, but it is lower than the sunset and is less important but still considerable.
- Before sleep, which is about 10 pm to 12 pm.

Sunset syndrome means that the Alzheimer's patient usually suffers depression at sunset and sometimes this mode continues until the end of the night [26–28]. Therefore, this time should be considered in the division of the day.

The membership function of the "Start Time" variable is shown in Fig. 3.

Alzheimer's patients are very sensitive about many reminders [25], Therefore only a series of activities carried out outside the normal time, are considered hazardous. The activities for this part are 7 activities including sleeping, relaxing, meal preparation, washing dishes, housekeeping, working, and leaving the home.

After defining the fuzzy inputs, the fuzz rules must be defined. Each fuzzy rule defines as Eq. 2.

$$\begin{aligned} &\text{IF } \left(input_1 is\, membership\, function_1\right) \text{ AND/OR } \left(input_2 is\right. \\ &\left. membership\, function_2\right) \ldots \text{ THEN } \left(output_n is\right. \\ &\left. output\, membership\, function_n\right) \end{aligned} \tag{2}$$

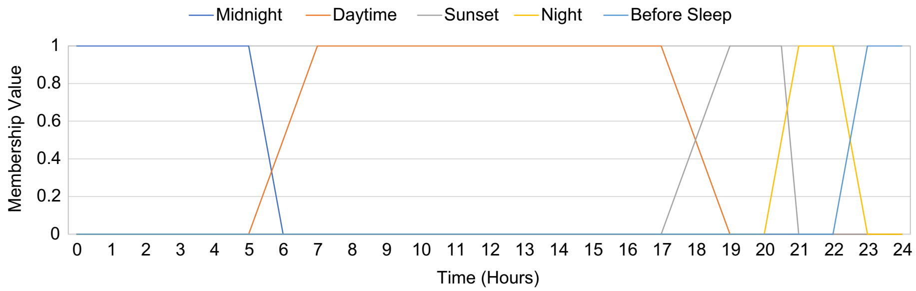

Fig. 3 Membership function of the "Start Time" variable (Midnight, Daytime, Sunset, Night, and Before sleep)

Figure 4 shows the all rules defined for FIS layer 1 based on the interviews with some Alzheimer sub-specialists, nurses, and caregivers. The abnormality of activity is regulated at three output membership functions: "Safe", "Medium", and "High".

35 rules defined for FIS layer 1. For example, as shown in Fig. 4, we have

IF (*Start Time is "Midnight"*) AND (*Activity is "Leave Home"*).

THEN (*Abnormality is "High"*).

3.3 Layer 2-Abnormality Detection by "ON" Interval Time of the Sensors

Another important factor in determining the abnormality of the activity is the time interval while the sensor is "ON". This indicates that the patient may have agitation or may have

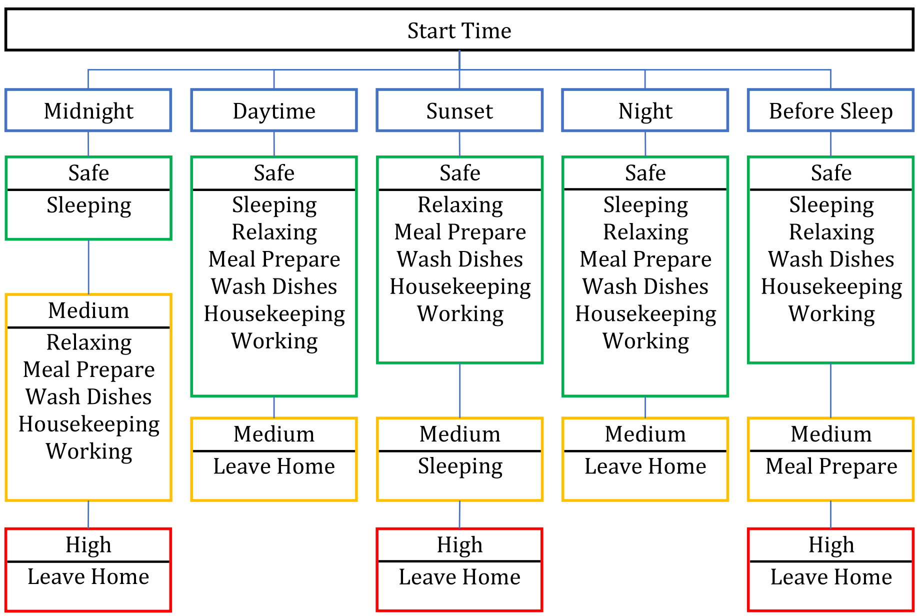

Fig. 4 The rules defined for FIS layer 1 with two fuzz inputs: the start time and activity; with one output: the abnormality level

fallen, and he may try to inform others. So, if the sensor is "ON" for an unusual duration of time, it is dangerous; of course, the type of activity is important. For example, the patient may be cleaning a part of the house, and the sensor of that particular place may be "ON" for half an hour which is not abnormal.

In layer 2, the proposed FIS has three inputs: the "ON" interval time of the sensor, the sensor type, and the activity. These three entries are discussed in more detail below.

3.3.1 "ON" Interval Time of the Sensor

The membership functions of the "ON" interval time are composed of 4 values as shown in Fig. 5:

- Short, which includes less than 4 min.
- Medium, which is about 4 to 25 min.
- Long, which is about 25 to 45 min.
- Very long, about 45 min and more.

3.3.2 Sensor Type

The second input of FIS layer 2 is the sensor type. The "ON" interval time has a separate meaning in different sensors. For example, if a person is sitting on the sofa, he is probably watching TV. If the sensor does not turn off for a long time, then it is a "Safe" activity, because the user is awake and he is constantly moving. Also, in sensors with high coverage capability, the patient may go to any part of that space and the sensor still stays "ON" for a long time. For this purpose, the sensors are divided into 6 groups (Note that this is a comprehensive classification and also applies to the next layers and may not be used in this layer). The details are as follows:

- Sleep sensors: when the user is sleeping in those places, staying silent is normal for a long time.
- Rest sensors: which include sensors that have a high level of coverage and may stay "ON" for a long time (however, not as long as the sleep sensors).
- Blind spots: sensors are located at places that are not covered by any other sensor.
- Door sensors: which indicate the opening and closing of the door.

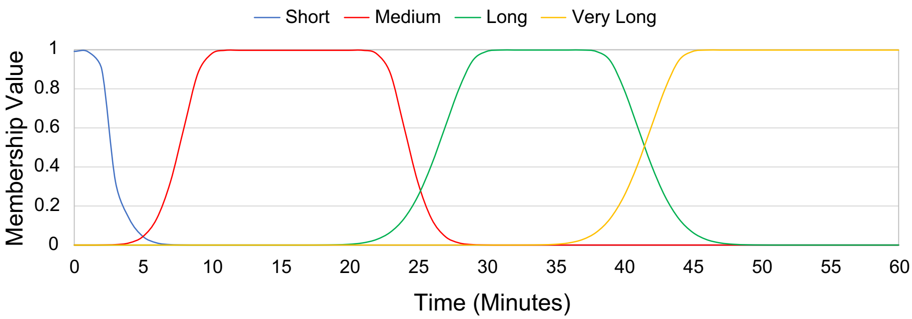

Fig. 5 Membership function of the "ON" interval time variable (Short, Medium, Long, and Very Long)

- Toilet sensors: are located in front of the toilet and bathroom.
- Other sensors: which include sensors that are not in any of the above groups.

For example, see the bedroom sensors in Aruba dataset [29], which is used in our experiments. As shown in Fig. 6, the sensors inside the bedroom include the four types of sensors which were referred to above: The M002 and M003, embedded in the bed, are in the sleep sensors group and are marked with a red circle. M004 is the toilet sensor type and is set in front of the toilet (marked with a green circle). When the person enters the bathroom, the sensor turns off and the duration of being off is the duration time that person is in the toilet. M007 is the relax sensor type and has high coverage (marked with a blue circle). The unmarked sensors are in other sensors' groups, because there is a low pause for them, and they just show the entering or exiting of the patient.

3.3.3 Activity Type

The third input is an activity type that is only considered for activities with some mobility, like meal preparation, housekeeping, and washing dishes.

3.3.4 Fuzzy Rules

With 4 values for "ON" interval time, 6 values for sensor type, and 8 values for activities, $4 \times 6 \times 8 = 192$ rules are defined. Of course, some rules have common in premise or consequent and can be merged. Some examples are described below.

Example 1 IF (*"ON" interval time is "Short"*) THEN (*abnormality is "Safe"*).

In this rule, it is defined that if the "ON" interval time is less than four minutes, then the other inputs are not important and, this activity is "Safe".

Example 2 IF (*"ON" interval time is "Medium"*) AND (*sensor type is "Toilet"*).

THEN (*abnormality is "Medium"*).

This rule means, if the patient stays around 25 min in the toilet, the risk level is "Medium" and should be considered.

Example 3 IF (*"ON" interval time is "Very long"*) THEN (*abnormality is "High"*).

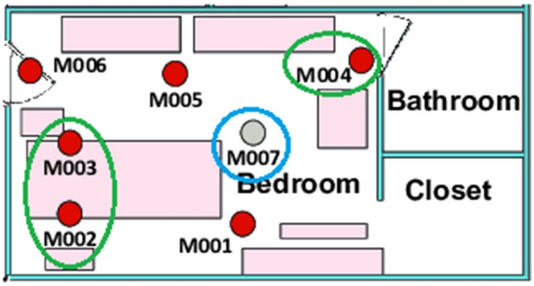

Fig. 6 The view of the embedded sensors in the bedroom in the Aruba dataset

This rule states that, if the "ON" interval time of the sensors is too long and over 45 min, it is abnormal, regardless of the sensor and the activity type. Because an elderly person can never be continuously moving and active up to 45 min and his body's strength does not allow him to do these activities (especially in activities that require high mobility). Thereby if that happens, it is unnatural and the patient may be in bad condition.

3.4 Layer 3-Abnormality Detection by "OFF" Interval Time the Sensor

As previously stated, the falling elderly is very dangerous and causes serious problems. Although the wearable sensors are designed to check this problem, the Alzheimer's patient may forget to wear them after bathing or changing clothes.

This layer examines the length of time that the sensor turns off and the first sensor that turns on after it. It means that, if there is no sign of the movement of the user and he stays motionless in one place more than a specified time, it is dangerous. The patient may have fallen.

Same as the previous layer, the "OFF" interval time depends on the type of sensor. For example, if the sleep sensor turns off for a few hours, it is normal. But if the toilet sensor turns off for 30 min, the patient may be ill or he might have fallen.

In layer 3, FIS has 2 inputs: sensor type and the "OFF" interval time. The sensor type is like layer 2, but the "OFF" interval time input is a little different. "OFF" interval time has 4 membership functions as shown in Fig. 7:

- Short, which includes less than 6 min.
- Medium, which is about 6 to 40 min.
- Long, which is about 45 min to 2 h.
- Very long, about 2 h and more.

There are 6 sensor types and 4 time zones, therefore there are $6 \times 4 = 24$ rules in layer 3. Below are some examples of rules.

Example 1 IF (*"OFF" interval time is "Medium"*) AND (*sensor type is "Sleep"*).

THEN (*abnormality is "Safe"*).

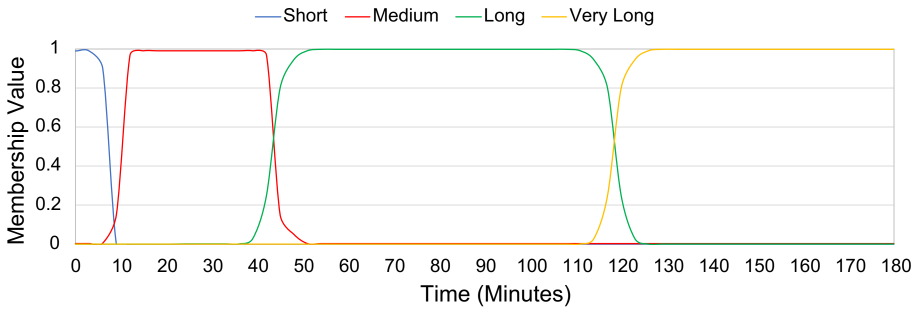

Fig. 7 Membership function of the "OFF" interval time variable (Short, Medium, Long, and Very Long)

This rule states that if the “OFF” interval time sensor is “Medium” (about 6 to 40 min) and the sensor type is a sleep sensor, this activity is “Safe” because the person is napping in his bed.

Example 2 IF (*“OFF” interval time is “Long”*) AND (*sensor type is “Sleep”*).

THEN (*abnormality is “Medium”*).

It says, if the sleep time is more than 2 h, it is a little abnormal, and the level of risk is increased. Based on researches on the elderly and the behavior of the people under investigation, it is abnormal staying in the toilet or bathroom for more than 2 h as well as relaxing, watching TV, and crossing the blind spots in the cited time.

Example 3 IF (*“OFF” interval time is “Very Long”*) AND (*sensor type is not “Sleep”*).

THEN (*abnormality is “High”*).

“OFF” interval time over 2 h is dangerous and it means that the patient is immobile and may have a serious problem.

Don’t forget that the start time of activity has been previously investigated in layer 1. Sleeping more than 2 h at midnight is a normal activity and has been labeled “Safe” in layer 1. So, when we check the sleeping activity in layer 3, it is in the daytime. The architecture of the proposed FIS in MATLAB is shown in Fig. 8.

4 Results

This framework has been tested on a device with an Intel Core i5 CPU processor and 2.66 GHz speed, with 4 GB RAM. For the implementation, MATLAB software has been used. The sensor data is downloaded from the Aruba dataset available on the CASAS [29] and its architecture is shown in Fig. 9. This home consists of the kitchen, dining (food served there), living room (the place to relax and watching TV), two bedrooms, a workroom, and two bathrooms, and the sensors are embedded in entrance doors or passage paths based on the needs of the user.

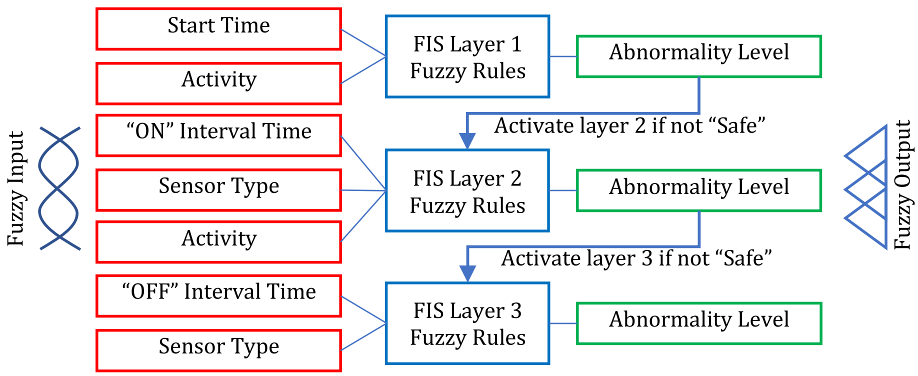

Fig. 8 Architecture of proposed FIS

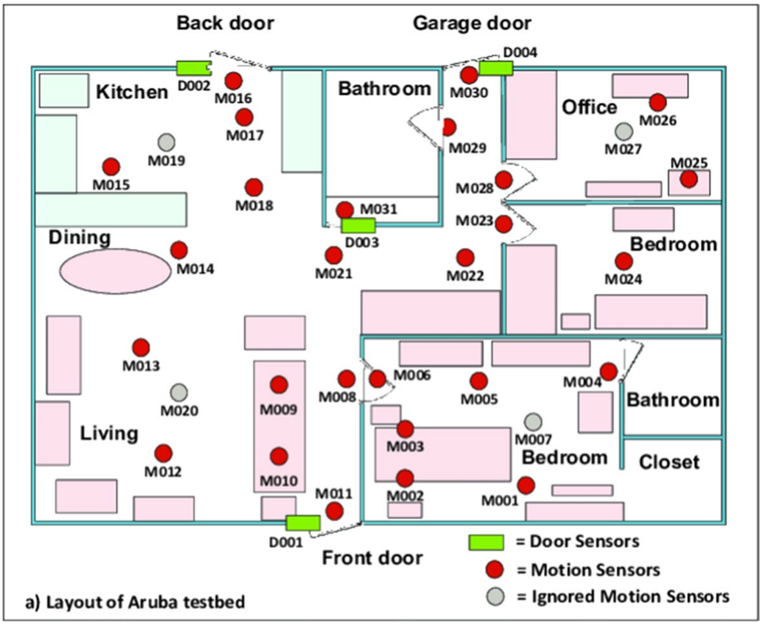

Fig. 9 The architecture of sensors that are embedded in the Aruba smart home

As an example, the bedroom located at the bottom of Fig. 9 on the right side is considered. In this bedroom, M001 reports the lower part of the room, sensors M002 and M003 are on the left and right side of the bed to record and report all the activities of the patient on the bed. M004 sensor is at the front door of the restroom to analyze the entrance, exit, and the stay duration of the patient. Sensor 5 examines the movements in the upper part of the room. M006 sensor is on when someone enters or exits the room and finally M007 is a sensor with a high range of coverage, which reports if other sensors fail to cover or report one area.

As shown in Table 1, we obtained 23,296 training data (8 days) and 7880 test data (3 days) after preprocessing and deletion of noisy data. Each is observable based on the type of activity.

4.1 Proposed NARX Model Accuracy

For the implementation of our NARX model, MATLAB R2019a NARX tools are used. As shown in Fig. 10, the generated network has two inputs x(t) (sensor data) and y(t) (previous activities). The output or y(t) is also the detected activity by the network. This network hidden layer has 10 neurons and its delays are set on 13 transactions. Delay is the number of previous sensor data and activities that are effective in network prediction.

The network has been tested for a delay value from 5 to 20, and the prediction error of the train and the test data have been observed. With increasing the delay value to 13, the errors significantly decrease. But with a delay of over 13, no noticeable change in errors was observed. Since increasing the delay value leads to more computation complexity, the delay is set to 13.

Table 1 The number of trains and test data for this experiment

	Train	Test
"'Work'"	1472	1277
"'Leave Home'"	112	44
"'Enter Home'"	99	54
"'Meal Preparation'"	7220	1759
"'Eating'"	1370	412
"'Housekeeping'"	4194	224
"'Relax'"	5613	3003
"'Sleeping'"	2089	781
"'Bed_to_Toilet'"	105	9
"'Wash Dishes'"	977	271
"'Re-sperate'"	45	46
Sum	23,296	7880

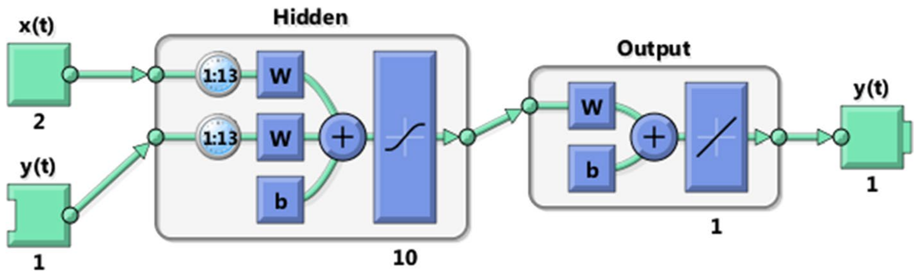

Fig. 10 NARX based neural network structure with 10 neurons and a delay of 13

Table 2 shows the confusion matrix of the NARX model. The last column shows the accuracy of each activity, and its precision and F-measure are calculated in the last two rows based on Eq. 3.

$$
\begin{aligned}
&accuracy(A) = \frac{TP_A}{TP_A + FN_A} precision(A) = \frac{TP_A}{TP_A + FP_A} \\
&F\_measure(A) = \frac{2 \times accuracy(A) \times precision(A)}{accuracy(A) + precision(A)}
\end{aligned}
\tag{3}
$$

where for activity A, TP_A is the number of correct predictions, FN_A is the number of mistake predictions, and FP_A is the number of activities predicted as A, while the actual activity is not A.

The cells on the table's main diameter (bold cells) represent the number of correct model predictions for each activity. As can be seen, evaluation criteria in most activities are higher than 90%, and also general accuracy of this model is 98% which indicates the very high accuracy of the proposed model. It means that almost all activities are detected correctly.

For example, in the sleeping column, 773 activities are predicted correctly $\left(TP_{sleeping} = 773\right)$. If we go down in the sleeping column, 3 activities were meal preparation but are predicted sleeping activity mistakenly. In bed to toilet row, 2 activities are also detected wrongly $\left(FP_{sleeping} = 3 + 2 = 5\right)$. The toilet is in the bedroom and both of them

Table 2 The confusion matrix of the NARX model with accuracy, precision, and F-measure of each activity

Activity	Sleeping	Relax	Enter Home	Leave Home	Wash dishes	Work	Meal preparation	Housekeeping	Eating	Bed to Toilet	Respeate	Accuracy
Sleeping	**773**	6	0	0	0	0	1	0	0	1	0	0.989
Relax	0	**2992**	0	0	2	0	6	0	2	0	1	0.996
Enter Home	0	0	**45**	9	0	0	0	0	0	0	0	0.833
Leave Home	0	1	8	**31**	0	1	1	1	1	0	0	0.704
Wash dishes	0	0	0	0	**268**	0	0	0	3	0	0	0.988
Work	0	2	1	0	0	**1262**	1	1	0	0	0	0.996
Meal preparation	3	6	2	0	0	5	**1742**	1	0	0	0	0.990
Housekeeping	0	0	0	0	0	2	1	**221**	0	0	0	0.986
Eating	0	0	0	0	0	0	6	1	**405**	0	0	0.983
Bed to Toilet	2	0	0	0	0	0	0	0	1	**6**	0	0.666
Resprate	0	1	0	0	0	0	0	0	0	2	**43**	0.934
Precision	0.99	0.99	0.80	0.77	0.99	0.99	0.99	0.98	0.98	0.66	0.97	
F-Measure	0.99	0.99	0.81	0.73	0.99	0.99	0.99	0.98	0.98	0.66	0.95	

use the same sensors. Therefore, these common sensors cause errors $\left(precision(sleeping) = \frac{773}{778} = 0.993\right)$.

The accuracy of most activities is above 90% except “Enter home”, “Leave home”, and “Bed to Toilet”. The reason for the low accuracy of the toilet activity is the low number of test data, and if one of six cases is predicted mistakenly, the accuracy, precision, and F-Measure reduce a lot. Also, in entering and leave home, the same sensors are used. This problem can be solved by embedding more sensors or by applying a stronger architecture.

4.2 NARX Model vs State-of-the-art Classification Model

In this scenario, the comparison between the accuracy of the NARX model and three state-of-the-art classification algorithms; decision tree, K_NN, and SVM; has been made. The comparison result is shown in Fig. 11. The results show that the NARX model is better than other algorithms in the detection of most activities.

Our NARX model has better performance than three other algorithms because it considers the sequence of the activities. For clarity, all models have worked well in detecting sleeping activity. Because a few sensors (see in Fig. 12) are used in the sleeping activity. Thus, the SVM, K-NN, and decision tree algorithms work with high accuracy even more than the NARX model.

But these three algorithms don’t have a good performance against the proposed NARX model in some activities, such as washing dishes and housekeeping. As shown in Fig. 13, these two activities use more sensors than sleeping. Thus, the algorithms cannot work well. This is the advantage of the time series model that detects the activities which use the sequence of sensors. For example, in the sleeping activity that is tracked by two sensors,

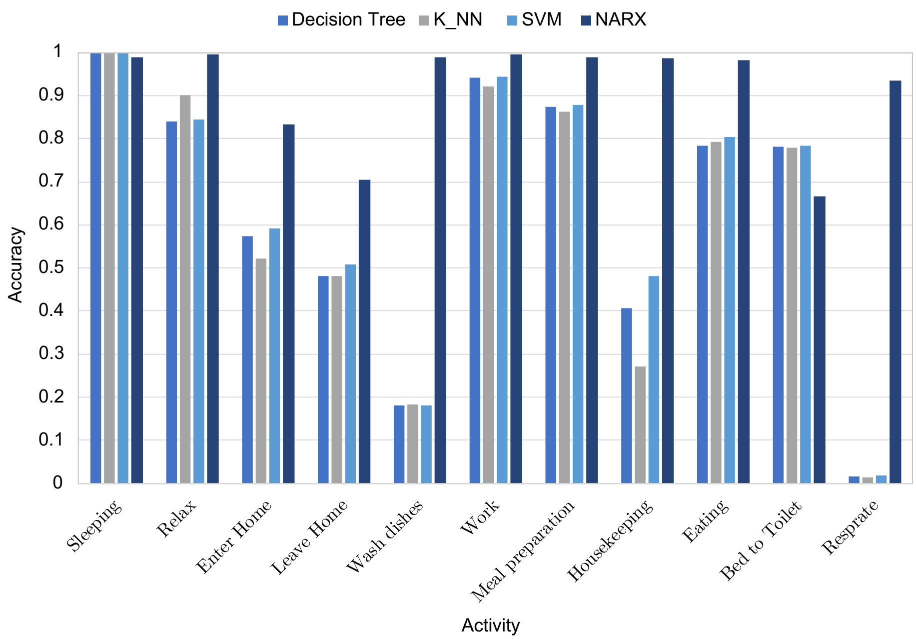

Fig. 11 Comparison between the accuracy of NARX model and Decision Tree, K_NN, and SVM

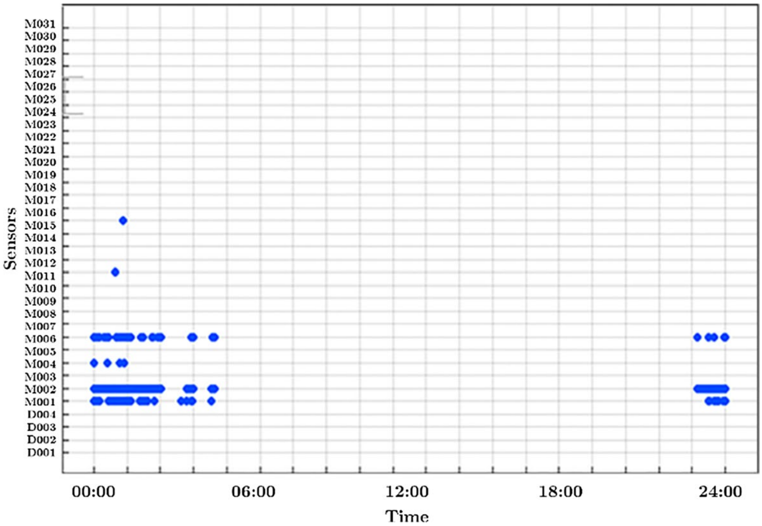

Fig. 12 The sensors used in the sleeping activity

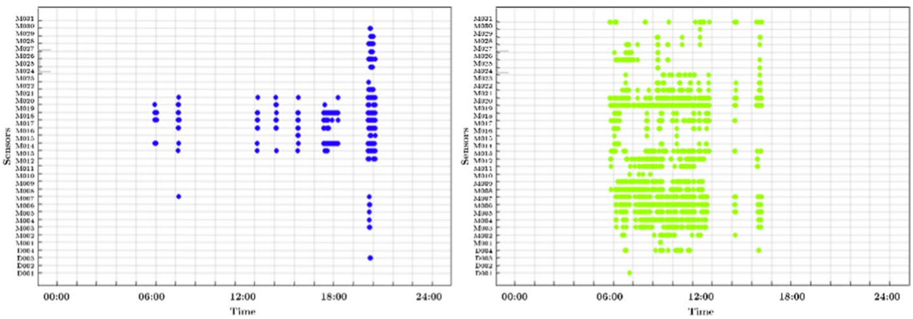

Fig. 13 The sensors used in the washing dishes and housekeeping

the accuracy of all algorithms is high, but in some others that are complex activities and the sequence of sensors is engaged, the NARX model can detect the pattern of sequences, while other algorithms lack this advantage.

4.3 Evaluation of the Fuzzy Inference System

Five Alzheimer's sub-specialists and ten caregivers helped us to evaluate the proposed FIS. We asked them to design some scenarios which may happen in patients' homes. On the other hand, the most frequent patterns which are happening in the dataset have been extracted. The days under study differed from the days selected for training and test. Finally, 100 scenarios have been selected among all candidates. Each scenario comprises four key features: activity type, start time, "ON" time, and "OFF" time. Table 3 shows two sample scenarios.

Table 3 Sample of the dataset

Start time	ID	Status	Duration time of ON/OFF	Type of activity
08:01:07	‘M007’	‘ON’	0:34	‘‘‘Sleeping’’’
15:28:42	‘M014’	‘OFF’	0:19	‘‘‘Eating’’’

All scenarios regenerated to questionnaire form. For example, sample 1 converted to “if the patient sleeps at 8 AM and the sensor is “ON” for about 30 min, then the abnormality level is …” and sample 2 converted to the scenario “if the patient is eating lunch at 15:30 and no other action was reported for about 20 min, then the abnormality level is …”. We made all efforts not to convey any opinions to the person who fills the forms.

Then we asked them to study the forms carefully and express their opinion about the abnormality of each scenario with “High”, “Medium”, and “Safe”. It is obvious that the responses are not the same because of their different personal experiences. The output of FIS was compared with the majority of expert votes in each scenario. The result is shown in Fig. 14.

FIS accuracy was 88%, compared to sub-specialists votes. In 80% of cases, the caregivers confirmed the FIS output. The lower accuracy may have been due to the greater number of caregivers and the dispersal of their votes. When we consider the votes of both groups together, the overall accuracy is 84%. However, FIS provides good accuracy, but it is expected, if the particular habits of each patient are included in the rules, the accuracy increase, and the system will be more applicable.

5 Conclusion

One problem of the elderly and Alzheimer’s patients is the care which this growing population needs. In this study, a smart home solution is proposed by employing a hierarchical architecture comprised of a Nonlinear AutoRegressive Network, and the 3-layer Fuzzy Inference System. The system tracks the behavior of the patient and the dangers he/she was exposed to. NARX time series model is applied because the current activity of the patient strongly depends on his previous activities and the sequence signals of correspondent sensors. Over 98% accuracy in detecting most patient activities shows better performance of the proposed NARX model than conventional predictive algorithms, especially complex activities in which more sensors are involved. After detecting the activity by the NARX

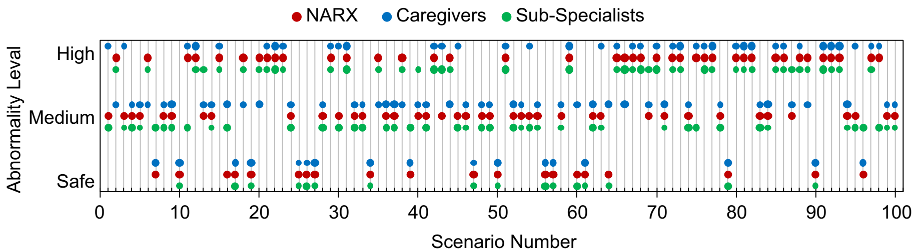

Fig. 14 Proposed FIS output vs Alzheimer sub-specialists and caregivers. The bubble size shows the number of voters

model, FIS determines its abnormality. The fuzzy rules have been extracted from valuable experiences of the Alzheimer's sub-specialists and caregivers. FIS's overall accuracy is 84%, which shows a high degree of accuracy compared with the other methods.

Declarations

Conflicts of interest The authors declare that there is no conflict of interest.

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