Intelligent Abnormal Residents' Behavior Detection in Smart Homes for Risk Management using Fuzzy Logic Algorithm

Bo Feng[1], Lili Miao[2*], HuiXiang Liu[3]
Shanxi Railway Vocational and Technical College, Taiyuan 030013, ShanXi, China[1]
Taiyuan University of Technology University, Taiyuan 030008, ShanXi, China[2]
Shanxi Railway Vocational and Technical College, Taiyuan 030013, ShanXi[3]

***Abstract*—In recent years, the population of sick and elderly people who are alone and need care has increased. This issue increases the need to have a smart home to be aware of the patient's condition. Identifying the patient's activity using sensors embedded in the environment is the first step to reach a smart home where the people around the patient can leave the patient alone at home with less worry. In literature, a variety of methods for detecting the performance of users in the smart home are discussed. In this study, a method for abnormal behavior detection and identifying the level of risk is proposed, in which fuzzy logic is used in cases such as when the activity start. Experimental results demonstrates that the proposed method achieved satisfied performance with 90% accuracy rate that presented better results compared to other existing methods.**

Keywords—Smart home; abnormal detection; behavior analysis; activity recognition; elderly people; fuzzy logic

I. Introduction

Over the past few years, the global elderly population has been steadily increasing, according to statistics from the World Health Organization (WHO). By 2363, the number of people aged 56 and above is projected to reach two billion, accounting for 22% of the elderly population [9]. The first cause of dependence and need in the elderly is considered and there are not enough people to take care of this population. With paying attention to the increase in the number of elderlies compared to people, the incidence of this disease has increased and the issue of taking care of them is also more important now [2,3].

Designing a smart home can help these people in a very effective way. Smart home uses user behavior among the sensors embedded in the environment. It has been investigated that he plays the role of a caretaker and only if he feels the need Musk, he informs it to one of the dependents of the patient - for further investigation; informs one of the problems that can be for an elderly person. The phenomenon of falling is usually accompanied by complications and physical disabilities and even death. So according to a report, death in people over 65 years of age 2007 to 2016 has increased by 31% [4,5].

In the phase of examining abnormal behavior, it should be noted whether the detection of abnormal behavior is for the purpose of detecting cyber-attacks on the smart home system or if it is meant for abnormal activities that occur by the patient himself. In relation to the first case, various articles [23-25] have been proposed to identify attacks by examining the sequence of various events performed by the user. But in this article, abnormal behavior refers to the second state and the abnormality of the patient's own activity is investigated.

In fact, there are two methods for detecting the abnormality of behavior, in the first method, normal behavior is modeled, and any new input that does not match this model is considered as abnormality. But in the second method, a pattern is found for the anomalies by using the background data, and with the entry of new data, if they match this pattern, they are identified as anomalies. The first strategy seems to be more efficient and realistic, because abnormal data is rarely seen in real life. As shown in Table I [10, 26], Forkan and colleagues have pointed out two defects of the anomaly detection system. The first one is the inability to predict the leading anomalies, and the second one is that the use of a context for decision-making has caused more false alarms [20].

All these issues increase the importance of designing a system to determine the unusual activity of users. In this research, firstly, user activity identification is presented in different ways. Secondly, determining the degree of abnormality of activity in different articles is discussed and in the third part, the model is presented for determination of the unusual level of user activity in smart homes and it is reviewed. Fourthly, the experimental results of the proposed method are presented and the method is compared to other methods. Finally, the paper concludes in the last section.

The research gap in this study is the lack of a method for detecting abnormal behavior and identifying the level of risk in smart homes for sick and elderly people who are alone and in need of care. While various methods have been proposed to detect users' performance in a smart home setting, there is still a need for a more comprehensive approach that can monitor and detect abnormal behavior in real-time and provide a level of risk assessment. This study aims to fill this gap by proposing a method that uses fuzzy logic to detect abnormal behavior and assess the level of risk, particularly when an activity starts. This will enable caregivers to monitor the patient's condition remotely and take appropriate actions when necessary, thereby providing better care and support for vulnerable individuals in smart homes.

*Corresponding author

TABLE I. ANALYSIS OF CURRENT ANOMALY DETECTION METHODS

Method	Advantages	Disadvantages
Classification (supervised)	Measure the accuracy of the model using the confusion matrix	1. It is needed huge data for the training phase 2. Manual labeling by humans
Clustering and statistics-based (unsupervised)	Not required to sample data	1. Efficiency depending on the type of data distribution 2. Not optimized for anomaly detection

II. RELATED WORKS

Numerous studies have been conducted on the security, energy management, and detection of user behavior—just a few of the features of the smart home [10-8]. In the behavior identification section, some researches identify unusual user behavior by using fall detection and some by using different data mining and analysis algorithms. The user's prior actions have generated funds for a variety of categories of individuals, including those with partial paralysis, Alzheimer's illness, Parkinson's disease, heart disease, children, and others [11].

In the user activity detection research area, different algorithms are used. In [92, 93] is used Flocking Algorithm and stated to detect user behavior. Comparing this algorithm to other approaches has the benefit that there is no need to determine the initial cluster number, but this system has not done any work in the field of assessing the risk for the elderly.

In [14], a hybrid algorithm called CBC-AR has been used. This approach uses the PCA technique to choose a set of features initially; then, the K-means algorithm is used to cluster the data. The NN-K algorithm is then used to classify each cluster individually in order to increase accuracy. However, this technique has a very low sensitivity to specific actions, such as leaving home and doing the dishes. It also needs better sensitivity to determine the risk factor.

According to the author in [9], modeling user behavior is inappropriate since people conduct a hierarchy of actions for a task, grouping into Alone. Clustering is employed in this article as part of a brand-new hybrid approach dubbed pattern-K. The FP Growth algorithm is used in this approach to find recurring patterns in the primary raw data after some pre-processing. The actions are clustered using the patterns that the algorithm has discovered in the following phase, and the last step employs the neural network algorithm to forecast the user's future behavior. As their results showed, the advantage of this method is to detect simultaneous and separate activities and also it has also been able to analyze the activities in different periods of time with different interpretations, however, no report of the results and final accuracy of the tests has been presented.

In the article [15], the SVM algorithm, which is effective for data classification, has been used in such a way that a series of features are first selected using the PCA algorithm, and after normalizing the data, the aforementioned algorithm is applied to the data.

In the article [6, 7] a hierarchical method for diagnosis of their activities and their abnormality have been used. The hierarchical framework is designed in such a way that the factors with higher priority are in lower layers, and each layer is executed if the lower layer reports abnormality of activity. In each layer, one of the artificial intelligence algorithms called MLN has been used to get its output. The algorithm's benefit is that in each layer, depending on the structure defined for it, both soft rules (rules obtained by the system from the routine in the data) and hard rules (rules known by people) can be used. However, this method is not enabled to identify the complex activities.

In the article [18], ESN is used to predict the activity values of a person. The benefit of this strategy over the others is that input data may be fed into the system at any moment, whereas with the earlier ways, the data had to be entered into the system all at once.

In the article [19], it has been investigated that it is possible for more than one person to live in a house, and to solve these problems. They used video cameras in three dimensions, and by processing these videos, the speed, type of behavior and other characteristics of each user can be determined. Different Bayesian networks characterized by these features are obtained and the best model is extracted using algorithms such as the hill climbing algorithm.

The accuracy of forecasting the following event (activity) using probabilistic approaches and LSTM networks was compared in the article [20], utilizing binary sensors, and this method reached 83% accuracy.

In the article [21], machine learning algorithms and ultrasonic sensors were used to predict the activity of one or two users present at home. The suggested system is able to identify the activities and residents in the house, which, of course, is less accurate in some activities when both people were at home.

In the article [22], in order to predict the next activity of the user, the activities are placed in separate nodes and by using the definition of fuzzy rules and FSM structure, it jumps from each node to another node, but in this article, a solution is also proposed to determine the level of risk. It has not been done and the accuracy is between 86 to 99% for different activities.

According to investigation of previous studies, although various methods have been proposed to deal with detecting abnormal behavior and identifying the level of risk in smart homes for sick and elderly people, still it is required to improve the accuracy rate in abnormal behaviors detection. This study aims to fill this gap by proposing a method that uses fuzzy logic to detect abnormal behavior and assess the level of risk, particularly when an activity starts. This will enable caregivers to monitor the patient's condition remotely and take appropriate actions, when necessary, thereby providing better care and support for vulnerable individuals in smart homes.

In the following, a new method for identifying and determining the amount of risk that arises in the occurrence of each activity is discussed. In this method, one of the important things in Alzheimer's patients, i.e., "starting time of each activity" is also investigated, from which one can understand the abnormality of the patient's behavior.

III. Methodology

One of the most important steps in detecting the abnormal state of users in smart homes is to determine the risk level of each activity, which causes each activity to be categorized as absolute, normal or abnormal. To take advantage of this feature, fuzzy logic has been used at this stage. The three characteristics of the activity start time, the duration of the sensor being on and the duration of the sensor being off are factors that are effective in determining the level of risk caused by the activity of a user living at home, which will be explained in detail below.

A. Activity Start Time

One of the important and influential factors in detecting the level of abnormality of an activity is the start time of that activity, which has been investigated using fuzzy logic. As shown in Fig. 1, this system gives the activity start time and the type of detected activity to the fuzzy logic to check the level of abnormality of the detected activity and the level of abnormality of the activity with three levels of warning: safe, moderate and high. If this warning is high, the result is sent to the output and does not go to the next layers, but if the warning is moderate, the warning level is sent to the next layer for further checks.

In the phase of examining the activity start time, it should be noted that Alzheimer's patients usually suffer from depression at sunset, and this state sometimes continues until the end of the night, and this state is called sunset syndrome [37, 36]. Therefore, this period of time should also be considered in dividing the day and night, and the patient's behavior during these times should be examined more carefully. After considering these things, a day with 24 hours is divided into five parts, which can be seen in Fig. 2:

- Midnight, which is from 12 o'clock to about 6 am
- Day, which is evening, from morning to noon
- Sunset, this is the time of sunset when the patient collapses due to various reasons such as depression,
- 4) Night, at this time until the end of the night, there is a possibility of depression, but this level of depression and anxiety is minor than at sunset and has fewer effect, but it is still important
- 5) Before sleep, this time is around 22:00 to 20:00.

The next input is the type of activity that is being performed, since according to the research done on this group of patients, indiscriminate reminders to Alzheimer's patients cause their disease to worsen, in order to prevent this issue, only a series of activities are considered that they are performed outside of normal hours. These activities are dinner, sleeping, resting (things like watching TV), preparing food, washing dishes, cleaning the house, and leaving the house.

Rules are defined once the fuzzy inputs are defined based on these inputs and taking into account the daily habits of the Alzheimer's patient, for example, if the patient washes dishes or prepares food at 2 in the morning, this is abnormal and by giving a lot of warning to the patient's caregiver informs him that the patient is probably not in a suitable mental condition and examines his condition. A diagram of the defined rules can be seen in Fig. 3. To define the rules, we consider the usual behavior of most people in the society (which was also obtained by examining the behavior of several elderly people) and assume that this person only sleeps and goes to the bathroom at night, and as a result, does things like cleaning the house and watching TV. It is unusual for this person if he does start preparing food from his sleep

B. Sensor ON Duration

Another key element in evaluating the degree of the unusualness of action is the length of time that each sensor is active. The patient may attempt to alert others to his health worsening and rescue himself if a sensor is on excessively. For this reason, a sensor is left on more than usual. It is also crucial to consider the nature of the activity. For instance, a patient may be cleaning a room in the house, which would be okay if the sensor did not switch off for roughly 30 minutes. With these considerations in mind, the third layer, which receives three entries, then assesses the unusualness of the activity. As shown in Fig. 4, these three inputs are,

- the duration of the sensor being on
- the type of sensor
- the type of activity that are given to the fuzzy logic and using defined rules. Outputs the degree of abnormality

A series of activities such as cleaning the house are activities that because the person is moving, the location sensor does not turn off even for half an hour, and this is normal. Therefore, the three activities of washing dishes, preparing food and cleaning the house are considered. Different sensors interpret the length of time as indicating something different. For instance, if a person is awake and sitting on the sofa, likely watching TV, it makes sense that the sensor in that location will not switch off. Or the sensors that have the ability to cover a space, the patient may go to any part of that space (where this sensor is in that space), stay on and stay on for a longer time or the door sensors that detect the opening and closing of the door can be on for up to 20 minutes. In this research, we divide the sensors into 6 groups. This division is comprehensive, as a result of being off during that period of time the next layer is also included, for example, if a person goes to the toilet or bathroom and according to the structure of the existing smart home, if there is no sensor in the toilet or bathroom, it is normal that no movement is reported for 20 minutes.

Based on this, the sensors are divided into the following six types:

- Sleep sensors, where the patient sleeps and as a result, it is natural for them to be off for a long time.
- Sensors that are included in the rest. They may have a high rate of coverage and remain active for a considerable amount of time (but not to the extent of sleep sensors).

- Blind spot sensors, which are situated in a location that is not, for a long distance, covered by any other sensor.
- Door sensors that record when a door opens and closes.
- In front of the toilet and bathroom doors are toilet sensors.
- Other sensors, which include sensors that do not fit into any of the aforementioned categories.

C. Sensor OFF Duration

As it was stated before, falling in the elderly is very dangerous and brings problems for them. The elderly will find it challenging, and a person with Alzheimer's may forget to wear the sensor after taking a bath or changing into new clothes if wearable sensors are employed to monitor the recurrence of this issue. This layer determines whether it is normal or abnormal if there is no indication of the user's presence in other areas and the user is in one location for an extended time. It also measures the time between a sensor turning off and the first sensor turning on after that. If it is marked and in a static state, it is dangerous and there is a possibility of the patient falling or getting worse. This time is different based on the sensor's type. For instance, if the bed sensor goes off for a few hours, it is normal because the person may have fallen asleep, but if the sensor in front of the toilet goes off for 30 minutes, there is a possibility of danger because the patient may be ill and as a result, he stayed in the bathroom for an unusual amount of time.

As shown in Fig. 5, the fuzzy logic of this layer has two inputs: the time the sensor is off and the type of sensor, which is divided into 6 groups as described in the previous section. And the duration of being off is divided into the same four categories in which the intervals are longer in this case.

The rules of the fourth layer are such that if the type of sensor is "toilet" and the patient enters the bathroom for more than 40 minutes, no sensor is turned on and there is no information about the patient, the patient is probably sick or something bad happened in the bathroom. For example, rule number 2 states that if the sensor is off for a moderate duration (about 6 to 40 minutes) and the type of sensor should be sleep sensor. The fact that the individual may have slept off on his bed makes this behavior reasonable, or in the case of the predefined rule, it is stated that if the duration is too long and more than two hours. In the case of any type of sensor except the sleep sensor, this is abnormal, and the longer this time is more than two hours, the greater the risk, because according to the behavior of the person under investigation and the research that has been conducted on several elderly people, sitting for more than two hours in the bathroom or toilet, as well as for resting and watching TV and for crossing blind spots, is considered unnatural.

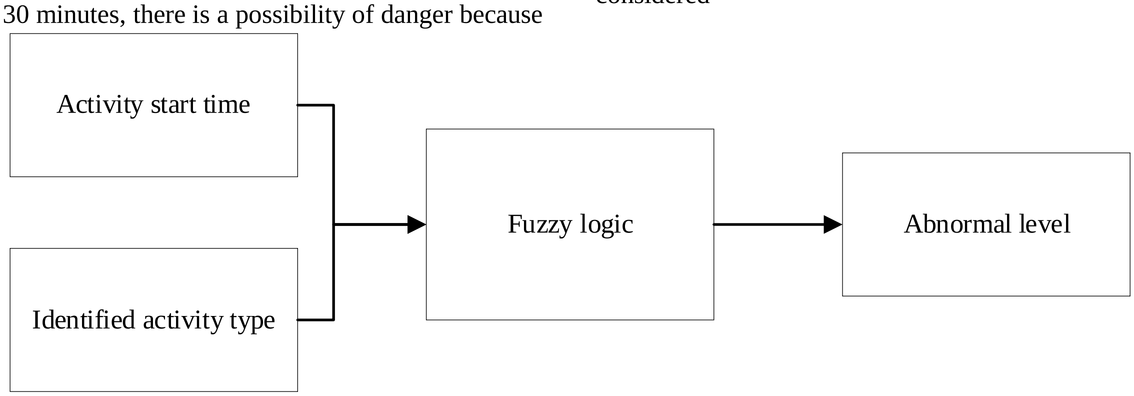

Fig. 1. Fuzzy logic inputs for activity start time.

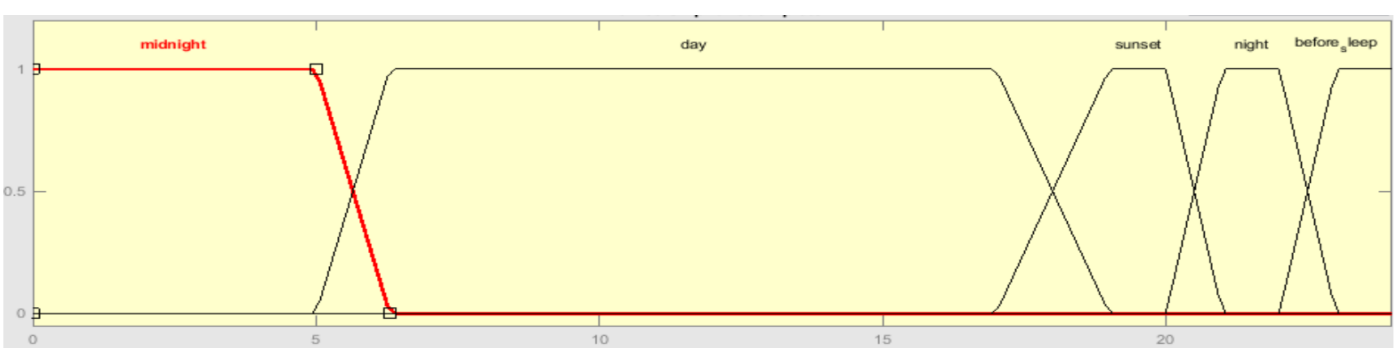

Fig. 2. Dividing a day into 5 categories.

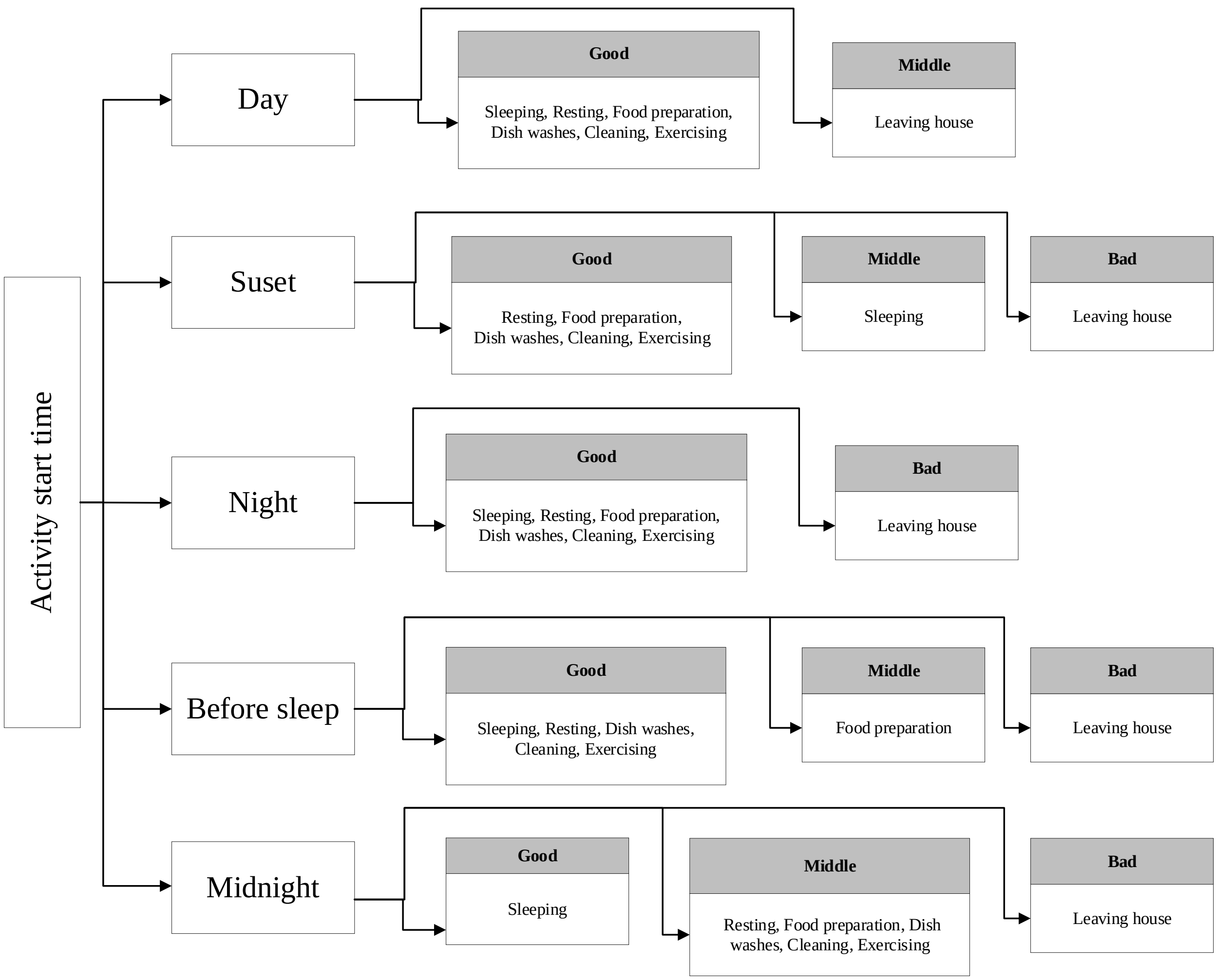

Fig. 3. Defined rules for activity start time.

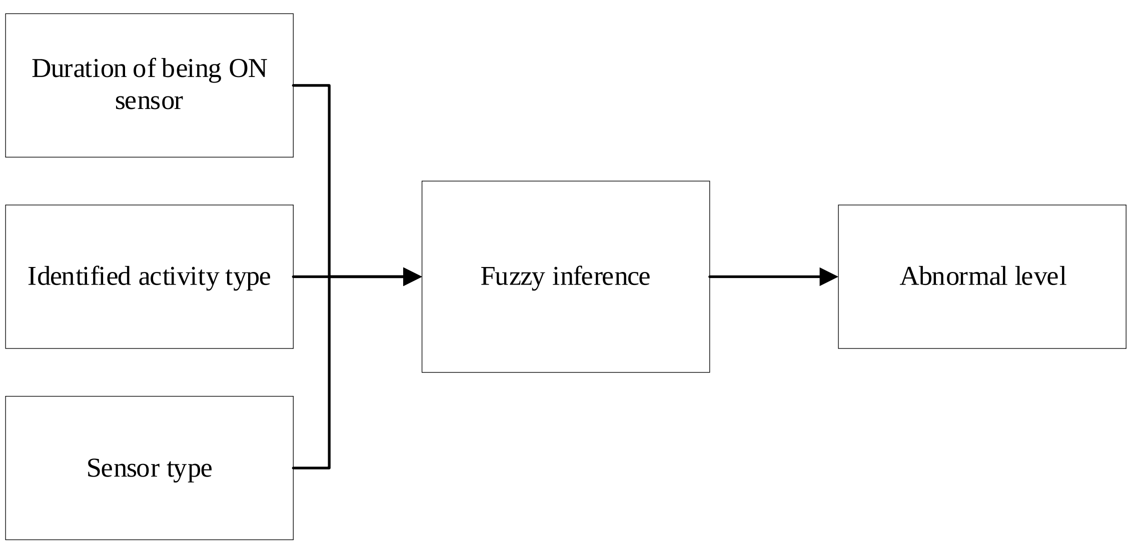

Fig. 4. Fuzzy logic inputs for the duration of the sensor being ON.

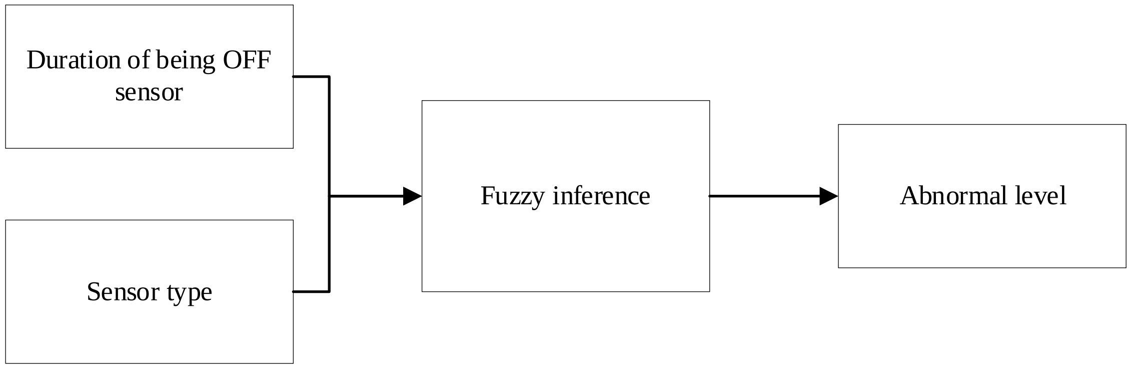

Fig. 5. Fuzzy logic inputs during sensor OFF time.

IV. Results and Discussion

To check whether our fuzzy logic is working properly, we could not find a dataset that includes checking the degree of abnormality of the activity. For this reason, we randomly selected a number of transactions of the Aruba dataset from the collection of CASAS datasets [38], the number of which was 48 transactions, and after obtaining the results of the system, according to the form prepared by a doctor and a person familiar with the behavior Elderly people and Alzheimer's were filled, a comparison was made between the results, which is given below as an example of the steps of the work method.

In order to check that "if the patient washes the dishes at 10 o'clock in the morning," in the first step, after the type of activity was detected using one of the algorithms of the activity type determination section, washing the dishes, this activity along with its start time was classified into the next step. The second one is sent and there, according to the rules defined for each person, the level of abnormality of that activity is determined in three stages. These scenarios were given to two experts in the same way and their average opinions about each scenario were calculated and compared with the specific results from the system.

In order to validate the system, we collected data for 20 individuals which 4 individuals exhibit abnormal behavior (i.e., positive) and 16 individuals exhibit normal behavior (i.e., negative). As experimental results shown, our algorithm correctly identifies 3 individuals with abnormal behavior and misclassifies 2 individuals with normal behavior as abnormal. In this case, we can calculate the performance metrics as shown in Table II,

TABLE II. Obtained Valuse for Performance Metrics

Performance Metric	Value
True Positive (TP)	16
False Positive (FP)	1
True Negative (TN)	2
False Negative (FN)	1

Based on TP, FP, TN and FN, True Positive Rate (TPR) and False Positive Rate (FPR) are calculated as shown in Table III.

TABLE III. Overall Performance

Performance Metric	Formula	Value
True Positive Rate (TPR)	TP / (TP + FN)	94%
False Positive Rate (FPR)	FP / (FP + TN)	33%
Accuracy	(TP + TN) / (TP + FP + TN + FN)	90%

In order to compare the proposed method with other existing methods, we experimented the Farhad et al. [14] and Casagrande et al. [20] on these 20 individuals. This experiment is conducted to prepare a fair comparison based on the same dataset. It is not tailored for a specific individual and is developed based on the demands and routines of old and Alzheimer's patients in general. Despite this, it offers decent accuracy. It is anticipated that if the patient's unique habits learned from his caregiver were taken into account, the accuracy would be better than it is now. Table IV presents the performance comparison between the proposed method and other existing methods.

TABLE IV. Performance Comparison between Proposed Method and Others

Method	**Accuracy rate**
Casagrande et al [20]	84%
Fahad et al [14]	88.6 %
The proposed method	90 %

As experimental results and overall performance comparison which obtained by TPR, FPR and accuracy rate, the proposed method achieved better accuracy rate in abnormal behavior detection compared to other existing methods.

V. Conclusion

In this research, firstly, a review of the works done in detecting the user's performance in the smart home, which includes two subcategories of fall detection and activity detection, was done. In the following, fuzzy logic was used to determine the level of risk of the patient's activity so that the habits of each patient can be obtained in the form of rules in accordance with his special conditions, and these rules can be used to determine the level of abnormality of the activities. In order to reach the defined goal, three options were used and according to them, the level of abnormality was reported. In order to reach the defined goal, three options were used and according to them, the level of abnormality was reported. These options include (1) the start time of the activity, (2) the duration of the sensor being on, and (3) the duration of the sensor being off and the patient actually being motionless. Another noteworthy point is that in the proposed method, due to the implementation of the method for people with special conditions, the wearable sensors were not used. Because in the case of using such sensors to check the occurrence of problems, it is difficult for the elderly, and especially for an Alzheimer's person, it may be associated with forgetting to wear the sensors after certain conditions such as going to the bathroom or changing clothes. Anyway, according to these mentioned conditions, the implementation of this layer also produces good results with 90% accuracy.

For future works, it is suggested to use a method to individualize this system and detect the presence of several users at home and implement the system for heart patients, children, etc. Furthermore, the hardware implementation of this model can also be of great help to make it more accurate.

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