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Situation Awareness in Ambient Assisted Living for Smart Healthcare

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ABSTRACT The success of providing smart healthcare services in ambient assisted living (AAL) largely depends on an effective prediction of situations in the environment. Situation awareness in AAL is to determine the environment smartness by perceiving information related to the surroundings and human behavioral changes. In AAL environment, there are plenty of ways to collect data about its inhabitants, such as through cameras, microphones, and other sensors. The collected data are complicated enough to go for an efficient processing in perceiving the situation. This paper gives an overview of the existing research results in multimodal data analysis in AAL environment to improve the living environment of the seniors, and it attempts to bring efficiency in complex event processing for real-time situational awareness. This paper thus considers multimodal sensing for detection of current situations as well as to predict future situations using decision-tree and association analysis algorithms. To illustrate the proposed approach, we consider elderly activity recognition in the AAL environment.

INDEX TERMS Ambient assisted living, M2M communication, Internet of Things, multimodal sensing, activity recognition, smart healthcare.

I. INTRODUCTION

Rapid population growth related to aging population and the growing number of senior citizens living alone are bringing challenges that affect our society. As the world's population ages, many seniors are simultaneously suffering from increased levels of ill health. World Health Organization (WHO) predicts that by 2050 two billion people will cross the age of 60, while half of the developing world population will be prone to become chronically ill [1]. As a person ages, he or she may become more vulnerable to various diseases, such as heart diseases, Alzheimer's, dementia, and diabetes mellitus that demands for the patients to be continuously monitored and assisted. Hospitalization of this large number will become quite expensive. However, without receiving sufficient care, elderly is at risk of losing their independence. This has created an urgent interest in ambient assisted living (AAL) domain. AAL is considered as a paradigm for addressing the problems related to hospitalization, cost efficiency, and elderly independence that resulted due to the aging population. Monitoring activities at home consider as a known practice to afford assistance and support the independence living of the elderly [2]. It also can be helpful in reducing costs for public health systems and in providing services to the older people for increasing his/her quality of life.

In AAL environment, a wide range of measurements can be acquired through sensors and devices that are seamlessly embedded within the environment, or it may be obtained through devices the resident wears or interacts with [3], [22]. The data collected from this setting are related to residents' vital signs, activities, and surrounding physical world objects, which can be leveraged to also infer users' behavior pattern. The recognition and recording of activities of daily living (ADL) are critical in AAL environment. It is especially important to understand what activities users are performing, how they're performing it, and its current stage. The importance of recognizing ADL stem from the fact that any low level of activity may indicate potential health problems and can give important signs of progression of certain diseases [4]. For example, Disturbed sleeping patterns could be caused, for example, by heart failure and chronic disease. Changes in gait, on the other hand, can be associated with early signs of neurological abnormalities joined to several types of dementias. These examples highlight the importance of continuous observation of behavioral changes in the elderly to detect health deterioration before it becomes critical. A study in [5] shows that patients with Alzheimer's disease (AD), rapidly loses the ability to perform ADL during the later stages of dementia.

Thus analyzing the elderly people behaviors and looking for changes in their activities is more than needed. The wider availability of sensor technology has made automatic activity recognition a reality. Accordingly, activities of a person can be tracked and continuously monitored by attaching a variety of sensors on various objects, locations, and the human body.

In this paper, we will consider our approach to recognize activity from IoT-AAL environment that provides multimodal data through machine-to-machine communication to facilitate situation awareness in AAL environment. As improved situation awareness allows responding to accidents and emergency situations in a timely and effective manner, reduce deaths and injuries, and reduce the resulting healthcare cost, we aim to make a contribution in this area.

II. RELATED WORK

This section covers existing work that employs a variety of sensors including video cameras and embedded sensors for detecting and monitoring activities to understand the situation at home or at AAL facility for elderly monitoring.

One of the primary focuses of smart health care is to understand the situation in AAL environment and to provide relevant services to the elderly people there [3]. Due to the advancement of technology, especially M2M technology that is a driving force for future Internet of Things (IoT), doctors can now interact with their patients remotely to get the updates on patients' health status and suggest appropriate medication. Also, it helps elderly people especially those with chronic illness to live independently. Besides, the new technological revolutions are helping the caregivers to understand the situation in AAL better. In the following, we comment on some works relevant to the support for elderly residents in AAL environment, media processing for humn movement, and the emergence of M2M in healthcare.

Hossain and Muhammad [6] define a cloud-based health monitoring framework that collects patients' ECG and other healthcare data and send it to the cloud. The cloud infrastructure is used to enable seamless access of the patients' data by healhcare professionals such as doctors, nurses and caregivers. A similar approach has been adopted by Shamim Hossain [7] within the context of cyber-physical system. The work in [8] focuses on recognizing patients' states including normal, pain, and tensed using a combination of speech and facial expression. The author claims to obtain 98.2% recognition accuracy, however, it is not clear how much this recognition of patients' states would contribute to the understanding of situation in AAL environment.

The work in [9] describes the application of image fusion in background subtraction, which in tern is helpful for different analysis tasks including object and activity detection. A different approach has been demonstrated in [12], which used Kinect Sensor to retrieve human movement in real-time. In AAL environment, identifying human movement can give important clue to perceive surrounding situations.

Teller and Stivoric [10] illustrate that technology can be integrated even in clothes or accessories, such as bracelets and watches, to measure, record, and transfer different vital signs. Mamykina *et al.* [11] describe a model, which monitors diabetic patients. In another work Coronato and De Pietro [13] propose a formal method-based situation understanding and abnormal behavior detection. They used intelligent agents to accomplish the situation detection in the environment.

The future of machine to machine (M2M) capabilities in the healthcare industry is rapidly being explored and detected. Hence, the healthcare industry will need to find the most useful ways to reach and treat patients, and M2M technology is one of the ways to achieve just that. Cheng Chen [14] and Fan and Tan [15] discuss the ways to develop Machine-to-machine technology for healthcare. Also, they present an overview of the challenges, research opportunities, and standardization activities of this domain. Shin *et al.* [16] have developed intelligent mobile sensor agents in a healthcare scenario in an M2M context which can sense blood pressure of a patient and can notify remote doctor before severe condition.

In this research, we focus on situation awareness in AAL environment utilizing M2M sensing framework. As improved situation awareness allows responding to accidents in a timely and effective manner, reduce deaths and injuries, and reduce the resulting healthcare cost, we aim to make a contribution in this area.

III. PROPOSED SYSTEM ARCHITECTURE

We propose an M2M-enabled architecture for improved situation awareness in AAL environment, which requires monitoring of health and well-being of elderly people in real-time, processing of huge volume of data for situation identification, and sharing of information for situation analysis and control. We show how M2M technology, coupled with advanced data analysis algorithms and techniques, can result in better situation model for service provisioning in AAL environment. The following section provides an overview of the conceptual system architecture and the different functions that are carried out by different modules of this architecture.

A. OVERVIEW

The proposed conceptual M2M-enabled architecture is intended to provide decision makers, specifically in a smart AAL environment, with the ability to assess environmental conditions instantaneously and intuitively. The goal is to provide real-time information on the patient's status and

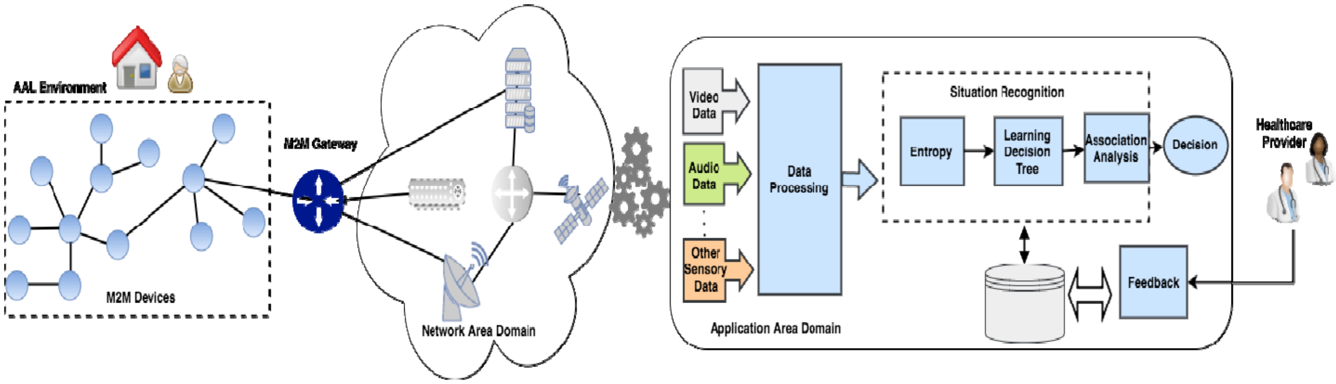

FIGURE 1. M2M-enabled architecture.

unusual situations to support short term/long term decisions at multiple levels, from personal to governmental. Data gathered by deployed sensors and devices located in the connected environment are used to understand the real world and then decide whether an action or alarm should be activated or not.

According to the main features of AAL system and M2M technologies, we propose a scalable architecture that enables M2M and multimodal sensing for rising SA in AAL environment. Figure 1 shows the proposed conceptual architecture. According to this architecture, the M2M devices in the AAL environment collect contextual data by observing the senior citizen and the environment around it through gateway. Gateway is important where it settles the heterogeneity between M2M devices and the internet. Gateway is essential to connect legacy things in Smart Home domain. The simplest form of an M2M gateway is a smartphone, where it considered as an integral part of our daily lives.

Figure 1 further shows several components that are used for data processing, situation recognition and feedback processing. The Data Processing unit processes multimodal data streams of varying data types collected from the environment. The Situation Recognition contains the model for recognizing activities. Based on the situation recognition, the system can make the decision. The final component is Feedback, which allows the healthcare provider to feed the system with all the unrecognizable situations. The following section describes the detail of the architecture in terms of the specific techniques proposed therein.

B. DATA COLLECTION

Ambient Assisted Living environment equipped with variety of sensors and devices. The role of deployed sensors and devices are to gather variety of data concerning the location of the resident(s), the object(s) they communicate with, and also health data. Data from all around the environment and residents gives the indication of the different situations. These data can in some combinations capture patterns representing physical and cognitive health conditions and then recognize when activity patterns begin to differ from the norm. In doing so, we aim to provide early robust detection of potential problems which may lead to serious health events if left unattended.

A wide range of measurements can be acquired through sensors and devices that are seamlessly embedded within the environment or are worn or interacted with by the seniors. The most common form of measurement that can be recorded remotely in AAL environment is probably the measurement of vital signs. This is because it can offer useful information for the assessment of resident's health, reduce the burden on health infrastructure related to cost and staff, as well as can be applied on a long-term basis to patients for detecting gradual deterioration in their health condition [19]. The common kinds of data acquired can involve the recording of parameters such as temperature, heart rate, blood glucose level, blood pressure, weight, and respiration rate.

In addition to health-related data, a number of sensors and devices have the ability to collect measurements of activity data to efficiently and unobtrusively infer users' behavior in their environment. This includes inferring which activity users are performing, how they're performing it, and its current stage.

Finally, the measurements of environmental parameters can be utilized to control heating, lighting, ventilation, and water temperature in a manner that reduces operating cost. Environmental perception is accomplished using a variety of sensors. There are sensors designed for detection of temperature, humidity, sound, strain, pressure, position, and light. While security has high priority in homes today, home monitoring cameras and connected door locks are among the most popular devices that produce data to infer security threats. Also, connected thermostats topped the list of the most popular products, which is used in heating and cooling in optimizing energy use. The Figure 2 shows a typical AAL environment highlighting different types of data that can be collected.

All the above-mentioned data can be gathered using different technology. In a recent review Kirsten Peetoom *et al.* [21] surveyed monitoring technologies used in AAL applications

FIGURE 2. Represents data heterogeneity in AAL environment.

to collect data. They identified five main types of monitoring technologies that detect ADL or significant events (e.g., falls of elderly people in-home). The identified technologies were body-worn sensors, video monitoring, pressure sensors, PIR motion sensors, and sound recognition, most frequently combined in a multi-sensor approach. Multi-sensor approach where information from multiple sensor technologies can be combined in a practical manner aims to improve the overall assessment and decision-making process.

Besides collecting data, the devices are capable of transmitting data autonomously or after receiving a data request. In the context of AAL applications, the M2M devices are principally low-power sensors and actuators, implanted in/around the patient's environment and/or actually worn by the user. These devices can interconnect in a short-range network using an embedded wireless communication module. This can collect multiple data streams of varying data types.

C. SITUATION RECOGNITION

The development of a Situation Awareness (SA) model that supports the system and users is a strong requirement in the architecture laid in Figure 1. Using the proposed approach, the surrounded environment is captured by the built model, and for the events to be occurred. In addition, it is necessary to judge the optimal decision and execute the action. This is explained by entropy calculation, building decision tree, and association analysis as follows.

1) ENTROPY CALCULATION

Entropy is a measure of the unpredictability of information content [18]. Entropy is used to choose the most appropriate attributes to be used in building Decision Tree (DT). The idea is that some attributes act as noise and outlier which in turn slow down the processing task. These calculations are carried out on the data allow us comparing any of these data must we have to divide into first to build a DT. The formula of entropy that uses the possibilities of the event is computed as:

$$E(S) = -\sum_{j=1,\ldots,k} P_j log P_j \qquad (1)$$

The approach proposes to determine the entropy gain for each set of sensory data and find the highest entropy gained sensory data set.

Let $E_{s_1 \ldots s_n}$ be the entropy for the $s_1, s_2, s_3, \ldots, s_n$ dataset and $ES_1, ES_2, \ldots, ES_n$ be the entropy for the $s_1, s_2, s_3, \ldots, s_n$ data set respectively.

The entropy gain for each of the individual data set can be computed as:

$$EG_1 = \left(E_{s_1 \ldots s_n} - ES_1\right), EG_2 = \left(E_{s_1 \ldots s_n} - ES_2\right), \ldots, EG_n = \left(E_{s_1 \ldots s_n} - ES_n\right) \qquad (2)$$

Then, the highest entropy gain can be computed as:

$$MAX(EG_1, EG_2, \ldots EG_n) \qquad (3)$$

Once the highest entropy gained data set is distinguished, then this process would be iterated for the reaming set of sensory data. We will use the collected sequences of the highest entropy-gained sensory data set into decision tree induction process to find an optimal decision tree that can express a particular situation in AAL environment.

In this phase, we proposed to use entropy as a feature selection method. After the sensor features are extracted, a decision tree model is trained.

2) BUILDING A DECISION TREE LEARNING MODEL

Learning is noteworthy as an algorithm necessary for decision making and behavior understanding. The model's detailed learning, by example and later by actual experience, represents knowledge acquisition technology that causes the model itself to generate the necessary knowledge as a hypothesis. Even if the knowledge is only partial and deficient, hypotheses are obtained by learning. Therefore, it becomes possible to complement the knowledge and gradually take better decisions and actions. Depending on what kind of information and situations are being learnt, various learning methods are being researched and developed. Learning of decision trees is one of the easiest classes of algorithms to learn structures, but it is one that is well-used and practiced successfully.

The learnt model is represented as a tree, called a decision tree. The purpose of the decision tree is to classify the data represented by a set of attributes and their values (attribute 1 = value 1,. . ., attribute n = value n) into what we call several classes. For example, I want to classify the daily activities of a user into a class such as eating or watching TV, using collected data. The decision tree is a tree structure for making such a judgment. The nonterminal node of the decision tree is labeled with an attribute and the branches emerging from it are given the possible values of that attribute. The final classification is written in the terminal node. When passing it as a question input, we follow the branch from the root of the tree while testing the value of the attribute, and output the classification of the final arrival terminal node as the judgment result. The decision tree generated is different depending on the order in which attributes are tested.

In this model, we use Information Theory (Entropy). The point of the idea is to select only one attribute with high "discriminatory power" in some sense and decide to test it first.

A collection of such data is called a training example for a learning algorithm. The learning algorithm outputs a decision tree which can reproduce the training example as closely as possible when receiving an input.

3) ASSOCIATION ANALYSIS

Association rule (AR) is a kind of pattern discovery. The aim of Association Analysis is to have a deep understanding of the relevance of data to utilize the rules collected using data from sensors, machines and so on. The ultimate goal of SA after identifying what is occurring is to know how to act in response to any particular situation. While the decision tree helps to build up a general picture of what is happening, association analysis break down the events in each object that has been interacted with, location or body posture to get clues as to what will occur next.

ARs first became known from market basket analysis, and the benefits have been used for promotional pricing or product placement. In the AAL domain, discovering hidden patterns in the collected data can help in SA projection. We need to learn the common relationships between the user and surrounding environment to have greater comprehension. Systems need more than one type of input to get the situation and more about what is happening to be able to make projections. The point is that AR can help to discover the patterns in our lives (context) so those rapid projections can be made about what will happen next, and to give computers the ability to understand the intentions of users.

In this approach, we use Frequent Pattern Growth algorithm (FP-Growth), where we can find frequent pattern in large datasets. It considered one of the efficient and scalable methods to create frequent patterns from the dataset. This is a two-step method where it creates a compact data structure called FP-tree. Then, it simply extracts the frequent attributes from FP-tree.

Consider A is a set of n attributes $A=\{a_1,a_2,a_3,\ldots,a_n\}$, and let I be a set of Resulted activities that are inferred by set of attributes called the instances $I=\{i_1,i_2,i_3,\ldots,i_n\}$. A rule is defined as an implication of the form:

$$X \Longrightarrow Y, \quad \text{where } X \subseteq A, \text{ Y is the classification of activities and is subset of I.}$$

We should calculate Support as given in equation 4 below:

$$Support\ (X) = \frac{|\{i \in I; X \subseteq i\}|}{|I|} \tag{4}$$

Next, we apply the support threshold to find the frequencies of occurrences (e.g. minimum support > 0.99). To find the most useful and efficient rules, we use LIFT as:

$$lift(X \Longrightarrow Y) = \frac{Support(X \cup Y)}{Support(X) \times Support(Y)} \tag{5}$$

After extracting the most relevant rules, we integrate them with the appropriate actions. Consider Z is a set of all defined actions that the system can response $Z=\{z_1,z_2,z_3,\ldots,z_n\}$ and R is the set of all the rules $R=\{\boldsymbol{x_1} \Longrightarrow \boldsymbol{y_1}, \boldsymbol{x_2} \Longrightarrow \boldsymbol{y_2}, \ldots \boldsymbol{x_n} \Longrightarrow \boldsymbol{y_n}\}$. Then we find the appropriate action to be integrated with the extracted rules as:

$$(X \Longrightarrow Y, Z) \tag{6}$$

where Z is an action in responce to particular situation

IV. EVALUATION

To evaluate our proposed approach in raising situation awareness in an Ambient Assisted Living context, we choose activities recognition as a way to prove it.

Activity recognition is the means of learning user physical behavior from multimodal data. In our work, we are especially interested in recognizing essential activities that have a significant influence on elderly health and severe situations.

In this section, we first describe the dataset used in evaluating the performance of our approach. We then provide the results of the evaluation phase and show the performance of the approach with several metrics.

A. DATASETS

To prove the feasibility of our approach in raising SA, we conducted preliminary activity inference on the datasets that were provided for us by INRIA University. According to [17], the datasets were collected by the several sensors deployed in the home care environment (i.e. experimental laboratory). The nature of chosen sensors was efficient and easy to live with, no need to wear or carry them. The sensors included video sensors and environmental sensors, which were placed in different locations in the environment.

The dataset provided by the INRIA University has 11-day folders for different patients containing environmental sensors and a folder named Movies, containing all the videos from four different cameras for each patient.

Unfortunately, the dataset was delivered with no ground truth. Hence, we had to deal with the activity labelling techniques. While studying human activities and behavior, it is important to use reliable methods for labelling people's activities. Labels provide a way to validate the results of the study. In this work, activity labels were used to train and test the accuracy of the activity recognition algorithms. We used direct observation to label the data. We went through all videos to label the datasets which was time-consuming and disruptive. Overall, we conducted preliminary activity inference on the datasets that were provided for us by INRIA University to prove the feasibility of our approach in raising SA.

B. PREPROCESSING

When studying human activities and behavior, it is challenging to understand what this data can tell us without preprocessing. The preprocessing phase is a major step in the data mining process. This transforms the raw data into another format that is comprehensible.

The facts about the dataset we started using is given in Table 1. Data preprocessing is a demonstrated technique for determining issues such as data incompleteness and

TABLE 1. Facts from dataset.

	Objects	Attributes	Missing values
Dataset	27	5	466

TABLE 2. Attributes in dataset.

Attribute	Description	Range
Location	It describes the user location by the object initiating by using	Kitchen, living room, bathroom
Body Posture	From camera, describes the body posture captured by camera	Standing, standing with arms up, standing with hand up, sitting on chair, binding
Sensor	The type of sensor attached to the object	Water flow, pressure, presence, video cameras, electrical, and contact switches
Object	Which object that the user is interacting with	It can be any object around the user
Value	The object state	Whether it's on or off
Time	Measure time, when the user did interact with a specific object	Record the event time

inconsistency. Thus, the representation and quality of data are a matter of high importance before running an analysis. In analyzing the multimodal data, we tried to organize the data and fill up with four categories, which are spatial, time, objects and person's posture. By knowing the four groups of information, we can recognize the activities to build a robust learning model to enhance picturing of the situation. We should feed the database with good practices or models to recognize the current situation.

Data from the deployed sensors has the following attributes summarized in Table 2. We collected data for a set of eight activities:

- Prepare a meal
- Wash dishes
- Eating
- On the phone
- Watching TV
- Sit-ups
- Toileting
- Brushing teeth.

The list of activities can be an infinite list. However, we have only targeted the elderly life in our study in order to narrow down our scope and to be more specific.

C. BUILDING DECISION TREE MODEL

In this section, we describe the building of a predictive model to predict the target activities using our approach. Entropy gain theory was introduced in the previous section for estimating and managing the feature selection to avoid tree overfitting. Using the entropy data, we now show how we implement the decision tree model.

TABLE 3. Attributes importance based on entropy calculations.

Attribute	Weight
OBJECT	0.814
LOCATION	0.625
SENSOR	0.247
BODY POSTURE	0.209
VALUE	0.200
WHEN	0.090
TIME	0.033

After preparing the data, we compute the information gain of each attribute to measure the attribute importance as in Table 3. Therefore, among these, the attribute that can obtain the maximum gain is adopted as the root of the decision tree, and the result becomes a partial decision tree.

Then, we run a decision tree learning algorithm to build the optimal tree to predict activities from sensors data.

D. ASSOCIATION ANALYSIS

The process of developing the association rule model is decomposed into four parts.

Part 1: data loading from the 11 new files and merged. The data summary shown in Table 4 reflects the data variables Location, Body Posture, Sensor, Object, value, and When. For each variable, we show the values it can take and its frequencies.

Part 2: It is the first performed analyze, which consist of finding the most frequent activity attributes. In Table 5 we show the obtained result, which contains the eight most frequent activity attributes with the highest support value.

Part 3: The second analysis consists of extracting association rules from data. We use the FP-Growth algorithm to learn the most frequent association rules. We find 2519 rules, 92 of them contain 2 items, 519 of them contain 3 items, 960 of them contains 4 items, 741 of them contain 5 items and the remained 207 contain 6.

We then select just the most relevant rules, which are the rules having a higher lift as shown in Table 6 (shown partially for three activities). Lift value tells us how much those two events are reliant on each other, and makes those rules possibly helpful for predicting the consequent in future informational collections.

Part 4: we integrate the extracting rules with the appropriate actions. According to what the model can predict we identify the actions in response to a particular situation. We defined two actions either it is the usual case where the situation is recognized or "Report'' with unrecognizable situations, as depicted in Table 7.

V. RESULTS AND DISCUSSIONS

A. RESULTS

The obtained tree is built from a training dataset containing just 75% from the whole data set, and the remaining 25% is

TABLE 4. Data summary with data variables.

LOCATION		BODYPOSTURE		WHEN	
Bathroom:	460	Standing with Arms Up	3258	MORNING	3552
Kitchen:	5657	Standing	2069	AFTERNOON	3167
Living_Room:	958	Standing with Hand Up	670	EVENING	355
		Sitting on Chair	352	MIDNIGHT	1
		Bending	260		
SENSOR		**OBJECT/ OBJECT STATUS**			
PRESENCE	3243	STOVE	1697	WASHBOWL.HOT	160
WATER	1560	SINK	1088	CUPBOARD.UPPER.CENTER	158
OPENCLOSE	1537	SINK.COLD	702	TV	154
USAGE	735	SINK.HOT	624	DRAWER.LOWER	141
		CHAIR.1	287	WASHBOWL	138
		ARMCHAIR	280	CUPBOARD.SINK	120
		REFRIGERATOR	265	WASHBOWL.COLD	74
		CUPBOARD.UPPER.RIGHT.2	262	MICRO_WAVE_OWEN	55
		DRAWER.UPPER	259	CUPBOARD	46
		CUPBOARD.UPPER.RIGHT.1	250	TEL	44
		CHAIR.2	193	FLUSH	42
				CUPBOARD.UPPER.LEFT	36

TABLE 5. Most frequent activity attributes.

Support	Items
0.800	LOCATION = KITCHEN
0.502	WHEN = MORNING
0.460	BODY POSTURE = Standing with Arms Up
0.458	SENSOR = PRESENCE
0.448	WHEN = AFTERNOON
0.292	BODY POSTURE = Standing
0.240	OBJECT = STOVE
0.220	SENSOR = WATER

TABLE 6. Rules based on lift values.

Rule	Premises	Conclusion	Lift
R_1	LOCATION = KITCHEN, BODY POSTURE = Standing with Arms Up , WHEN = AFTERNOON, OBJECT = STOVE	ACTIVITY= Prepare A meal	2.118
R_2	LOCATION = LIVING_ROOM, SENSOR = USAGE, OBJECT = TV	ACTIVITY = Watching TV	17.208
R_3	WHEN = MORNING, SENSOR = PRESENCE, LOCATION = BATHROOM, OBJECT = WASHBOWL	ACTIVITY = Ignore	17.945

used in testing the accuracy of the model. The obtained result in the decision tree model is 94.60% recognition rate. The result obtained is shown in Table 8.

TABLE 7. Corresponding actions to particular rules.

Rule	Action
R_1	Normal
R_2	Normal
R_3	Report

In Figure 3, we visualize the obtained rules in order to analyze and interpret them. The visualization displays the scatterplot of the 2518 rules, where the horizontal axis is considered as support, the vertical axis is considered as confidence, and lastly the shading is the lift. The scatterplot shows that in the generated rules where the highest lift founded according to confidence and support. For example, the marked rules in Figure 3 are very good because it have higher lift and higher confidence too.

B. DISCUSSIONS

Using simple representation of the dataset, we noticed that there are minority activities and majority activities (for example Prepare a Meal has 3319 instances, and Watching TV has just 291 instances). Accordingly, the classifier has some difficulties in detecting the minority activities. Also, we can see which object affects the activity directly.

The result in the previous section shows that the proposed method can achieve more accurate results using data gathered from everywhere/anywhere, calculating entropy to choose the best feature and building the decision tree. The developed predictive model, generated through learning the decision tree algorithm, can be a helpful tool. The model used to

TABLE 8. Confusion matrix of tree model.

Predicted \ True	Ignore	Watch-ing TV	Pre-pare A meal	Sit-ups	Using Tele-phone	Toilet-ing	Eating	Wash-ing Dishes	Brush-ing teeth	Washing hands / face
Ignore	310	3	3	3	0	0	2	17	0	0
Watching TV	1	236	1	24	1	1	11	2	0	0
Prepare A meal	17	8	3256	3	1	1	24	42	0	0
Sit	2	27	3	270	0	0	23	4	0	0
Using Telephone	0	1	2	0	62	0	0	0	0	0
Toileting	0	0	3	0	0	135	0	1	0	2
Eating	4	10	9	24	0	0	91	6	0	0
Washing Dishes	16	6	42	5	1	1	9	2108	0	0
Brushing teeth	0	0	0	0	0	1	0	2	71	6
Washing hands / face	0	0	0	0	0	0	0	0	7	154
Classification Accuracy			**94.60%**							

TABLE 9. Performance measurements of tree model.

Activity	Watching TV	Prepare A meal	Sit-ups	Using Telephone	Toileting	Eating	Washing Dishes	Brushing teeth	Washing hands / face
Precision	85.20%	97.14%	82.07%	95.38%	95.74%	63.19%	96.34%	88.75%	95.65%
Recall	81.10%	98.10%	82.07%	95.38%	97.12%	56.88%	96.61%	91.03%	95.06%
F-measure	0.83	0.97	0.82	0.95	0.96	0.60	0.96	0.90	0.95

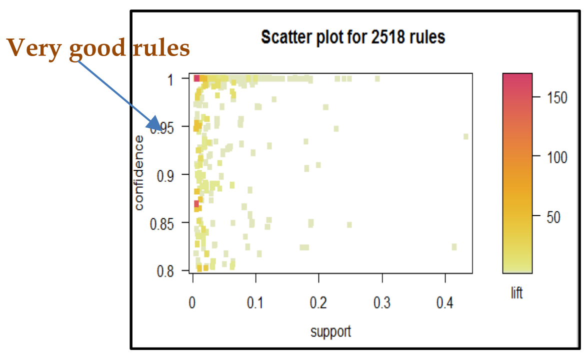

FIGURE 3. Scatter plot for rules.

predict user's behavior reliably without necessarily expecting to control it. The decision tree gave different alternative paths that represent measured actions or choices. This is followed by events with different chances of occurrence. The DT model represents what the user is doing based on the objects they interact with and/or the videos from surveillance. The obtained tree model shows that the recognition performance was quite well. It has a prediction accuracy of 94.60%.

As seen in Table 9, the Tree model performance, Eating activity prediction has the lowest score where the model cannot predict or distinguish between eating or leisure activities such as Watching TV; it has common attributes such as time, location and objects (e.g. the user can eat while the TV is on). Earlier from Table 8, we can see that the model has difficulties to distinguish between Eating and Watching TV/Sit-ups. Hence, Eating and Watching TV have the lowest scores since the model will have the same elements in the two situations.

In Table 9, Preparing a Meal, Toileting and Washing Dishes have the highest scores (recall value) 98.10%, 97.12% and 96.61% in a row. Because each and every one of these activities has different clear attributes that help in predicting it precisely. On the other hand, if we tried to predict precisely whether the user was washing his face or brushing his teeth it would have been more complicated since the attributes to predict these two activities are very much the same.

C. COMPARISON

In this section, we will compare our results with some studies to prove that up to what extent our results are precise.

TABLE 10. Accuracy between proposed model and previous work.

	Watching TV	Prepare A meal	Sit-ups	On The Phone	Toileting	Eating	Washing Dishes	Brushing teeth	Washing hands / face
Proposed Model	85.20%	97.14%	82.07%	95.38%	95.74%	63.19%	96.34%	88.75%	95.65%
Zouba et al. [23]	-	80%	86%	-	-	-	81%	-	-
Fleury et al. [24]	-	-	-	89.5%	93.75%	97.80%	-	64.30%	-
Chernbumroong et al. [4]	-	-	-	-	-	93.04%	86.00%	85.56%	-
Lee et al. [25]	92%	-	91%	92%	-	-	-	-	-

Table 10 represents our results in compare to others recent studies for the recognition of a set of daily activities that are similar to what is in our study.

Firstly, we compare our results to approach that use the same dataset. According to [23], they've shown the result of primitive activities (e.g. use stove) and complicated activities (e.g. Prepare lunch). The prediction of the primitive was doing well, but regarding complicated activities, their approach which depends on an extension of event description language was less accurate.

In [24], they've classified the activities of daily living e using Support Vector Machines (SVM) algorithm. In [4], ADLs have been classified of an older adult using multi-sensor worn on the wrist. As seen in Table 10, the results are high performance and practical. Lee and Lin [25] explain how to identify the user's situation in a smart home environment using the user's motion data from a wearable device and location data. Their approach to model construction is based on a decision tree and hidden Markov model (HMM) with the help of location data.

The proposed method can deliver comparable or even higher accuracy comparing to previous works considering the location, Time and Object attributes.

VI. CONCLUSION

In this paper, we propose an M2M-enabled architecture for improving situational awareness in AAL environment. It offers the scalability and flexibility required by the smart homes to assist older adults. Furthermore, the proposed research will have a significant impact on smart healthcare, which is promoted by the smart city movement.

The architecture shows how M2M technology, coupled with advanced data analysis algorithms and techniques, can result in better situation model for service provisioning in AAL environment. The preliminary results of the proposed model show that the adoption of a multimodal sensing approach (a video data complemented by other sensors) has improved the situation identification performance of the activity recognition in comparison to those based only on video data. We plan to work further on this by impleenting the framework on cloud platform in order to support several AAL environments at the same time.

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