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Context-Aware Elderly People Activity Recognition Using Dempster-Shafer Theory In Iot Environment

Deeba.K[1] , RA.K. Saravanaguru[2]
[1]Research Scholar,[2]Associate Professor
[1,2] School of Computer Science and Engineering,Vellore Institue Technology,Vellore Tamilnadu, India
*[1]deebakanmani@gamil.com,[*2]saravanan.k@vit.ac.in*

Abstract

Presently, from the population's elderly people, the average is gradually increasing, so taking care of those people smart home plays a crucial role. To ensure safety, maintain their self-sufficiency, and healthy. In this paper, the smart home is used to increase the quality of the user's life. This paper provides a framework for implementing Dempster-Shafer's theory on the basis of context-aware rules that enhance the overall accuracy of Monitoring and recognition of activities by elderly people. A system, an Ambient Assistant Living (AAL), is used for elderly people's behavior and ability to understanding their context from the data, which is derived through sensor networks. The knowledge is inferred by the Dempster-Shafer Theory (DST) approach is used to remove uncertainty from collected data and used the Context-Aware Multi Layer Architecture (CA-MLA). AAL system is used to provide support for elderly people to be insecure and independent life by the novel system, detect the elderly people's health conditions, and predict the inaccurate behaviors in their activities. So we have to send alerts to caregivers or family members. To this end, the efficiency of the proposed experimental results is performed by the smart home.

Keywords: *Context-awareness, Dempster Shafer theory, Ambient Assistant Living, Multi-sensor data fusion, smart home, Activity Recognition, IoT, CA-MLA.*

1 Motivations and Related Work

Nowadays, for the first time in history, most people can expect to live into their 60s and beyond.[1] Recent studies carried out by the World Health Organization report that, by 2020, people aged 60 years and older will outnumber children younger than 5 years, and that there will be more than two billions of elderly people by 2050 [2]. Pervasive computing support is becoming important for assisted living, particularly older adults, because the global cost of care for these people who face cognitive disability has been made increasingly unsustainable [3]. There is more and more evidence that environmental protection may be an important way to help older people manage their everyday activities [4]. In this paper, the authors aim to focus on user behavior and elderly people's health condition monitoring. The author used the approach is a dynamic bayesian network, the rule-based system is used to detect anomalies, and during the critical situation, it can be sent the alerts to family members or caregivers. The performance analysis shows the better result is 80.5% [5]—monitoring activities of daily life in a smart home by using three-layered context-aware architecture. The functionality of this paper is the high level of knowledge extraction from low-level data. For monitoring the activities, the upper-level ontology model has used [6]. This paper presents the ALFs system for people with cognitive disabilities or physical disabilities. ALF is used to support the daily activities of the healthcare assistance of people. An IoT system is presented for anomaly detection and assistance request in ALF by using wearable devices. The author extracted the positive results from tests, and it produces the system reliability and stability [7]. This paper aims to detect health-related changes and behavioral conditions of patients, the one who is continuously monitoring in the home by using pattern recognition models. To detect abnormalities in daily activities and irregularity of the everyday behaviors' of the living can be monitored through Hidden Markove Model (HMM) approach [8]. Ambient assisted living can be maintained for

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independent elderly adults and improve the quality of life and cost of living. The author concentrated on the Activity Recognition Monitoring (ARM) by comparing three approaches (SVM, ANN, and SVM, HMM) on real data. By comparing these algorithms, hybrid SVM-HMM obtains the highest accuracy [9]. The author focused on elderly people's behavioral analysis to prevent mild cognitive impairment (MCI) and frailty problems. It will give the guarantee three vital features i) connected appliances usage monitoring ii) continuous ambient parameters monitoring iii) both indoor and outdoor environment localization [10].

The author proposed a solution is focused on activity recognition and patients monitoring, which is mainly based on physicians and patients [11]. Nowadays, the researchers are concerned about increasing a selection of assisted technology is called "Ambient Intelligence." It is support for elderly people independent living which aims to create a quality of life and better health care so it will increase the long life for assisted people [12]. Increasing aged people population creates the problems like caregiver burden, individual living and increase the cost of health care, assisted living technologies motive to development of secure and independent aging. Present AAL systems assure many openings for Monitoring and improving the older adult's health conditions as well as maintaining the autonomy of older adults [13]. Ambient Assisted Living includes assisted living technologies and ambient intelligence. It is used for curing and monitoring the health condition and also improves the wellness of older adults. AAL tools are used for medication remainder, mobile alert system, human monitoring system, and fall detection system, the surveillance system of the older adult health conditions and etc. [14, 15]. Proposed multi-model data analysis is used to get efficiency in the real-time situation and improve the older adults living environment and also to improve the AAL environment of the situational awareness author designed M2M-enabled architecture. Association analysis algorithms and decision-tree can be used for predicting future situations [16]. By using the Bayesian models approach, we can identify the modalities from the heterogeneous sensor. Sensor fusion aims to find a particular activity from the modalities [17]. The authors proposed a review and discussion of multisensor data fusion and algorithms widely used. It is a technology is used to getting information from different heterogeneous sensors, which requires an accurate and efficient information fusion process to find the user's activity of the present situation [18].

Human activity recognition is getting more and more data from available sensors and obtained fixed vectors of dimension. The user's individual knowledge can be proposed by using the evidence theory framework. The powerful matrix representation is defined for routine user knowledge, which is used for the decision of source. Device battery power can be saved by using this approach, and the computational cost reduced when it increases the number of sensors. With the SVM classification, accuracy can be higher than 95% [19]. Fusion techniques are essential for the combination of multiple sensors to draw more precise results since the data of a single sensor do not provide enough proof to deduce an activity [26]. In this paper, unique layer architecture is proposed for daily activity recognition, and it is based on sensor-based smart homes by using the Dempster Shafer Theory (DST) evidence [20]. Multi-sensor data fusion is an emerging technology in context-aware applications, and the results of data fusion targeting to produce either qualitative or quantitative benefits include: reduces the ambiguity, robustness, and improves the accuracy. This paper proposed a temporal and Dempster evidence theory is used multisensor data fusion methodology for indoor activity recognition in the smart home [21]. In this paper, the author offers Smart Home Caregivers System (SHCS), which is used to collects information about the patients like respiratory rate, oxygen leakage, normal and abnormal situations can be monitored through the sensor [27]. Context-aware publish and subscribe (CAPS) method used for gestational diabetes mellitus diabetes monitoring for patients [29].

2 Context-Aware Multi-layer Architecture (CA-MLA)

An Ambient Assisted Living (ALL) framework provides is a multi-layered architecture presented in Fig.1to gather and aggregate raw data from various sensors with increased levels of abstraction, so that the actual user situation is explicitly understood for e.g., normal, abnormal, and emergency. The reasoning technique is used to get the high-level knowledge of data, and it will perform in series action.

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The reasoning technique is used to get the high-level knowledge of data, and it will play in sequence action. The first level of a layered architecture is a sensor manager. Send the request message to sensors to get the raw data needed to obtain a higher level of data. Next, in this pre-processing level, the data stream can be analyzed, which is to detect filtering, aggregating, and inferring the raw data used to improve the accuracy. After this pre-processing stage, it is changed as context data, which is called as contextualization. It is the process of switching from raw or sensor data into context data [30-33].

The activity recognition module is the main level in the layered architecture of the AAL system. Compact with the uncertain sensor data, we can use the probabilistic approach, which is based on dempster Shafer theory (DST) in this part, low-level sensor data and context information can be used to detect the activity recognition by the user. Based on the present performance of the user activities, we have to produce high-level context information. Through the activity recognition module, we can create a user profile that is used to represents the user behavior based on DST. Next, the highest level of architecture is context reasoning. It can infer the user's activity, which is detected through the Activity Recognition module ad user's condition by combining sensor data and coming from health sensors data and users, profile historical data. The sequence of actions and repeated manual alters to be performed by the assurance to user's well-being. Secure and safety by the context reasoning. The user's condition is in critical or anomalous the context reasoning can fire the alert system, which is sent to the user's proper caregivers or family members. To modify the user environment have to control the ventilation lighting system, air conditioning, and heating the context reasoning fire the actuator manager; it is a combination of actuator and sensor.

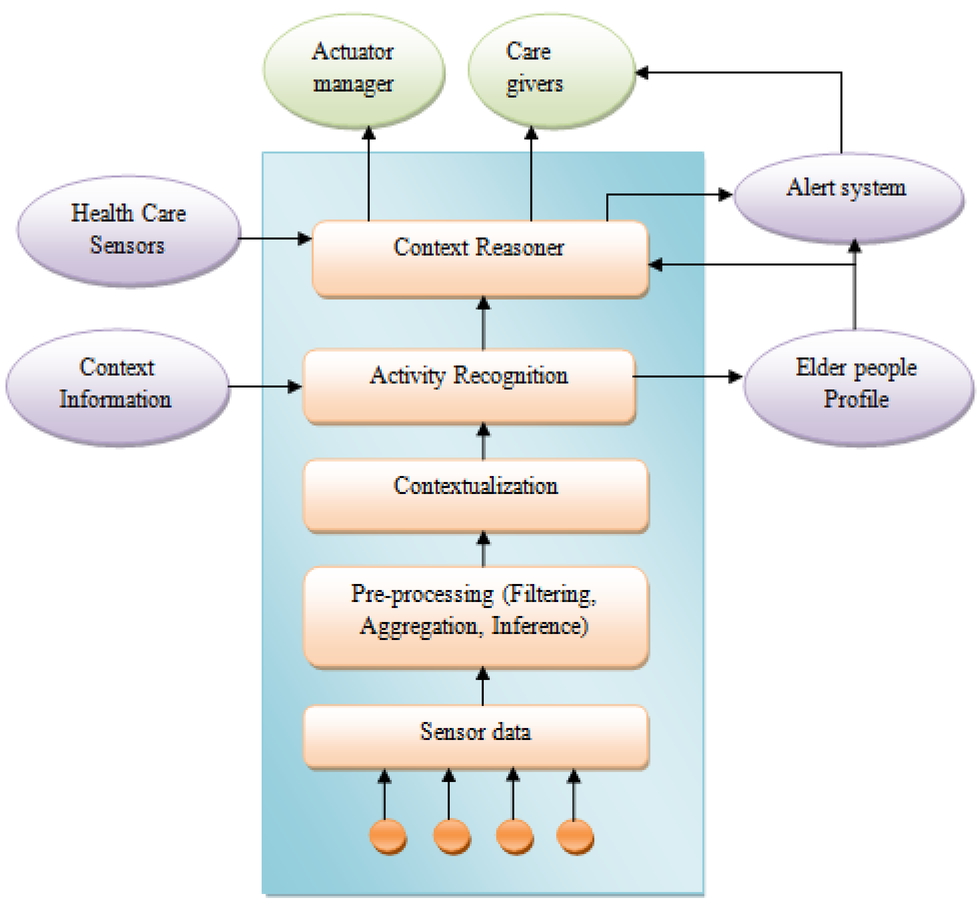

Figure 1. Overview of Context-aware Multi-layered architecture (CA-MLA)

2.1 Activity Recognition Module

The main module of the AAL system is the activity recognition module. Activity Recognition Module (ARM) performs the multisensor data fusion method with the fact of DST and to cope with the necessary imprecision of sensor and knob the dynamic phenomena. The theory of Dempster-Shafer, also known as the theory of beliefs, generalizes the subjective probability theory of Bayes [23]. The theorem of Bayes is a way to find a probability if we know some other probabilities. The Bayesian theory requires probabilities for each issue of interest; beliefs allow us to base degrees of belief on probabilities for a related question for one question. These degrees of belief may or may not have the mathematical probability properties. Dempster-Shafer theory (DST) is a mathematical theory of evidence-based on the theory of belief functions, also referred to as evidence theory. It is a general framework for uncertainty with reasoning. DST is used to combining pieces of evidence from different sources and arrives at a degree of belief (represented by a belief function) that takes into account all the available evidence [22].

$m : 2^{\Theta} \rightarrow [0,1]$

$$m : \phi = 0$$
$$\sum_{X \subseteq \Theta} m(X) = 1 \qquad (1)$$

Equation (1) is a function of the necessary probability assignment's $m(X) \rightarrow A$ primary assignment of probabilities for set A. ϕ and X is the empty set and subset of Θ.

Belief function

$$Bel : 2^{\Theta} \rightarrow [0,1] \qquad (2)$$

$$Bel(X) = \sum_{B \subseteq X} m(B)$$

Where Bel refers to the sum of the beliefs, belong precisely to the elements of set A. B is a subset of Θ.

$$Pl : 2^{\Theta} \rightarrow [0,1]$$
$$Pl(X) = \sum_{B \cap X \neq \phi} m(B) \qquad (3)$$

Pl(x) in equation (3) is the sum of all beliefs common to the elements of set A. that is, the degree of belief leftovers plausible.

Dempster's rule plays a significantly meaningful and exciting role in aggregating evidence from multiple sources. Let X_i be a subset of Θ and $m_1(X_i)$ be a mass assignment for hypothesis X_j collected from the j_{th} source.

Subsets $\{X_{1,} X_{2,} X_3 .... X_n\}$

Mass assignments $\{m_1, m_2, m_3\}$

DST rule is given below

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$$m\{X\} = \{m_1 \oplus m_2 \oplus ....m_n\}(X)$$

$$m\{X\} = \frac{1}{1-k} \sum_{B \cap A = X \neq \phi} m_1(B) m_2(A) \tag{4}$$

Where

$$K = \sum_{B \cap A = \phi} m_1(B) m_2(A) \tag{5}$$

$$\left[K = 1 - \sum_{r=c} m_1(X_1) m_2(X_2) ....m_n(X_n) \right]$$

Equation (4) and (5) shows that DST's rules which will calculate the masses and constant over the set of all pieces of evidence.

In summary, the theory of D-S allows mass to be assigned to sets or intervals and is designed for fallacious reasoning using evidence from multiple sources.

2.2 CA- Rule-based Reasoning

To get the user's comfort and health condition, from the origin of the lower-levels of modules, the information can be received, which is adopted by Context Reasoner to satisfy the user's needs current situation can be executed by the consequential sequence of actions. By using the rule-based inference engine jess, the Reasoner has implemented [23]. According to logical rules, Jess explains a pattern matching algorithm for query a knowledge base. The rule defined as "if<condition>then<action>" form, the rules can be executed when every individual condition is satisfied. User condition property is the most significant property on the basis of Reasoner behavior. The user describes the assumed condition, and it takes three probable values includes normal, abnormal, and emergency. User-condition property is used to change the system alerts level; accordingly, the process of data fusion is used to alter the amount and type of sensor information dynamically with the beneficiary. The condition normal suggests that the user has been in health, and no abnormalities or urgently were noticed. The system arrives power-saving mode; nonuse sensors keep on turned off mode, concentrating on monitoring the user carefully, ensuring the user comfort, and sending alert messages periodically. The abnormal conditions can occur when the sensors are moderate moves unusual stage or if the users skip over the usual activities [24]. In this instance, to determine the importance of the situation, the system requires increasing the accuracy, and it can send the alerts when the abnormal condition remains. At last, by analyzing both information and vital signs from the activity Recognition module and If we detect a severe or protracted anomaly, then the system enters in emergency mode. In this, the small subunit of the rules can be put-upon through the system, and it can be described how the system changed the behavior dynamically and conclude the user-condition property.

The first rule places the system into the abnormal condition if the user's blood pressure is out of the ordinary, and the user is sitting on the bed:

high blood pressure in Abnormal condition:

- If (blood pressure is "high") and (activity is "sitting on the bed") then

  User-condition "abnormal."
- If (blood pressure is "high") and (activity is "relax") then

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User-condition" abnormal."

- If (blood pressure is "high") and (activity is "eating") then

  User-condition "abnormal."

It merits to see that the same blood pressure reading is regular if the user is doing walking, as demonstrated by the following rule.

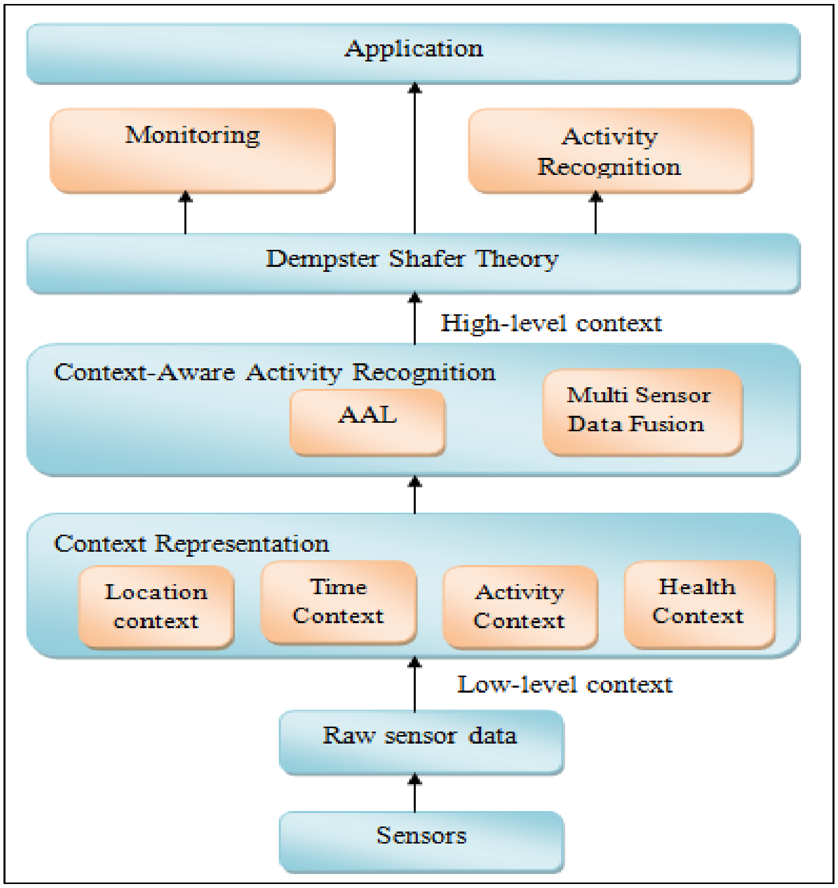

Figure 2. Overview of daily Monitoring and recognition of activities

High Blood Pressure in normal condition

- If (blood pressure is "high") and (activity is "walking") then

  User-condition "normal."

- If(blood pressure is "high") and (activity is "exercising") then

  User-condition "normal."

- If(blood pressure is "high") and (activity is" meal preparation")then

  User-condition "normal."

For this situation, the high blood pressure is clarified by the stress of performing physical exercise. The system accurately disambiguates the sensor reading and construes that the user-condition is normal.

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At last, the accompanying rule is activated when the system identifies a medical emergency, and the user is lying on the floor in trouble.

Heart Rate in an emergency condition

- If (heart rate is "very high") and (activity is "laying on the floor") then

  User-condition "emergency."
- If (heart rate is "very high") and (activity is "sitting") then

  User-condition "emergency")
- If (heart rate is "very high") and (activity is "eating") then

  User-condition "emergency")

Send alerts to family members, caregivers, and medical staff. The system perceives the reality of the emergency and quickly sends proper alerts to the included individuals and medical staff. It merits to see that the user can also drive the system to enter the abnormal state, by expressly requesting aid, by denoting a condition of trouble.

3 Context-awareness

In the architecture, multiple-level of context information is designed and used. The multilevel nature of the system permits and supports the reuse of information obtained or implied by lower-level modules. This kind of architecture, higher-level modules developed completely, makes use of the context information from the lower-level of implementation. For instance, using high-level components of the knowledge can be performed by the user activity. The algorithm can be accepted by the Activity Recognition module even it's ignored that can be considered as a smart virtual sensor responsible for perceiving the activity performed by the user. Below the Reasoner, abstraction can be connected to all the modules which are delineated in Fig 2, which recommends as possible view of the proposed architecture, AAL system can be highlighted between the modules and data flow.

In more detailed, the physical sensor can be capture form data and knowledge streams from low-level to high-levels. The user's condition and the environment are in a high-level description. In the application situation of AAL, the extraction of the knowledge can be represented by the physical input sensor. This process can be ordered in three classes, such as personal sensors, expert health sensors, and ambient sensors. Personal sensors may be inserted into smartwatches and smartphones; wherever the user can go, these sensors thus follow along with them, for example, gyroscopes and accelerometers. The combination of their readings can be viewed as a virtual posture sensor equipped for recognizing whether the user is sitting, standing up, or lying on the bed or on the floor.

Ambient sensors, for example, temperature, motion, lighting, and door sensors, are pervasively positioned in the smart home and comprise the primary input of the Activity Recognition module. Information originating from these ambient sensors can be used to combined and gather the user's location with room-level granularity, so encouraging a virtual location sensor that creates some portion of the context information developed by higher-level modules. The set of context information is enhanced with straightforward time-related information rather than position and location, for example, the day, the time of day and the month.

The input of the Virtual Activity Sensor is ambient sensor and context information. The output of the virtual activity sensor is thus joined with historical user data to derive the user context, which is a high-level portrayal of what the user is doing and why. An instance of user context is "After breakfast, and the user is taking medicine correctly. The user can perform a series of actions accurately, which is recognized and comparing those actions with users everyday agenda. It is incorporate taking exact medicines after breakfast (e.g., Eating pursued by taking medicine) then to efficiently decide the user condition.

The gathered user condition and the output of the virtual activity sensor are merged with data. It is originating from specialized health sensors, measure vital signs, blood pressure, heart rate, respiration rate.

4. Experimental analysis

In a smart home, all rooms were deployed from various types of sensors so that the proposed system is evaluated in smart homes. Sensor data can get it from the Aruba data set, which is obtained from the Washington state university CASAS smart home project.

In this paper, we have used three types of context, such as location context, time context, and activity context. Based on these context types, we will recognize the activity of elderly people. From the table, the diversity index describes how activities are conducted uniformly in specific functional areas of the smart home. The average duration is calculated based on no of activities and time slices for each event based on the data set.

Information based on Location Context: The first collection of tests discussed here is to illustrate the importance of position context information derived from ambient sensors. In general, we examined the various characteristics of the most typical daily living behaviors in a smart home in the ALL application scenario. Table 1 estimates the average duration, diversity index, and time slices related to each activity in the given setting is summarized. We examined every activity in a smart home, which we divided into rooms and then finding the daily activities of the elderly in multiple rooms, and those conducted at various locations. Here we have taken the activity with the highest and lowest activity of diversity indexes such as sleeping, housekeeping, and eating. Fig.3 shows the performance of the activity of sleeping, housekeeping, and meal preparation.

The Aruba dataset is explained daily living of 11 activities, includes housekeeping, eating, work, meal preparation, a bed to toilet, relax, wash dishes, leave home, enter the home, and a respirator (high blood pressure treatment device) [25].

Table 1. CASAS dataset [28] of diversity index, avg duration, and time slices

Activity	**Diversity Index**	**Avg. duration**	**# Time slices**
Housekeeping	1.942	00:20:30	1,373
Eating	1.340	00:10:30	5,366
Work	0.800	00:18:00	6,010
Meal preparation	1.997	00:08:00	25,246
Bed to toilet	0.713	00:02:30	912
Relax	1.064	00:36:00	197,072
Wash dishes	0.853	00:07:30	978
Leave home	1.156	00:00:30	173
Enter home	1.296	00:00:30	173
sleeping	0.615	04:03:30	192,433
outside	0.734	01:50:00	89,498
Respirator	0.749	00:09:00	110
Other	1.895	00:12:30	114,244

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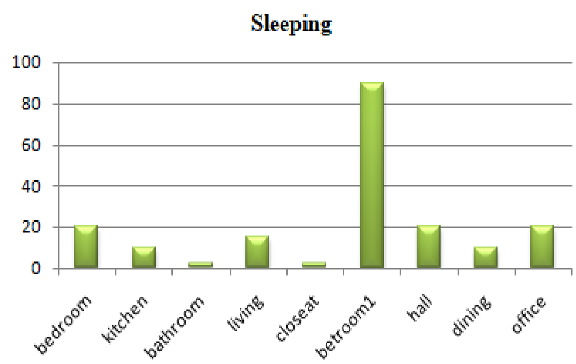
Information based on Time Context:

In this step, we introduce time-related context and through analysis of the significance of certain context attributes related to the time of the day, day of the week, and month. We start by examining the system's output while changing the specificity of the day node. From the time context, our findings showed that the accuracy of F-score of the method could be enhanced by manually splitting the day into four parts includes, Morning (7 AM -11 AM), afternoon (11 AM – 7 PM), evening (7 PM – 10 PM), night (10 PM – 7 AM). Likewise, the time cycle follows closely to all phases of activities changes by the user in a single day, which is illustrated in Fig.4.

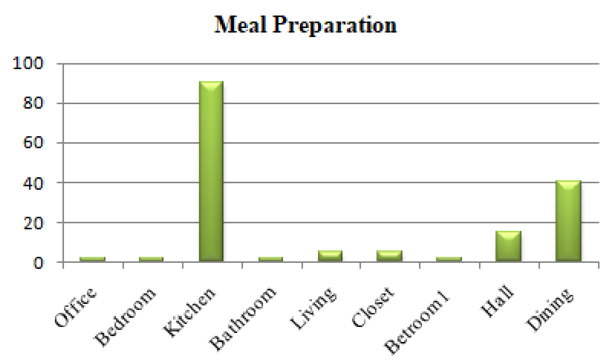
Information based on Activity Context:

We have noted that certain activities have a much higher average time than others. For example, sleep takes approximately 5 hours on average; while eating, it takes nearly 10 minutes. We noticed that the activity context demonstrates that the average duration of more extended activity than the others. For instance, housekeeping and average sleeping duration are 5 hours, but eating activity 10 to 15 minutes generally. Just a few activities are a similar duration. Other activities are related to each other. So this type of context fails to get the information about the activity from the sensors.

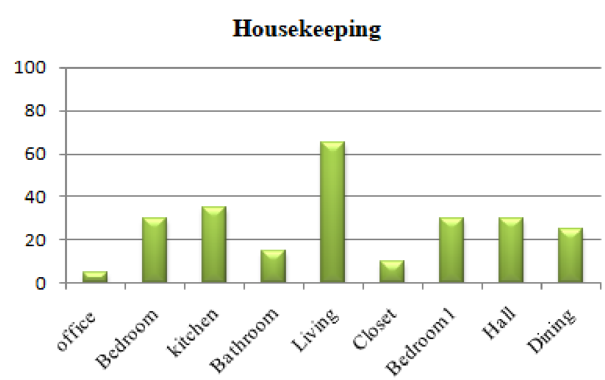
Health context: Health context is used to get the data from healthcare sensors. Here, context reasoning is used to get the high-level context data from low-level data. Fig 1 represents the activity recognition module, which is used to provide the contextualized data for context reasoning. The reasoning is used to get the information based on the elderly people's activity is abnormal, and it will inform the caretaker in the form of an alarm system.



(a) Sleeping Activity



(b) Meal Preparation Activity



(c) Housekeeping Activity

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Figure 3. The activities of lowest (a) highest (b) (c) diversity index

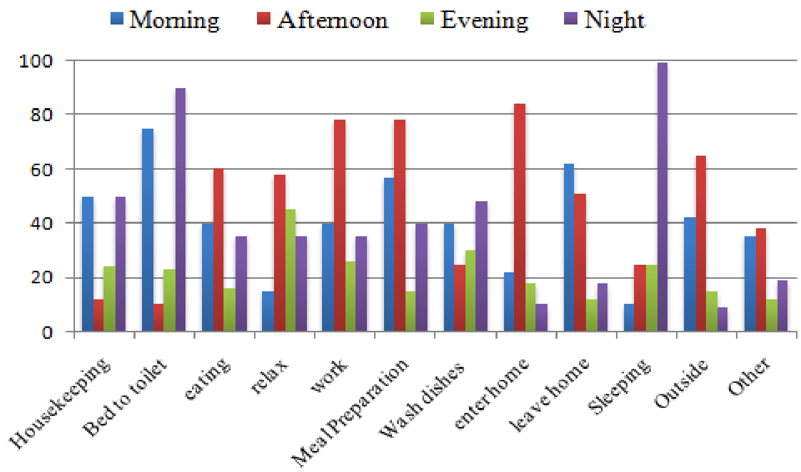

Figure 4. Information-based Time Context

Performance Analysis

To evaluate the efficiency of the behavior of the recognition system, we have taken the overall metric accuracy. The accuracy of inference is calculated by the data that is the activity of the people.

The accuracy of the inference are calculated by using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

The accuracy equation is used to calculate the accuracy of inference; it is used to estimate the total number of records, which is categorized by the classifier.

As a measure of reliability, we have defined precision that is positive predictive value and recall that is the sensitivity for calculating completeness of the system, which is represented below.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Precision, recall, and F-score is used to define the harmonic mean of precision and recall. Given below is the F-score formula.

$$F - score = 2 * \frac{\mathrm{P.R}}{\mathrm{P + R}}$$

The accuracy, precision, average uncertainty, recall, and F-score achieved by using both the sensors of virtual times and locations is shown in Fig.4. To increase the accuracy of activity recognition, the combination of context attributes is essential because these results can be modified by up to 12 percent. Figure shows the remarkable average accuracy and outcome of this accuracy is particularly good, as the other activity is especially hard to identify [24].

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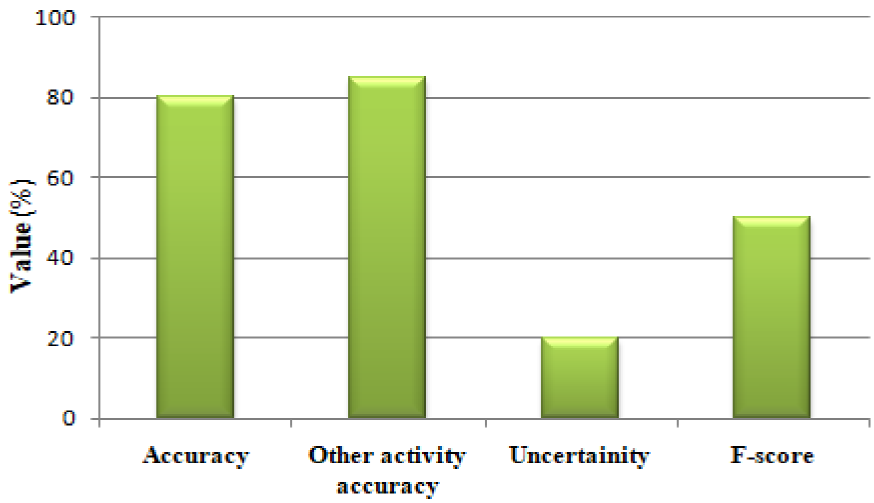

Figure 4. Average accuracy, uncertainty, and other ignored activities of accuracy and F-score of the system

5. Conclusions

This paper outlines new methods of applying the Dempster- Shafer Theory using rule-based reasoning for elderly people activity recognition under uncertainty. In this paper, we use context-aware multi-layered architecture (CA-MLA), which permits the system to understand the present situation and to identify the abnormalities and emergency situations in the health and behavior of the elderly people. Inform them if they miss an essential daily routine of activities, and it may give alert to family members and caregivers. Context-aware for Ambient Assisted Living system, which tries to enhance the standard of living of elderly and disabled people by assisting them to live peacefully and comfortably in their own home. Here, three types of context are used, which include: time, location, and activity. Based on the context types, user activity can be recognized.

We have illustrated the eligibility of this method in the application scenario for recognition of user activity in a smart home environment. The findings have reported that it is essential to choose the right combination of context information to increase the inference accuracy among various situations. The architecture achieved 75 percent development of activity recognition accuracy with the context information estimation on smart home (IoT) environment.

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