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EDITORIAL PREFACE

This is *First* Issue of Volume *Nine* of International Journal of Human Computer Interaction (IJHCI). IJHCI is an International refereed journal for publication of current research in Human Computer Interaction. Publications of IJHCI are beneficial for researchers, academics, scholars, advanced students, practitioners, and those seeking an update on current experience, state of the art research theories and future prospects in relation to applied science. Some important topics covers by IJHCI are affective computing, agent models co-ordination and communication, computer mediated communication, innovative interaction techniques and user interface prototyping for interactive systems etc.

The initial efforts helped to shape the editorial policy and to sharpen the focus of the journal. Started with Volume 9, 2019, IJHCI appears with more focused issues related to human computer interaction studies. Besides normal publications, IJHCI intend to organized special issues on more focused topics. Each special issue will have a designated editor (editors) – either member of the editorial board or another recognized specialist in the respective field.

This journal publishes new dissertations and state of the art research to target its readership that not only includes researchers, industrialists and scientist but also advanced students and practitioners. IJHCI seeks to promote and disseminate knowledge in the applied sciences, natural and social sciences industrial research materials science and technology, energy technology and society including impacts on the environment, climate, security, and economy, environmental sciences, physics of the games, creativity and new product development, professional ethics, hydrology and water resources, wind energy.

IJHCI editors understand that how much it is important for authors and researchers to have their work published with a minimum delay after submission of their papers. They also strongly believe that the direct communication between the editors and authors are important for the welfare, quality and wellbeing of the Journal and its readers. Therefore, all activities from paper submission to paper publication are controlled through electronic systems that include electronic submission, editorial panel and review system that ensures rapid decision with least delays in the publication processes.

To build its international reputation, we always work hard and try to disseminate the publication information through Google Books, Google Scholar, Open J Gate, ScientificCommons, Docstoc, Scribd, CiteSeerX and many more. Our International Editors are working on establishing ISI listing and a good impact factor for IJHCI. We would like to remind you that the success of our journal depends directly on the number of quality articles submitted for review. Accordingly, we would like to request your participation by submitting quality manuscripts for review and encouraging your colleagues to submit quality manuscripts for review. One of the great benefits we can provide to our prospective authors is the mentoring nature of our review process. IJHCI provides authors with high quality, helpful reviews that are shaped to assist authors in improving their manuscripts.

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Framework for A Personalized Intelligent Assistant to Elderly People for Activities of Daily Living

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Abstract

The increasing population of elderly people is associated with the need to meet their increasing requirements and to provide solutions that can improve their quality of life in a smart home. In addition to fear and anxiety towards interfacing with systems; cognitive disabilities, weakened memory, disorganized behavior and even physical limitations are some of the problems that elderly people tend to face with increasing age. The essence of providing technology-based solutions to address these needs of elderly people and to create smart and assisted living spaces for the elderly; lies in developing systems that can adapt by addressing their diversity and can augment their performances in the context of their day to day goals. Therefore, this work proposes a framework for development of a Personalized Intelligent Assistant to help elderly people perform Activities of Daily Living (ADLs) in a smart and connected Internet of Things (IoT) based environment. This Personalized Intelligent Assistant can analyze different tasks performed by the user and recommend activities by considering their daily routine, current affective state and the underlining user experience. To uphold the efficacy of this proposed framework, it has been tested on a couple of datasets for modelling an "average user" and a "specific user" respectively. The results presented show that the model achieves a performance accuracy of 73.12% when modelling a "specific user", which is considerably higher than its performance while modelling an "average user", this upholds the relevance for development and implementation of this proposed framework.

Keywords: Affect Aware Systems, Behavior Analysis, Smart and Assisted Living, Smart Home, User Experience, Affective States, Human Computer Interaction, Elderly People.

1. INTRODUCTION

The current century has seen a rapid increase in the population of elderly people [1] and it is predicted that their population is to even exceed the number of children within a few decades [2,3]. This rapid increase in the number of elderly people, mostly characterized by the increase in population of young elderly (aged between 65 to 85 years) as shown in Figure 1, is primarily due to improved conditions of health, assisted living facilities and declining fertility across the world [2]. Increasing age, which is characterized with the increasing needs for caregiver and healthcare solutions is starting to become a burden on the world's economy [4]. The number of elderly people across the world with dementia has doubled in recent times [5] and their number is predicted to again double by the year 2030, leading to approximately 76 million people with dementia worldwide. In 2010 alone, approximately $604 billion costs were incurred to the healthcare industry in looking after people with dementia and this number is increasing at an alarming rate. [5]

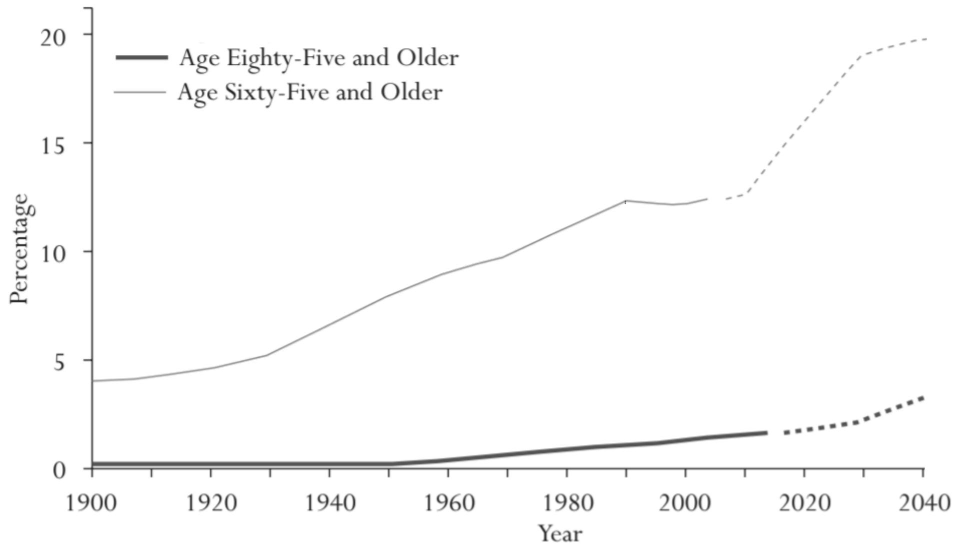

FIGURE 1: The current and predicted increase of elderly people: aged 65-85 and aged 85+ compared. (based on data about the population of elderly people from World Health Organization [9]).

For technology to sustain this ever-increasing population of elderly people and address their requirements, impactful and forward-looking urban development policies by governments and sustainable infrastructures implemented with technologies, for example smart homes, are necessary to support and enhance the quality of life experienced by them.

The application of Affect Aware Systems in an Internet of Things (IoT) based smart and connected environment holds the potential to serve as a long-term feasible solution to address this challenge. In the context of a smart home, Affect Aware Systems may be summarized as intelligent systems that can analyze the affective components of user interactions with an aim to assist the user to perform daily activities and improve their user experience in the context of their day to day goals. To enhance the quality of life experienced by elderly people and reduce their anxiety towards adapting to new technologies, it is essential for Affect Aware Systems to not only analyze user behavior [6] but also to recommend activities based on affective states [7] and the underlining user experience, to create a reliable, assistive, trustworthy and context-aware environment for assisted and ambient living.

The essence of providing such technology-based solutions lies in the effectiveness of technology to address the diversity in elderly population which can be broadly characterized by their varying age group, gender and differences in their background [8]. This diversity in the elderly population leads to varying experiences resulting in different habits and diverse nature of user interactions. Elderly people can broadly be subdivided into two sub-groups based on their age – (1) Young elderly – aged 65 to 85 and (2) Old elderly - aged 85 and above. These specific sub-groups are also diverse in terms of their gender and recent research [9, 10] has shown that this also leads to different characteristics of user interactions in elderly people.

Recent researches [11-20] in the field of affective computing and human-computer interaction for improving the quality of life of elderly people by providing cost effective solutions to address their needs have mostly focused on modelling an “average user”, however there is quite often a gap between the "average user" for which a specific technology is proposed and the "actual user" that exists - thereby leading to ineffectiveness of the assistive technology to aid the user. Therefore, this paper proposes the framework for development of a Personalized Intelligent Assistant that can adapt according to the user interactions performed by any “specific user” and recommend activities based on daily routine, current affective state and the underlining user experience, to improve the quality of life experienced by elderly people in the context of their day to day activities in a smart home.

This paper is organized as follows: Section II provides an overview of related works in this field. Section III provides details about the proposed framework which is followed by Section IV which discusses the results and findings. The conclusion and scope for future work is presented in Section V which is followed by references.

2. RELATED WORK

This section reviews the recent researches in this field which have focused on activity recognition and activity recommendation for creation of assistive living spaces in the context of smart home environments. Activity recognition models can broadly be classified into two categories – knowledge-based models and data driven models. Knowledge based approaches mostly make use of ontologies to infer about activities. Azkune et al. [11] proposed a multilayered framework to analyze human activities in the context of a smart home. The architecture consisted of multiple layers which were associated with the tasks of acquisition of the data collected from wireless sensors, understanding the semantics, and providing descriptive knowledge of the recognized action or task.

In the work done by Riboni et al. [12], ontologies were not used to infer the specific activity being performed but they were used to validate the result inferred by the activity recognition model. The model developed a knowledge base of tasks associated with different context parameters in a smart home environment and used a combination of probabilistic reasoning and statistical modeling to analyze different activities. Nevatia et al. [13] developed a formal language, based on image recognition, for analyzing activities based on video recordings and real time streaming video data.

Data driven approaches for activity recognition have typically involved implementation of machine learning and data analysis methods. Kasteren et al. [14] developed an activity analysis model that involved representing different activities using each state of a Hidden Markov Model (HMM). The model had features to understand the raw data coming from motion sensors and analyze the rate of change of the instantaneous readings of this raw data, to infer about the given activity being performed by the user.

Cheng et al. [15] developed a hierarchical model with three layers to perform activity recognition based on video content analysis using multiple kernel learning methods. This approach was able to analyze both individual and group activity based on motion information by taking into consideration action trajectories and the information about effect of these actions on the context parameters. Skocir et al. [16] developed a system consisting of infrared sensors based on Artificial Neural Networks (ANNs) for activity recognition. The system was able to infer enter and exit events in different rooms in a smart home based on sensor information.

A context aware task recommender system was developed by Doryab et al. [17] to augment practitioners' performances in a specific hospital environment. The system detected the course of actions performed by the user at a given point of time and recommended tasks that were associated to these courses of actions from a knowledge base. A recent work by Thakur et. al [18] proposed a framework that analyzes multiple activity instances performed by different users, to provide a general definition for the given activity in the specific environment. This work also proposed an activity recommendation system that could identify distractions and recommend tasks to the user as per this general definition of an activity in the given environment. An unsupervised recommender system was proposed by Rasch [19] that analyzed the habits of the users and communicated with other systems to create habitable user experiences. A recommender system in the domain of healthcare was developed by Vavilov et al. [20] to recommend different tasks to patients to aid their recovery. A recommender system based on individual profiling method was proposed by Mark C et al. [21]. It develops individual profiles in its memory for all the users to be able to recommend tasks to individuals in a better way. Gong et al. [22] analyzed social media information of users to gather more information about the non-verbal aspects of user interactions to recommend better tasks. A recommender system based out of content filtering and neighborhood based collaborative filtering was proposed by Lai et al. [23].

Majority of the works [11-16] done in this field have focused on activity recognition by various methodologies. The few works [17-23] that have focused on developing activity or task recommender systems, have mostly taken into consideration user interactions of multiple users to define an “average user” and recommend tasks or actions based on the same. However, in a realistic scenario, the traits and characteristics of this “average user” might be significantly different from a “specific user” in the given context, owing to the user diversity. This could lead to failure of such systems to effectively assist users in the given environment and lead to barriers in the context of fostering human-technology partnerships. Therefore, the need to provide a technology-based solution that can adapt to user interaction patterns of any “specific user” and create an assistive environment for elderly people to improve their quality of life and augment their performances in the context of their day to day goals, is highly necessary. This serves as the main motivation for this work.

A couple of related works that have been used to propose this framework are (1) A Complex Activity Recognition Algorithm (CARALGO) for analyzing human behavior [24] and (2) A Complex Activity Based Emotion Recognition Algorithm (CABERA) for Affect Aware Systems [25] to analyze the emotional response associated to different complex activities.

According to CARALGO [24]. any complex activity (WCAtk) can be broken down into small actions or tasks – these are called atomic activities (At) and the context parameters that affect these atomic activities are called context attributes (Ct). Each of these atomic activities and context variables are associated with specific weights based on probabilistic reasoning. Each complex activity has a set of specific atomic activities that are essential for performing the activity – these are called core atomic activities (γAt) and the context parameters affecting them are called core context attributes (ρCt). Based on the weights of atomic activities and context attributes associated to the complex activity, every complex activity is associated with a threshold function (WTCAtk) that helps to determine the occurrence of that activity. The total weight for any given occurrence of this complex activity should be equal to or greater than the value of its threshold function for the complex activity to have been successfully performed. In the event when the weight is less than the value of the threshold function, it helps to infer that the activity was not completed successfully by the user which could be due to several factors. CARALGO also helps to identify the start atomic activities (AtS), start context attributes (CtS), end atomic activities (AtE) and end context attributes (CtE) related to a complex activity.

CABERA [25] helps to analyze the emotional response of different complex activities in the context of a smart home based on the probabilistic analysis of complex activities using atomic activities and their associated context attributes. It starts with analyzing the condition for occurrence of the complex activity by checking for the threshold condition. Thereafter the atomic level analysis of the complex activity is performed to identify the most important atomic activity and the associated most important context attribute. Then probabilistic reasoning principles are applied to analyze the nature of occurrence of this complex activity at different time instants. This is done by studying the nature of the most important atomic activity and the associated most important context attribute over these time instants when the activity occurred. This helps in drawing an inference about the emotion (positive or negative) associated to the complex activity at the given time instant.

3. PROPOSED WORK

Implementation of this proposed framework for development of a Personalized Intelligent Assistant for recommending Activities of Daily Living (ADLs) to elderly people in a smart home comprises of the following steps:

1. Develop a database of user interactions in the context of day to day activities and ADLs in a smart and connected IoT-based environment.
2. Determine interesting characteristics of complex activities in terms of their context parameters. This involves analyzing the appliance usage patterns in the context of a given complex activity.

3. Analyze multiple activity instances based on daily routine and investigate the time sequence of multiple activities to identify typical macro activities.
4. Use CARALGO to analyze the multimodal aspects of user interactions associated to these macro activities by extracting the atomic activities, context attributes, core atomic activities, core context attributes, start atomic activities, start context attributes, end atomic activities and end context attributes.
5. Use CABERA to deduce relevant patterns of these activity occurrences that provide indication about the affective state of the users performing these activities.
6. Use a supervised learning approach to relate the emotional response of users to user experiences associated to these activities.
7. Develop a supervised learning approach to implement a recommender system that can recommend complex activities based on these patterns, affective states and the associated user experience.

This proposed framework was implemented to first model an "average user" and then model a "specific user" from two different datasets to observe the differences in its performance and working in the two different scenarios, which is presented next. This implementation was done in RapidMiner [28]. RapidMiner is a data science software platform which provides an integrated development environment for implementation of data analysis, machine learning, deep learning and natural language processing algorithms.

RapidMiner is developed on an open core model which provides a GUI to enable users to execute workflows which are defined as "processes" in RapidMiner repository. These "processes" can be simulated by connecting multiple "operators" in a logical sense and as per the requirement of the given "process". Each "operator" is RapidMiner is associated with the basic definition of a specific task or function which can be modified each time by the user as per the requirement. There are currently two versions of RapidMiner available – the free version and the commercial version. For implementation of this framework as discussed in the subsequent sections, the free version of RapidMiner [28] was used.

3.1 Implementation of the Framework to model an "average user"

This involved analyzing activities from a subset of the UK Domestic Appliance Level Electricity (DALE) dataset [27]. The UK DALE dataset consists of details about appliance usage patterns related to different complex activities, measured with a time resolution of 6 seconds, in five different smart homes in Sothern England, recorded over a period of three years from 2012 to 2015.

These appliance usage patterns have been analyzed to obtain information about the different complex activities performed in different smart homes. Figure 2 shows different instances of occurrences of these complex activities from this dataset.

Two specific activity states, according to CARALGO are analyzed in this approach. For each time instant, '1' represents the fact that the activity was performed and '0' represents the fact that the activity was not performed. The analysis involved studying the occurrences of multiple instances of the same activity over specific time intervals to study their associated patterns.

Thereafter the atomic activities and context attributes associated to all these complex activities were analyzed. The different instances of occurrences of the complex activities – Using Washing Machine and Cooking in Kitchen are shown in Figures 3-4. The CARALGO analysis of all the complex activities – Watching TV, Using Laptop, Using Subwoofer, Using Washing Machine, Cooking in Kitchen, Using Microwave and Using Toaster are shown in Tables 1-7.

This analysis by CARALGO involved identifying the actions or tasks performed by the user while doing the given complex activity along with studying the context parameters on which these actions or tasks were performed. The process then involved associating weights to these

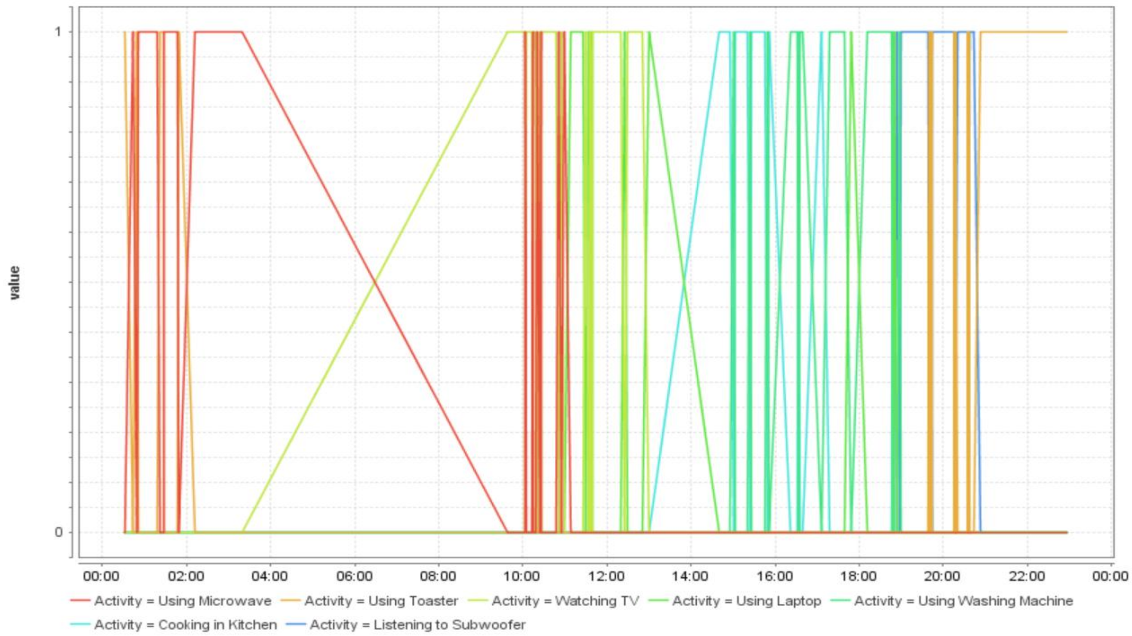

FIGURE 2: Different instances of activity occurrences from the UK DALE Dataset. This includes the complex activities of Watching TV, Using Laptop, Listening to Subwoofer, Using Washing Machine, Using Microwave, Cooking in Kitchen and Using Toaster.

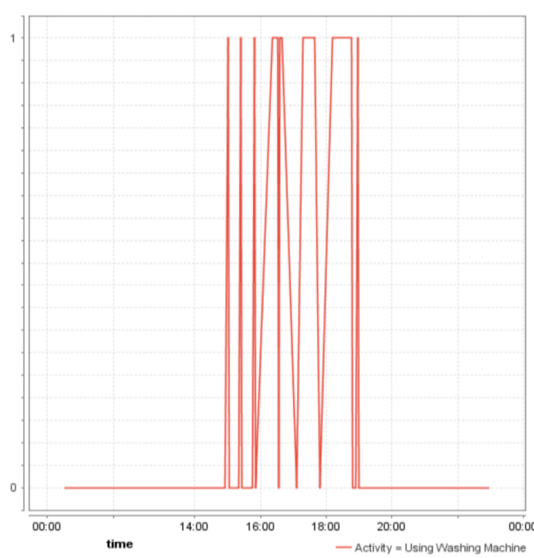

FIGURE 3: Multiple instances of the complex activity of Using Washing Machine.

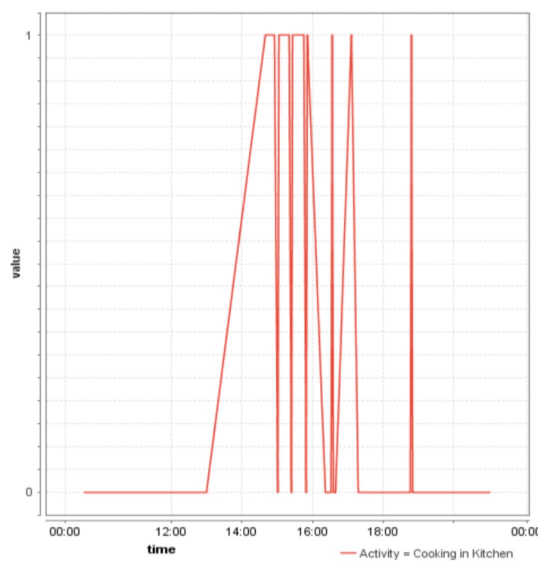

FIGURE 4: Multiple instances of the complex activity of Cooking in Kitchen.

respective atomic activities and context attributes based on probabilistic reasoning. Based on the weights of these atomic activities and context attributes the core atomic activities, core context attributes, start atomic activities, start context attributes, end atomic activities, end context attributes and the threshold weight for the given activity were determined. For analyzing each of these complex activities the person was assumed to be in a sitting position before the start of the activity. For instance, for the complex activity of making food using microwave, as illustrated in Table 6, the activity analysis initiates with the process of the person moving towards the microwave and following the step by step sequence of performing the activity, based on the given context parameters and scenarios. The atomic activities and context attributes were assigned weights by probabilistic reasoning.

The respective atomic activities are: At1: Standing, At2: Walking Towards Microwave, At3: Loading Food In Microwave Bowl, At4: Setting The Time, At5: Turning on microwave, At6: Taking Out Bowl, At7: Sitting Back. The weights associated to these respective atomic activities are: At1: 0.10, At2: 0.12, At3: 0.14, At4: 0.15, At5: 0.25, At6: 0.18, At7: 0.06. The context attributes associated to these atomic activities are: Ct1: Lights on, Ct2: Kitchen Area, Ct3: Food Present, Ct4: Time settings working, Ct5: Microwave Present, Ct6: Bowl cool, Ct7: Sitting Area. The weights associated to these respective context attributes are: Ct1: 0.10, Ct2: 0.12, Ct3: 0.14, Ct4: 0.15, Ct5: 0.25, Ct6: 0.18, Ct7: 0.06.

As observed from the analysis shown in Table 6, the atomic activities At4, At5 and At6 have the highest weights so they are considered as the core atomic activities for this complex activity. The context parameters associated with these core atomic activities, Ct4, Ct5 and Ct6 are thus considered as the core context attributes. The atomic activities At1 and At2 and their associated context attributes Ct1 and Ct2 are concerned with the user getting up from the sitting position and initiating the process of this complex activity of making food using the microwave. Thus, they are identified as the start atomic activities and the start context attributes respectively. Similarly, the atomic activities At6 and At7 and their associated context attributes Ct6 and Ct7 relate to the user completing this activity and sitting down to enjoy the food. Thus, they are identified as the end atomic activities and end context attributes respectively.

TABLE 1: Analysis by CARALGO of the Complex Activity of Watching TV (WT).

Complex Activity WCAtk (WT Atk) - WT (0.67)	
Weight of Atomic Activities WtAti	At1: Standing (0.15) At2: Walking towards TV (0.15) At3: Turning on the TV (0.25) At4: Fetching the remote control (0.15) At5: Sitting Down (0.08) At6: Tuning Proper Channel (0.12) At7: Adjusting Display and Audio (0.10)
Weight of Context Attributes WtCti	Ct1: Lights on (0.15) Ct2: Entertainment Area (0.15) Ct3: Presence of TV (0.25) Ct4: Remote Control Available (0.15) Ct5: Sitting Area (0.08) Ct6: Channel Present (0.12) Ct7: Settings working (0.10)
Core γAt and ρCt	At2,At3,At4 and Ct2,Ct3,Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6, At7 and Ct5, Ct6, Ct7

TABLE 2: Analysis by CARALGO of the Complex Activity of Using Laptop (UL).

Complex Activity WCAtk (WT Atk) - UL (0.82)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Laptop Area (0.15) At3: Turning on Laptop (0.28) At4: Typing log in password (0.23) At5: Sitting Down near Laptop (0.06) At6: Opening Required Application (0.10) At7: Connecting any peripheral devices like mouse, keyboard etc. (0.08)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10) Ct2: Laptop Table (0.15) Ct3: Laptop Present (0.28) Ct4: Log-in feature working (0.23) Ct5: Sitting Area (0.06) Ct6: Required Application Present (0.10) Ct7: Peripheral devices (0.08)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2, and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 3: Analysis by CARALGO of the Complex Activity of Listening to Subwoofer (LTS).

Complex Activity WCAtk (WT Atk) - LTS (0.70)	
Weight of Atomic Activities WtAti	At1: Standing (0.13) At2: Walking Towards Subwoofer (0.18) At3: Turning on the Subwoofer (0.23) At4: Plugging the CD/DVD/Storage Device for Playing (0.16) At5: Adjusting Sound Controls (0.11) At6: Adjusting Display Controls (0.11) At7: Sitting Down (0.08)
Weight of Context Attributes WtCti	Ct1: Lights on (0.13) Ct2: Entertainment Area (0.18), Ct3: Subwoofer Present (0.23) Ct4: CD/DVD/Storage Device Present (0.16) Ct5: Sound Controls Working (0.11) Ct6: Display Controls Working (0.11) Ct7: Sitting Area (0.08)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 4: Analysis by CARALGO of the Complex Activity of Using Washing Machine (UWM).

Complex Activity WCAtk (WT Atk) - UWM (0.72)	
Weight of Atomic Activities WtAti	At1: Standing (0.08) At2: Walking Towards Machine (0.20) At3: Turning On Machine (0.25) At4: Pouring Detergent (0.08) At5: Loading Clothes (0.20) At6: Adjusting Timer (0.12) At7: Sitting Down (0.07)
Weight of Context Attributes WtCti	Ct1: Lights on (0.08) Ct2: Laundry Area (0.20) Ct3: Washing Machine present (0.25) Ct4: Detergent Available (0.08) Ct5: Presence of clothes (0.20) Ct6: Timer settings working (0.12) Ct7: Sitting Area (0.07)
Core γAt and ρCt	At3, At5 and Ct3, Ct5
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 5: Analysis by CARALGO of the Complex Activity of Cooking Food Using Kettle (CFWK).

Complex Activity WCAtk (WT Atk) - CFWK (0.60)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Kettle (0.16) At3: Loading Food Into Kettle (0.19) At4: Turning On Burner (0.12) At5: Adjusting Heat (0.09) At6: Adding spices in Food (0.11) At7: Stirring (0.07) At8: Turning Off burner (0.12) At9: Sitting Back (0.04)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10) Ct2: Kettle Present (0.16) Ct3: Food to be cooked (0.19) Ct4: Burner Turning On (0.12) Ct5: Heat Settings (0.09) Ct6: Food spices (0.11) Ct7: Stirrer (0.07) Ct8: Burner Turning off (0.12) Ct9: Sitting Area (0.04)
Core γAt and ρCt	At2,At3 and Ct2,Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At8, At9 and Ct8, Ct9

TABLE 6: Analysis by CARALGO of the Complex Activity of Making Food Using Microwave (MFUM).

Complex Activity WCAtk (WT Atk) - MFUM (0.73)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Microwave (0.12) At3: Loading Food In Microwave Bowl (0.14) At4: Setting The Time (0.15) At5: Turning on microwave (0.25) At6: Taking Out Bowl (0.18) At7: Sitting Back (0.06)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10), Ct2: Kitchen Area (0.12), Ct3: Food Present (0.14), Ct4: Time settings working (0.15), Ct5: Microwave Present (0.25), Ct6: Bowl cool (0.18), Ct7: Sitting Area (0.06)
Core γAt and ρCt	At4, At5, At6 and Ct4, Ct5, Ct6
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 7: Analysis by CARALGO of the Complex Activity of Making Breakfast Using Toaster (MBUT).

Complex Activity WCAtk (WT Atk) - MBUT (0.73)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Toaster (0.12) At3: Putting bread into Toaster (0.15) At4: Setting The Time (0.15) At5: Turning off toaster (0.25) At6: Taking out bread (0.18) At7: Sitting Back (0.05)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10), Ct2: Kitchen Area (0.12), Ct3: Bread Present (0.15), Ct4: Time settings working (0.15), Ct5: Toaster Present (0.25), Ct6: Bread cool (0.18), Ct7: Sitting Area (0.05)
Core γAt and ρCt	At3, At4, At5 and Ct3, Ct4, Ct5
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

To study the patterns between these different complex activities with respect to time, the different time instants when each of them occurred were clustered using K nearest neighbor classification. During the process of clustering each cluster represented a different complex activity. These clusters were plotted to visualize and understand the patterns of these complex activities as well as analyze the sequence in which they were performed. This is shown in Figure 5.

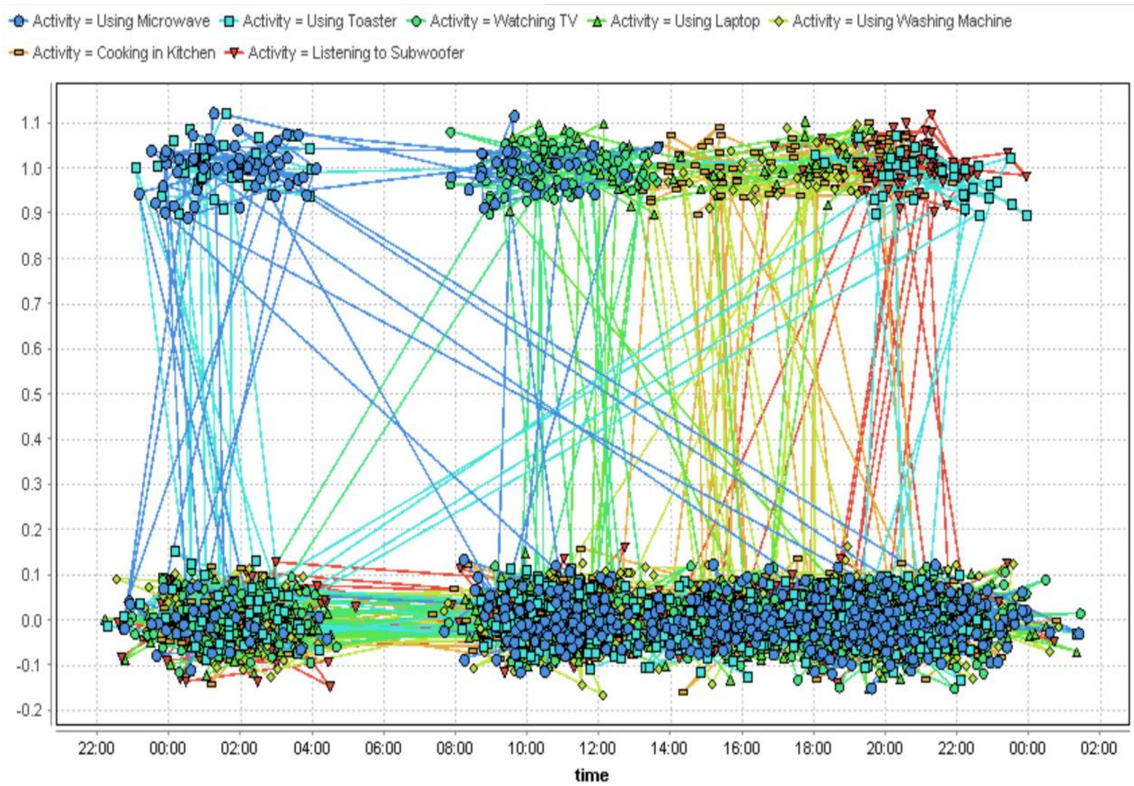

FIGURE 5: Cluster Based Analysis showing patterns and associations between different complex activities from the subset of the UK DALE dataset [27].

After analyzing through CARALGO, the different instances of these complex activities were analyzed through CABERA [25] to find the emotional response associated to each of their occurrences. Thereafter, a related work [26] was used to relate these emotional responses to the user experience associated to the different occurrences of these respective activities. This work [26] involves a random-forest based supervised learning model which uses the information about the emotional response of a complex activity to map it to a good or bad user experience.

This information was used to develop a complex activity recommendation system in RapidMiner [28] by considering the specific time instants when these activities were performed, the users affective state for each of these instances and the underlining user experience. This system is shown in Figure 6 and the flowchart of the same is shown in Figure 7. The input data to this system consisted of different complex activities retrieved from a subset of the UK DALE dataset [27]. This data was split into training set and test set as 70% training data and 30% test data. The test data was used to determine the performance accuracy of this system, which is discussed in the next section.

On running this system, for each activity performed by the user, it would evaluate the possibility of recommendation of all other activities by assigning confidence values to each of them. These confidence values indicated likeliness of the user performing each of those activities next, based on the time instant, affective state and user experience. A greater value of this confidence indicated a greater probability of that specific activity being performed next by the user. The activity with the highest confidence value was recommended by the system for the given activity. The output of the system showed the current activity, the confidence values associated to all other activities and the recommended activity based on these confidence values. This is illustrated in Figure 8 and Figure 13, by screenshots of some of the output values, when the system modelled an "average user" and a "specific user" respectively.

In Figure 8, the output data consists of one attribute named "Activity" which is the actual activity that was performed by the user after the current activity. The next attribute named "prediction(Activity)" lists the activity recommended by the system. The next subsequent attributes list the confidence values indicating the degree of likeliness of the user performing the other activities for each given complex activity. These respective attributes are confidence(Using Microwave), confidence(Listening to Subwoofer), confidence(Watching TV), confidence(Using Laptop), confidence(Using Washing Machine), confidence(Cooking in Kitchen) and confidence(Using Toaster).

Similarly, in Figure 13, the output data consists of one attribute named "Activity" which is the actual activity that was performed by the user after the current activity. The next attribute named "prediction(Activity)" lists the activity recommended by the system. The next subsequent attributes list the confidence values indicating the degree of likeliness of the user performing the other activities for each given complex activity. These respective attributes are confidence(Sleeping), confidence(Watching TV in Spare Time), confidence(Showering), confidence(Eating Breakfast), confidence(Leaving), confidence(Eating Lunch) and confidence(Eating Snacks).

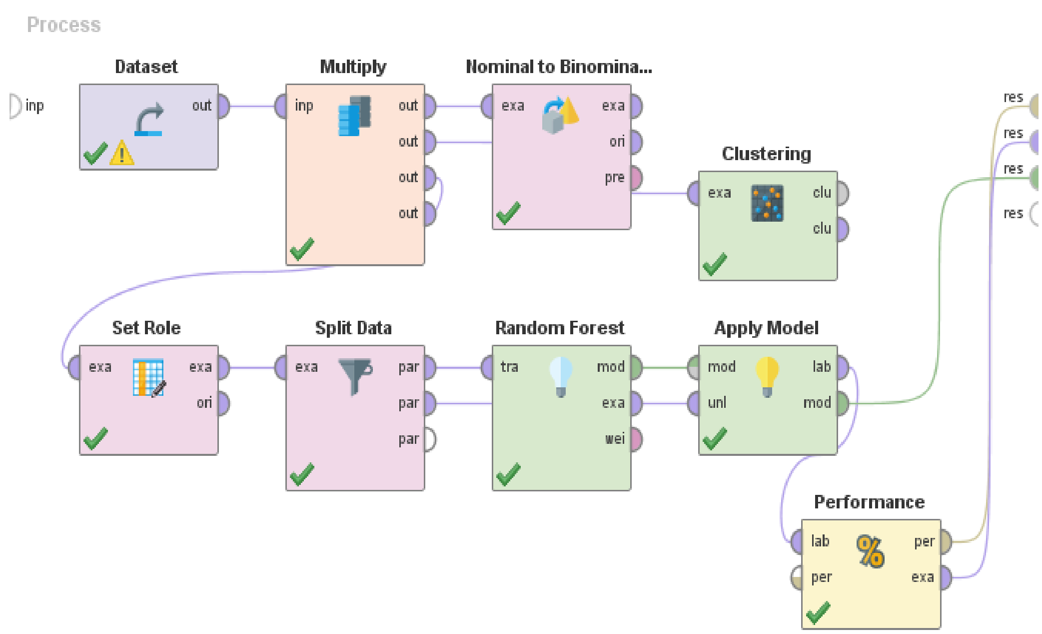

FIGURE 6: The system developed in RapidMiner for implementation of this framework.

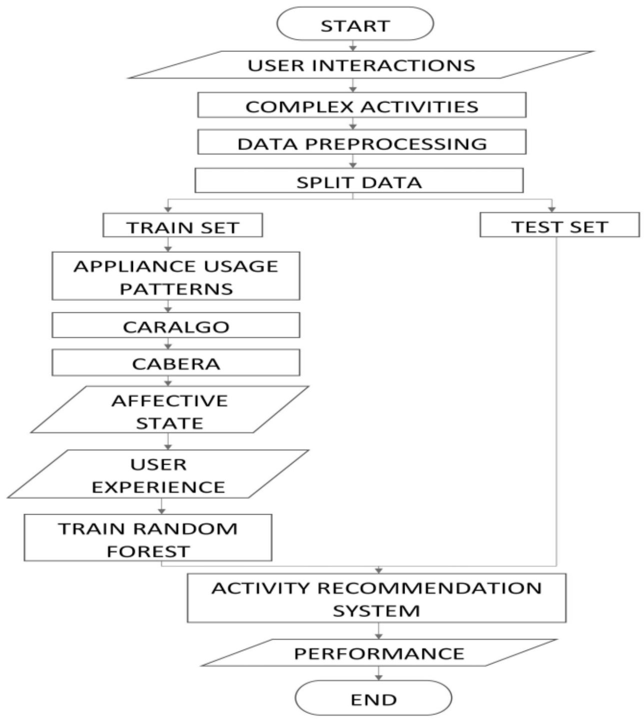

FIGURE 7: Flowchart of the system developed in RapidMiner for development of this Framework.

Row No.	Activity	prediction(Activity)	confidence(...	confidence(...	confidence(...	confidence(...	confidence(...	confidence(...	confidence(...
1	Using Microwave	Using Microwave	1	0	0	0	0	0	0
2	Using Microwave	Using Microwave	0.990	0.010	0	0	0	0	0
3	Using Microwave	Using Microwave	0.587	0	0.413	0	0	0	0
4	Using Microwave	Using Microwave	0.696	0	0.294	0.010	0	0	0
5	Using Microwave	Using Microwave	0.684	0	0.316	0	0	0	0
6	Watching TV	Watching TV	0.404	0	0.596	0	0	0	0
7	Using Laptop	Using Laptop	0	0	0.131	0.869	0	0	0
8	Using Laptop	Using Laptop	0.080	0	0.018	0.902	0	0	0
9	Using Laptop	Using Laptop	0	0	0	0.890	0	0.110	0
10	Using Washing M...	Using Washing M...	0	0	0	0.020	0.980	0	0
11	Using Washing M...	Using Washing M...	0	0	0	0	0.880	0.120	0
12	Cooking in Kitchen	Cooking in Kitchen	0	0	0	0	0.370	0.630	0
13	Cooking in Kitchen	Cooking in Kitchen	0	0	0	0	0.074	0.926	0
14	Cooking in Kitchen	Cooking in Kitchen	0	0	0	0	0.004	0.996	0

FIGURE 8: Screenshot of the output of the system which shows the recommended complex activities when modelling an "average user". The respective attributes are Activity, Prediction(Activity), confidence(Using Microwave), confidence(Listening to Subwoofer), confidence(Watching TV), confidence(Using Laptop), confidence(Using Washing Machine), confidence(Cooking in Kitchen) and confidence(Using Toaster).

3.2 Implementation of the Framework to model a "specific user"

To evaluate the performance of this framework on a "specific-user", the framework was then tested on a dataset which consisted of Activities of Daily Living (ADLs) performed by an elderly person (in the age range of 65-85) in the context of a smart home. This dataset was a result of the work done by Ordóñez et al. [29]. This work consisted of developing a smart IoT-based environment which comprised of multiple sensors that were used to perform activity recognition to sense ADLs in a smart home, over 24 hours for a period of 22 days. It involved the use of ANN (Artificial Neural Network) and SVM (Support Vector Machines), within the framework of an HMM (Hidden Markov Model) to develop a learning model that analyzed different complex activity occurrences and recorded the same with time stamps. The work also compared the performance of this hybrid learning model with other learning models to uphold the efficacy of same in correctly understanding ADLs in a smart home setting.

The different ADLs that were a part of this dataset consisted of the complex activities of Sleeping, Showering, Eating Breakfast, Leaving for work, Eating Lunch, Eating Snacks and Watching TV in Spare Time. Multiple occurrences of these complex activities from this dataset with respect to time have been shown in Figure 9 for illustration. The same system (just the input was changed to this dataset) as shown is Figure 6, was used to implement this activity recommendation model and the flow of actions were also the same as shown in Figure 7. Similar to the methodology for modelling an “average user”, this analysis involved studying the different occurrences of these complex activities with respect to time, the associated affective states of the user for each of these occurrences and the underlining user experience to build the complex activity recommendation system. The different instances of occurrences of the complex activities – Making Breakfast and Eating Lunch are shown in Figures 10-11. The CARALGO analysis of all the complex activities – Sleeping, Showering, Eating Breakfast, Leaving for work, Eating Lunch, Eating Snacks and Watching TV in Spare Time are shown in Tables 8-14.

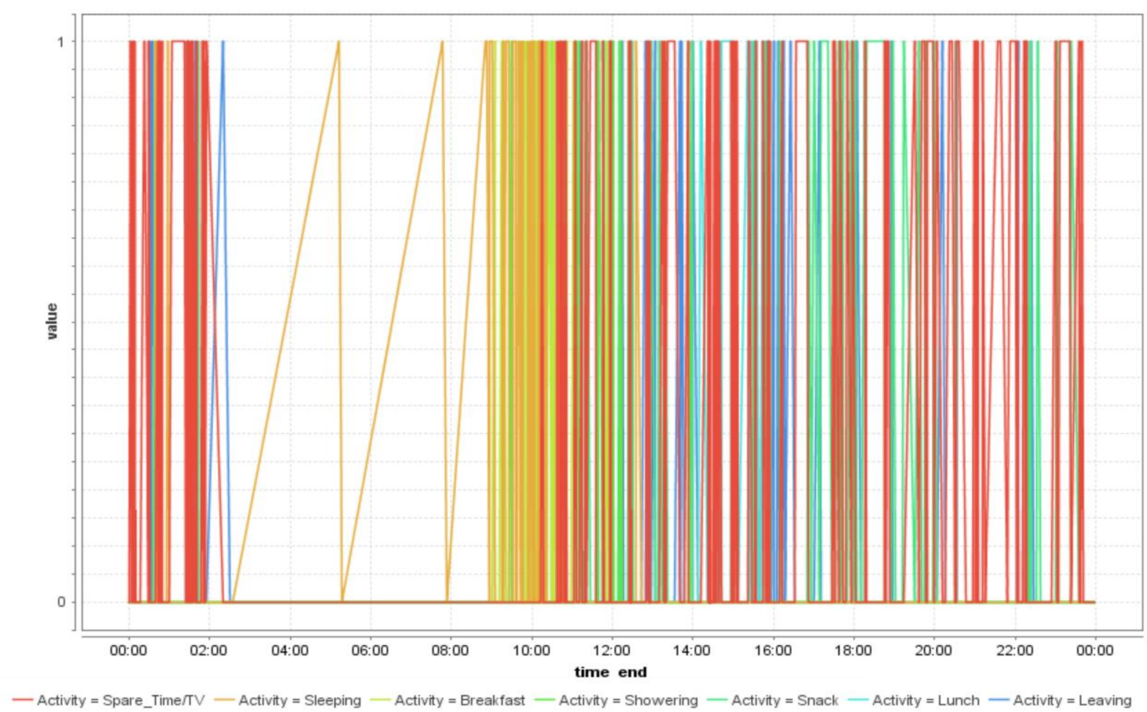

FIGURE 9: Different instances of activity occurrences from the dataset [29]. This includes the complex activities of Sleeping, Watching TV in Spare Time, Showering, Eating Breakfast, Leaving, Eating Lunch and Eating Snacks.

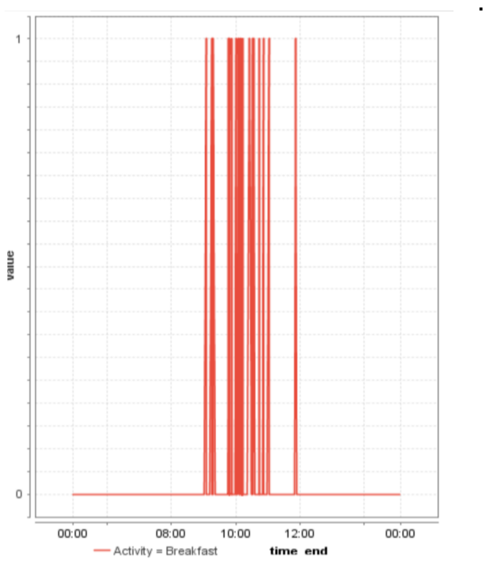

FIGURE 10: Multiple instances of the complex activity of Eating Breakfast.

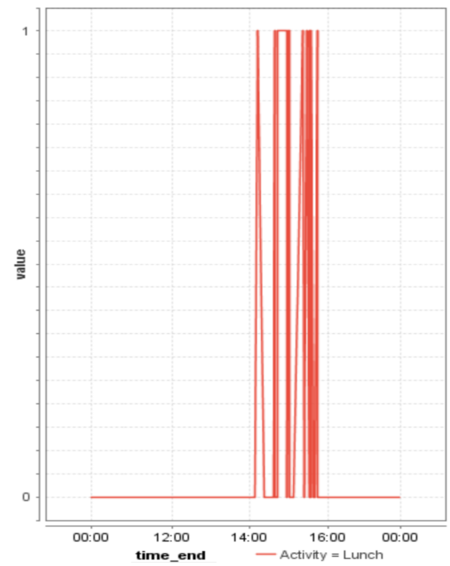

FIGURE 11: Multiple instances of the complex activity of Eating Lunch.

TABLE 8: Analysis by CARALGO of the Complex Activity of Leaving (LV).

Complex Activity WCAtk (WT Atk) - LV (0.68)	
Weight of Atomic Activities WtAti	At1: Standing (0.12) At2: Putting on dress to go out (0.32) At3: Carrying bag (0.30) At4: Walking towards door (0.13) At5: Going out of door (0.13)
Weight of Context Attributes WtCti	Ct1: Lights on (0.12), Ct2: Dress Present (0.32), Ct3: Bag present (0.30), Ct4: Exit Door (0.13), Ct5: Door working (0.13)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At4, At5 and Ct4, Ct5

TABLE 9: Analysis by CARALGO of the Complex Activity of Watching TV in Spare Time (WTV).

Complex Activity WCAtk (WT Atk) – WTV (0.68)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards TV (0.30) At3: Turning on TV (0.28) At4: Tuning in the correct channel (0.15) At5: Starting to watch TV (0.17)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10), Ct2: Entertainment Area (0.15), Ct3: TV present (0.15), Ct4: TV working (0.15), Ct5: Seating area (0.17)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5 and Ct5

TABLE 10: Analysis by CARALGO of the Complex Activity of Making Breakfast (MB).

Complex Activity WCAtk (WT Atk) - MB (0.73)	
Weight Of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Kitchen (0.12) At3: Loading Food In Microwave (0.14) At4: Turning on Microwave (0.25) At5: Setting The Time (0.15) At6: Taking lout prepared breakfast (0.18) At7: Sitting down to eat (0.06)
Weight Of Context Attributes WtCti	Ct1: Lights on (0.10), Ct2: Kitchen Area (0.12), Ct3: Microwavable food Present (0.14), Ct4: Time settings (0.15), Ct5: Microwave Present (0.25), Ct6: Microwave Working (0.18), Ct7: Sitting down to eat (0.06)
Core γAt and ρCt	At4, At5, At6 and Ct4, Ct5, Ct6
Start AtS and CtS	At1, At2 and Ct6, Ct7
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 11: Analysis by CARALGO of the Complex Activity of Eating Lunch (EL).

Complex Activity WCAtk (WT Atk) – EL (0.72)	
Weight of Atomic Activities WtAti	At1: Standing (0.08) At2: Walking towards dining table (0.20) At3: Serving food on a plate (0.25) At4: Washing Hand/Using Hand Sanitizer (0.20) At5: Sitting down (0.08) At6: Starting to eat (0.19)
Weight of Context Attributes WtCti	Ct1: Lights on (0.08) Ct2: Dining Area (0.20) Ct3: Food present (0.25) Ct4: Plate present (0.20) Ct5: Sitting options available (0.08) Ct6: Food quality and taste (0.19)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6 and Ct5, Ct6

TABLE 12: Analysis by CARALGO of the Complex Activity of Eating Snacks (ES).

Complex Activity WCAtk (WT Atk) – ES (0.72)	
Weight of Atomic Activities WtAti	At1: Standing (0.08) At2: Walking towards dining table (0.20) At3: Serving food on a plate (0.25) At4: Washing Hand/Using Hand Sanitizer (0.20) At5: Sitting down (0.08) At6: Starting to eat (0.19)
Weight of Context Attributes WtCti	Ct1: Lights on (0.08) Ct2: Dining Area (0.20) Ct3: Food present (0.25) Ct4: Plate present (0.20) Ct5: Sitting options available (0.08) Ct6: Food quality and taste (0.19)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6 and Ct5, Ct6

TABLE 13: Analysis by CARALGO of the Complex Activity of Going to Sleep (GTS).

Complex Activity WCAtk (WT Atk) – GTS (0.72)	
Weight of Atomic Activities WtAti	At1: Standing (0.12) At2: Walking Towards Bed (0.23) At3: Turning Off lights (0.28) At4: Setting Alarm (0.22) At5: Using blanket (0.15)
Weight of Context Attributes WtCti	Ct1: Lights on (0.12) Ct2: Bed Present (0.24) Ct3: Light switch working (0.28) Ct4: Alarm working (0.22) Ct5: Blanket Present (0.15)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At4, At5 and Ct4, Ct5

TABLE 14: Analysis by CARALGO of the Complex Activity of Taking Shower (TS).

Complex Activity WCAtk (WT Atk) – TS (0.72)	
Weight of Atomic Activities WtAti	At1: Standing (0.08) At2: Walking Towards Shower Room (0.20) At3: Carrying soap and/or shampoo (0.25) At4: Carrying Towel (0.20) At5: Turning on shower (0.14) At6: Turning off shower (0.13)
Weight of Context Attributes WtCti	Ct1: Lights on (0.08) Ct2: Shower room unoccupied (0.25) Ct3: Soap/Shampoo present (0.20) Ct4: Towel present (0.20) Ct5: Shower working (0.12) Ct6: Shower tap working (0.15)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6 and Ct5, Ct6

To study the patterns between these different complex activities with respect to time, the different time instants when each of them occurred were clustered using K nearest neighbor classification. During the process of clustering each cluster represented a different complex activity. These clusters were plotted to visualize and understand the patterns of these complex activities as well as analyze the sequence in which they were performed. This is shown in Figure 12.

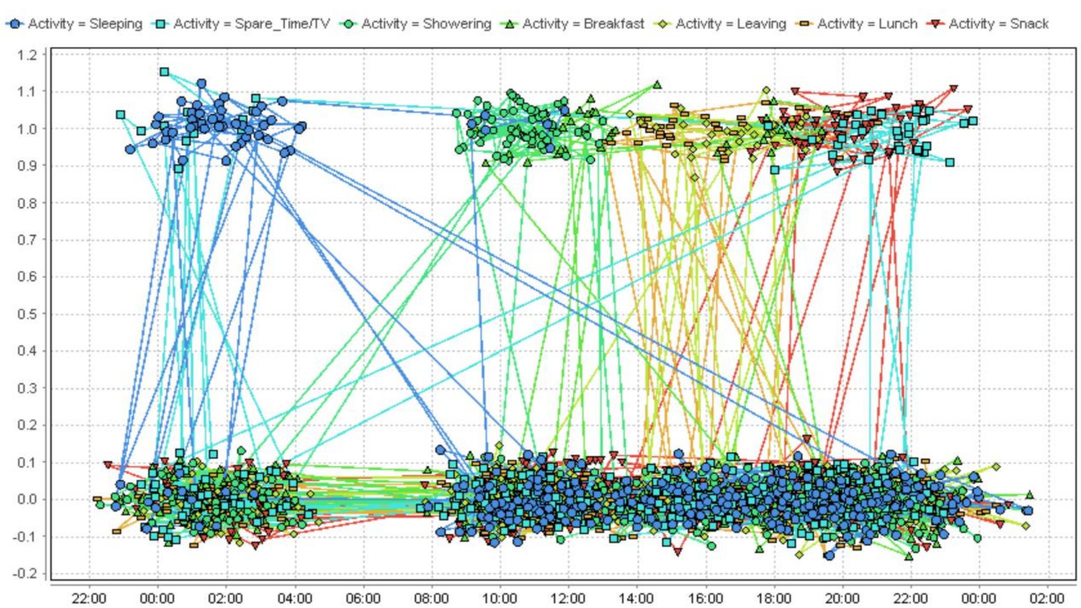

FIGURE 12: Cluster Analysis (KNN Nearest neighbor) of the different activities from the dataset [29] to analyze the patterns and associations amongst them.

Row No.	Activity	prediction(A...	confidence(...	confidence(...	confidence(...	confidence(...	confidence(...	confidence(...	confidence(...
1	Spare_Time/...	Spare_Time/...	0.097	0.903	0	0	0	0	0
2	Sleeping	Sleeping	0.903	0.097	0	0	0	0	0
3	Sleeping	Sleeping	0.983	0.017	0	0	0	0	0
4	Showering	Showering	0	0	1	0	0	0	0
5	Showering	Showering	0	0	1	0	0	0	0
6	Showering	Showering	0	0	1	0	0	0	0
7	Breakfast	Breakfast	0	0	0.074	0.926	0	0	0
8	Breakfast	Breakfast	0	0	0.323	0.677	0	0	0
9	Breakfast	Leaving	0	0	0	0.477	0.495	0.028	0
10	Lunch	Lunch	0	0	0	0.342	0.094	0.564	0
11	Lunch	Lunch	0	0	0	0.004	0.430	0.567	0
12	Snack	Lunch	0	0.020	0	0	0	0.794	0.186
13	Snack	Snack	0	0	0	0	0	0	1
14	Snack	Snack	0	0	0	0	0	0	1

FIGURE 13: Screenshot of the output of the system which showed the recommended activities when modelling a "specific user". The respective attributes are Activity, prediction(Activity), confidence(Sleeping), confidence(Watching TV in Spare Time), confidence(Showering), confidence(Eating Breakfast), confidence(Leaving), confidence(Eating Lunch) and confidence(Eating Snacks).

4. RESULTS AND DISCUSSION

The performance accuracies of this framework, in the form of confusion matrices, for modeling an "average user" and for modeling a "specific user" are shown in Figures 14 and 15 respectively. As observed from Figure 14, the overall performance accuracy of this model when modeling an "average user" is 62.59%. The respective sub-classes here being the different complex activities from the subset of the UK DALE dataset [27] that were used for developing this activity recommendation model. These different complex activities being Using Microwave, Using Toaster, Watching TV, Using Laptop, Using Washing Machine, Cooking in the Kitchen and Listening to the Subwoofer; with Watching TV having the highest sub-class precision of 77.78% and Using Toaster having the lowest sub-class precision of 47.62%.

accuracy: 62.59%

	true Using Mi...	true Using To...	true Watching...	true Using La...	true Using W...	true Cooking ...	true Listening...	class precisi...
pred. Using ...	15	10	1	0	0	0	0	57.69%
pred. Using T...	3	10	0	0	0	0	8	47.62%
pred. Watchin...	6	0	21	0	0	0	0	77.78%
pred. Using L...	0	0	0	7	4	2	0	53.85%
pred. Using ...	0	0	0	4	8	1	0	61.54%
pred. Cookin...	0	0	0	4	1	13	3	61.90%
pred. Listenin...	0	1	0	0	0	4	13	72.22%
class recall	62.50%	47.62%	95.45%	46.67%	61.54%	65.00%	54.17%	

FIGURE 14: Confusion Matrix showing the performance accuracy of the system when it modeled an "average user" from the subset of the UK DALE dataset [27].

accuracy: 73.12%

	true Sleeping	true Spare_Ti...	true Showering	true Breakfast	true Leaving	true Lunch	true Snack	class precisi...
pred. Sleeping	12	2	1	0	0	0	0	80.00%
pred. Spare_...	0	6	0	0	0	0	3	66.67%
pred. Shower...	3	0	16	0	0	0	0	84.21%
pred. Breakfast	0	0	0	8	0	0	0	100.00%
pred. Leaving	0	0	0	3	6	1	0	60.00%
pred. Lunch	0	0	0	0	3	7	1	63.64%
pred. Snack	0	6	0	0	0	2	13	61.90%
class recall	80.00%	42.86%	94.12%	72.73%	66.67%	70.00%	76.47%	

FIGURE 15: Confusion Matrix showing the performance accuracy of the system when it modeled a "specific user" - an elderly person (aged in range of 65-85 years) from the dataset [29].

To evaluate the efficacy of this framework for modelling a "specific user", the system was tested on a dataset [29] which consisted of Activities of Daily Living (ADLs) performed by a "specific user" (elderly person, age group: 65-85 years) in the context of a smart home. As can be observed from Figure 15, the performance of the model significantly increased in this scenario. The respective sub-classes were again the different complex activities from the dataset [29] that was used for developing this recommendation model. These different complex activities being Sleeping, Showering, Eating Breakfast, Leaving for work, Eating Lunch, Eating Snacks and Watching TV in Spare Time. In this case, the complex activity of Eating Breakfast had the highest sub-class precision, with its value being as high as 100% and the complex activity of Leaving for Work had the lowest sub class precision with a value of 60%.

For modeling an "average user", the model took into consideration multiple traits, different interaction patterns, varying affective states and different user experiences of all the users who performed those complex activities at different time instants. The recommendation of complex activities based on this "average user" modelling significantly varied in comparison to the interaction patterns of the "actual user" and this explains the reason for the low performance accuracy for that specific scenario. On the other hand, when the system was implemented for a "specific user" the demographics, interaction patterns and context parameters surrounding the user were known. This allowed the system to train itself based on the interaction styles, affective states and user experience that were specific to the given user. Thus, the complex activity recommendations made by the system mostly matched the interaction patterns of the user under consideration, which attributed to a greater performance accuracy of the system.

The application of activity centric computing in the context of smart homes has been of significant focus to researchers in the field of human-computer interaction. However, the approaches for activity recognition proposed by recent researchers [11-16], as discussed in this paper, were applied in specific settings and were tested on specific groups of users accessible to the respective authors. Research works in this field have shown that the diversity in users tend to have an impact on the way people interface with technology and behave in any given setting. So, to make activity recognition in the context of smart homes more reliable and suited to varying diversities in users, it is essential that activity recognition approaches do not get affected by universal diversity. The activity recognition approach, CARALGO [24] used in this work, is based on probabilistic reasoning and analyzes the probability of occurrence of different atomic activities with respect to their context attributes to infer about the occurrence of a complex activity. CARALGO [24] is not confined to a specific setting and can easily be implemented in any IoT-based environment. Also, CARALGO [24] has also been found to have a very high-performance accuracy of 88.5% in correctly analyzing human activities; which is much higher than the performance accuracies of the above-mentioned approaches [11-16] for activity analysis.

Speaking in terms of elderly people, who often have face Mild Cognitive Impairment (MCI), leading to forgetfulness, memory problems and cognitive issues, it is essential for the future of smart home intelligent technologies to not only analyze their behavior but also to recommend activities for development of an assistive environment to support independent living. Therefore, in addition to activity recognition, this framework presents an approach for activity recommendation in a smart home. The previous works on activity recommendation were mostly based on analyzing the user's daily routine to recommend tasks and actions. Research in this field has shown that a user may not always follow his or her daily routine. This can be due to various reasons out of which emotion, belief, desire and intention [30] of the user at that specific instant play a significant role in deciding the nature of activities that the user intends to perform next. Thus, it is essential for adaptive and assistive systems to be able to analyze the users affective state in addition to the users daily routine, before recommending activities to the user. This proposed framework uses CABERA [25] – to analyze the users affective state and uses clustering methods to develop relationships between the different activities performed by the user on a daily basis, so that while recommending a complex activity to the user both these aspects, i.e. the users affective state as well as the users daily routine are taken into consideration.

In addition to the above, the recent works in this field of activity recommendation in a smart home, as discussed earlier [17-23] which have focused on activity recommendation in specific settings, have modelled an "average user" by analyzing user interaction patterns of multiple users. The essence of developing an assistive environment for elderly people to help them perform their daily routine tasks is to create adaptive technologies that can foster their independent living in the context of their ADLs. To achieve the same, it is important for intelligent systems to be able to adapt according to the varying user interaction patterns leading from the diversity in elderly people. Therefore, this work proposes the framework for such a personalized intelligent assistant that can adapt with respect to the diversities in elderly people and recommend complex activities to help them have a better quality of life. The results presented in this work compare the performance of an activity recommendation system modelling an "average user" and an activity recommendation system modelling a "specific user". It is observed that there is a 16.8% increase in the performance accuracy of the system when it models a "specific user" and this upholds the relevance of the proposed framework and its implementation in the future of smart homes and smart environments for helping elderly people perform ADLs. The performance accuracy of 73.12%, achieved by this framework for recommending complex activities to a "specific user" is also higher than majority of the activity recommender systems as discussed in [17-23].

5. CONCLUSION AND FUTURE WORK

To increase the assistive nature of Affect Aware Systems in the context of smart and connected IoT-based living spaces for improving the quality of life experienced by elderly people, it is not only essential to analyze user behavior, but it is also important to help them augment their performances in the context of their day to day goals. Cognitive issues, weakened memory, disorganized behavior and even physical limitations [2, 3] are some of the major problems that elderly people face with increasing age.

Recent researches [11-20] in this field which have focused on providing technology-based solutions to address these needs of elderly people have these limitations – (1) Majority of these systems [11-16] have focused on multimodal ways of activity recognition with limited scope of augmenting the performance of the user in the given context; (2) The few task recommendation systems that have been developed [17-23] model an "average user". The traits and characteristics of this "average user" could be significantly different from a "specific user" owing to the user diversity; (3) The models are mostly applicable in specific environments, for instance a hospital room [17] and have limited scope for their implementation in any given context.

It is essential to address this "gap" in making technology-based solutions more relevant by improving their ability to address the diversity in users and adapt according to the specific needs of elderly people, to enhance their quality of life and augment their performances in the context of their day to day goals. This paper, therefore, proposes a framework for development of a

Personalized Intelligent Assistant that can analyze the tasks performed by elderly people in a smart home environment and recommend activities based on their daily routine, affective states and the underlining user experience, by adapting to the specific interaction styles of the "specific user" being modelled.

The proposed framework has been tested on a couple of datasets to uphold the relevance of the same. The presented results discuss the performance of this framework for modeling an "average user" and a "specific user". The comparison of the performance characteristics of the two systems, upholds the efficacy of this model to address and adapt to the needs of a "specific user" in a given smart environment. To the best knowledge of the authors, no prior work has been done in this field that integrates the concept of affect aware systems with activity centric computing to develop a framework that can recommend complex activities to elderly people in the context of a smart home environment to help them perform ADLs.

Future work along these lines would involve deployment of multiple sensors to set up a smart and connected IoT-based environment. Thereafter this Personalized Intelligent Assistant would be implemented in real time to analyze the effectiveness of the same in recommending ADLs to elderly people to improve their quality of life and enhance user experiences, by modelling each user as a "specific user" in the given context.

6. REFERENCES

[1] David E. Bloom and Dara Lee Luca, "The Global Demography of Aging: Facts, Explanations, Future" Working Paper Series, PROGRAM ON THE GLOBAL DEMOGRAPHY OF AGING AT HARVARD UNIVERSITY (PGDA), Paper No. 130, August 2016.

[2] Tommy Bengtsson and Kirk Scott, "The Ageing Population", 2nd Chapter in Population Ageing - A Threat to the Welfare State?, ISBN 978-3-642-12611-6, eISBN 978-3-642-12612-3.

[3] Tony Carter and Peter Beresford, "Age and change", Joseph Rowntree Foundation 2000, Published York Publishing Services, 2000, ISBN 1 902633 81 4.

[4] Hajime Orimo, Hideki Ito, Takao Suzuki, Atsushi Araki, Takayuki Hosoi, Motoji Sawabe, "Reviewing the definition of elderly", International Journal of Geriatrics and Gerontology International 6(3), Feb 2006.

[5] Kowal P, Dowd JE. Definition of an older person. Proposed working definition of an older person in Africa for the MDS Project. Geneva: World Health Organization; 2001.

[6] Jong-bum Woo, Youn-kyung Lim, "User experience in do-it-yourself-style smart homes" Proceedings of UbiComp2015, Osaka, Japan, DOI: 10.1145/2750858.2806063.

[7] Xuesheng Qian, Yifeng Xu, Jing Zhang, Zhengchuan Xu,"Happy Index: Analysis Based on Automatic Recognition of Emotion Flow" ICMSS '17: Proceedings of the 2017 International Conference on Management Engineering, Software Engineering and Service Sciences, January 2017.

[8] Thorpe, L., Davidson, P., & Janicki, M.P. (2000). Healthy Ageing - Adults with Intellectual Disabilities: Biobehavioural Issues. Geneva, Switzerland: World Health Organization.

[9] World Health Organization, "World Report on Ageing and Health" Technical Report 2015, ISBN 978 92 4 156504 2.

[10] Seltzer, Judith A. and Jenjira J. Yahirun, "Diversity in Old Age: The Elderly in Changing Economic and Family Contexts", In Diversity and Disparities: America Enters a New

Century, edited by John Logan. The Russel Sage Foundation, November 2014, ISBN: 978-1-61044-846-8.

[11] Azkune, Gorka & Almeida, Aitor & López-de-Ipiña, Diego & Chen, Liming. (2015). Extending knowledge-driven activity models through data-driven learning techniques. Expert Systems with Applications. 42. 10.1016/j.eswa.2014.11.063.

[12] Riboni, D., Bettini, C., 2009. Context-aware activity recognition through a combination of ontological and statistical reasoning. In: Proceedings of the international conference on Ubiquitous Intelligence and Computing. Springer Berlin/Heidelberg, pp. 39–53.

[13] Nevatia, R., Hobbs, J., Bolles, B., 2004. An ontology for video event representation. In: CVPRW ’04: Proceedings of the 2004 Conference on Computer Vision and Pattern Recognition Workshop Volume 7. IEEE Computer Society, Washington, DC, USA, p. 119.

[14] van Kasteren, T., Noulas, A., Englebienne, G., Kr¨ose, B., Sep. 2008. Accurate activity recognition in a home setting. In: UbiComp ’08: Proceedings of the 10th International Conference on Ubiquitous Computing. ACM, Seoul, Korea, pp. 1–9.

[15] Zhongwei Cheng, Lei Qin, Qingming Huang, Shuqiang Jiang, Shuicheng Yan, Qi Tian, “Human Group Activity Analysis with Fusion of Motion and Appearance Information”, Proceedings of the 19th ACM international conference on Multimedia, Pages 1401-1404, Scottsdale, Arizona, USA — November 28 - December 01, 2011.

[16] Pavle Skocir, Petar Krivic, Matea Tomeljak, Mario Kusek, Gordan Jezic, “Activity detection in smart home environment”, Proceedings of the 20th International Conference on Knowledge Based and Intelligent Information and Engineering Systems , Sept. 5-7, 2016.

[17] Afsaneh Doryab and Jakob E. Bardram, “Designing Activity-aware Recommender Systems for Operating Rooms”, Proceedings of the 2011 Workshop on Context-awareness in Retrieval and Recommendation, Feb 13, 2011.

[18] Nirmalya Thakur and Chia Y. Han, “A Context Driven Complex Activity Framework for Smart Home”, Proceedings of the 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) 2018, Vancouver, Canada, Nov. 1-3, 2018.

[19] Katharina Rasch, “An unsupervised recommender system for smart homes” Journal of Ambient Intelligence and Smart Environments 6 (2014) 21–37 21 DOI 10.3233/AIS-130242.

[20] Vavilov, D.; Melezhik, A.; Platonov, I. Healthcare Application of Smart Home User's Behavior Prediction. In Proceedings of the 2014 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 10–13 January 2014; pp. 323–326.

[21] Claypool, M. Combining Content-Based and Collaborative Filters in an Online Newspaper. In Proceedings of Recommender Systems Workshop at ACM SIGIR, Berkeley, CA, USA, 19 August 1999.

[22] Gong, J.; Gao, M.L.; Xu, B.; Wang, W. A hybrid recommendation algorithm based on social networks. In Proceedings of the International Conference on Heterogeneous Networking for Quality, Reliability, Security and Robustness, Taiwan, 19–20 August 2015.

[23] Lai, S.; Liu, Y.; Gu, H.; Xu, L.; Liu, K.; Xiang, S.; Zhao, J.; Diao, R.; Xiang, L.; Li, H.; Wang, D. Hybrid Recommendation Models for Binary User Preference Prediction Problem. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge Discovery and Data Mining, San Diego, USA, 21–24 August 2011.

[24] Saguna, Arkady Zaslavsky and Dipanjan Chakraborty, “Complex Activity Recognition Using Context-Driven Activity Theory and Activity Signatures”, ACM Transactions on Computer-Human Interaction, Vol. 20, No.6, Article 32, Dec. 2013.

[25] Nirmalya Thakur and Chia Y. Han, “A Complex Activity Based Emotion Recognition Algorithm For Affect Aware Systems”, Proceedings of the IEEECCWC 2018 Conference,08-10 January, 2018, Las Vegas, USA.

[26] Nirmalya Thakur and Chia Y. Han, “Methodology for Forecasting User Experience for Smart and Assisted Living in Affect Aware Systems” Proceedings of the 8th International Conference on the Internet of Things (IoT 2018), Santa Barbara, California, 15-18 October 2018.

[27] K. Jack and K.William, ``The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes,'' Sci.Data, vol. 2, p. 150007, Sep. 2.

[28] O. Ritthoff, R. Klinkenberg, S. Fisher, I. Mierswa, S. Felske. YALE: Yet Another Learning Environment. LLWA’01 – Tagungsband der GI-Workshop-Woche Lernen– Lehren – Wissen Adaptivitat. University of Dortmund, Dortmund, Germany. Technical Report 763. 2001: 84-92.

[29] Ordóñez, F.J.; de Toledo, P.; Sanchis, A. Activity Recognition Using Hybrid Generative/Discriminative Models on Home Environments Using Binary Sensors. Sensors 2013, 13, 5460-5477.

[30] Tibor Bosse, Edwin Zwanenburg “There’s Always Hope: Enhancing Agent Believability through Expectation-Based Emotions” Proceedings of the 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, 10-12 Sept. 2009, Amsterdam, Netherlands.

Framework for an Intelligent Affect Aware Smart Home Environment for Elderly People

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Abstract

The population of elderly people has been increasing at a rapid rate over the last few decades and their population is expected to further increase in the upcoming future. Their increasing population is associated with their increasing needs due to problems like physical disabilities, cognitive issues, weakened memory and disorganized behavior, that elderly people face with increasing age. To reduce their financial burden on the world economy and to enhance their quality of life, it is essential to develop technology-based solutions that are adaptive, assistive and intelligent in nature. Intelligent Affect Aware Systems that can not only analyze but also predict the behavior of elderly people in the context of their day to day interactions with technology in an IoT-based environment, holds immense potential for serving as a long-term solution for improving the user experience of elderly in smart homes. This work therefore proposes the framework for an Intelligent Affect Aware environment for elderly people that can not only analyze the affective components of their interactions but also predict their likely user experience even before they start engaging in any activity in the given smart home environment. This forecasting of user experience would provide scope for enhancing the same, thereby increasing the assistive and adaptive nature of such intelligent systems. To uphold the efficacy of this proposed framework for improving the quality of life of elderly people in smart homes, it has been tested on three datasets and the results are presented and discussed.

Keywords: Affect Aware Systems, Behavior Analysis, Smart and Assisted Living, Smart Home, User Experience, Affective States, Human Computer Interaction, User Experience.

1. INTRODUCTION

The ever-increasing population of elderly people has been one of the characteristics of this modern century. Currently there are around 962 million elderly people [1] across the world and they account for nearly 8.5 percent of the world's total population as shown in Figure 1. Recent studies [2] have predicted that by the year 2050 the population of elderly people will become around 1.6 billion globally and will end up outnumbering the population of younger people worldwide. Their number is further expected to increase and reach 3.1 billion by the year 2100.

FIGURE1: The population of elderly people shown as a percentage of the global population, according to world population data by World Bank [3].

With increasing age, the various needs in terms of personal, social and healthcare requirements increase. The number of elderly people across the world with dementia has doubled in recent times [4] and their number is predicted to again double by the year 2030, leading to approximately 76 million people with dementia worldwide. In 2010 alone, approximately $604 billion costs were incurred to the healthcare industry in looking after people with dementia and this number is increasing at an alarming rate [4]. It is essential for modern day policy makers to develop systems and technologies that are equipped with functionalities to adapt and address these needs of elderly people. The challenges for policy makers in this context, is to design technologies that are affordable and sustainable and can help to improve the quality of life experienced by elderly people.

“The United Nations Principles for Older Persons” [5] adopted by United Nations General Assembly has identified a number of characteristics to determine and improve the quality of life experienced by elderly people. Some of the prominent ones are independence, participation, proper care, self-fulfillment and dignity. In addition to these, these principles also include the necessity to provide intelligent environments that are adaptable with respect to the dynamic needs of the elderly population and the need to develop technologies that can help elderly people retain their level of physical, mental and emotional well being in the context of their day to day routine activities.

According to recent reports of the World Health Organization, the shortage of caregivers is one of the issues in this regard. The current number of caregivers across the world is only 7.2 million and their population is expected to increase to around 12.9 million by 2035, which is significantly less as compared to the large scale predicted population increase of elderly people [6]. Smart home technology has been the focus of recent researchers to provide technology-based solutions to support elderly care and address their dynamic needs with increasing age. In an Internet of Things (IoT)-based smart home environment, the ability of smart devices to interact with the users and communicate with each other is being envisioned as a major resource to enhance the quality of life experienced by elderly people.

Recent researches [7-18] in the field of human computer interaction and affective computing for improving the quality of life experienced by elderly people have mostly focused on developing systems that can analyze multimodal aspects of user interactions to understand the underlining user experience. These technologies possess limited functionalities to enhance the user experience of the given activity or task being performed. Therefore, this paper proposes a framework for implementation of an intelligent affect aware smart home environment that can predict user experiences of activities even before users start engaging in those. This framework would provide means to enhance the interactions between users and systems and ensure adaptive and ambient living spaces for enhancing the quality of life experienced by elderly people in smart homes. This paper is organized as follows: Section II provides an overview of related works in this field. Section III provides details about the proposed framework which is followed by Section IV which discusses the results and findings. The conclusion and scope for future work is presented in Section V which is followed by references.

2. LITERATURE REVIEW

An indoor navigation system based on sensor networks, in the context of a smart home was proposed by Abascal et al. [7]. In this research, sensor technology was used to understand the instantaneous position of the user in the given environment and the same information was used by an intelligent wheelchair to help elderly people with disabilities navigate the given environment. This research also proposed the use of a handheld device that operated based on sensor data, to help elderly people with cognitive issues navigate properly in the given IoT space.

Chan et al. [8] proposed a model for monitoring the behavior of elderly in the context of their multimodal interactions with devices in a smart home. This system possessed the functionality to alert both formal and informal caregivers in the event of a fall. Yared et al. [9] developed an intelligent cooking environment to prevent any accidents to elderly people taking place in the kitchen. This work involved developing a knowledge base which consisted of the normal readings of various parameters of appliances present in the kitchen area. The system was equipped with the ability to understand any deviations from these normal running conditions to detect the condition of an accident in the kitchen.

Kim et al. [10] proposed an RFID based location tracking system to ensure the safety of elderly people in a smart home environment. The system had a knowledge base developed by monitoring people with respect to the average time they spend while interacting with different devices and systems in the context of their day to day living. The location tracking system was able to identify the location of the user in the given environment and analyze if the user was spending more time for performing a specific task with an aim to improve the mental well being of the user.

Deen [11] used a combination of sensors, wireless communication systems, electronic devices and intelligent computing technology to develop a system that can measure different physiological signals from the walking patterns of elderly people, with an aim to monitor their behavior and alert medical practitioners for any event that needed their attention. Civitarese et al. [12] proposed an intelligent system that could analyze multimodal aspects of user interactions to infer about elderly people successfully completing Activities of Daily Living (ADLs). The system was able to analyze user interactions in this context to understand about symptoms of Mild Cognitive Impairment (MCI) in elderly people.

Iglesias et al. [13] proposed a system that could collect the health information about elderly people by analyzing their interactions with touch-based interfaces. The system was also able to use wireless sensors to monitor them to analyze events of drastic changes in this health information to alert caregivers for addressing their needs and issues. Angelini et al. [14] proposed a smart bracelet to be used by elderly people while performing activities both in indoor and outdoor environments. This bracelet could collect information about the health status of the individual and alert the user of abnormal conditions. The device also possessed the ability to remind the user of medications and other daily routine tasks to enhance the overall well being of the user. Khosla et al. [15] conducted usability studies to propose a social robot that could interact with elderly people in a smart home to help them perform different Activities of Daily Living (ADLs).

Tarik et al. [16] developed an intelligent activity recognition system for helping elderly people perform different activities in a smart home environment. The activity recognition system was equipped with the functionality to analyze a given activity being performed by the user and it also possessed the ability to perform intelligent decision making on whether to assist the user in the given activity being performed. Sarkar [17] proposed an intelligent robot called "NurseBot" that consisted of a scheduler to maintain the information about different medications that need to be taken by elderly people. It also possessed the functionality to deliver these specific medicines to elderly people as per their requirement. In a recent research by Thakur et al. [18], an intelligent system called CABERA – A Complex Activity Based Emotion Recognition Algorithm was proposed which could analyze the emotional response of the user in the context of different activities in a smart home to relate it to the underlining user experience.

Most of these works [7-14] have focused on multimodal ways of activity analysis with a focus on analyzing the user experience in the context of the given activity. Researchers [15, 17] have also focused on developing assistive robots to help users perform daily routine activities. This provides limited scope for enhancing the user experience of the given activity being performed by the user. The need to provide technology-based solutions that can not only analyze the user experience of different activities but also predict the same even before the activity is being performed, would serve as an essential characteristic of affect aware assistive technology to improve the quality of life experienced by elderly people in a smart home environment. This serves as the main motivation for this work.

This proposed framework extends the work done by Thakur et al. [18] which involved a methodology for forecasting user experiences in affect aware systems. The work in [18] was based on using probabilistic reasoning principles to develop rules between emotion, mood and outcome of any given activity to train a learning model to forecast the user experience. The main limitations of that work are (1) It is confined to a specific dataset and relevance of the work for other user interaction datasets or real time implementation is not discussed by the authors (2) The authors do not discuss the performance accuracy of the model that they use to infer emotions associated with different activities (3) The learning approach used by the authors does not yield a very high performance accuracy and (4) The authors did not discuss the relevance of the proposed learning method and whether or not it outperforms the other learning approaches. This proposed framework not only addresses these concerns but also discusses the approach for implementation of the proposed framework in any user interaction dataset as well as for real time user data.

A related work – Complex Activity Recognition Algorithm (CARALGO) has been used to propose this framework. Using CARALGO [19], any complex activity (WCAtk) can be broken down into small actions or tasks – these are called atomic activities (At) and the context parameters that affect these atomic activities are called context attributes (Ct). Each of these atomic activities and context variables are associated with specific weights based on probabilistic reasoning. Each complex activity has a set of specific atomic activities that are essential for performing the activity – these are called core atomic activities (γAt) and the context parameters affecting them are called core context attributes (ρCt). Based on the weights of atomic activities and context attributes associated to the complex activity, every complex activity is associated with a threshold function (WTCAtk) that helps to determine the occurrence of that activity. The total weight for any given occurrence of this complex activity should be equal to or greater than the value of its threshold function for the complex activity to have been successfully performed. In the event when the weight is less than the value of the threshold function, it helps to infer that the activity was not completed successfully by the user which could be due to several factors. CARALGO also helps to identify the start atomic activities (AtS), start context attributes (CtS), end atomic activities (AtE) and end context attributes (CtE) related to a complex activity.

3. PROPOSED WORK AND RESULTS

Implementation of this proposed framework for predicting user experiences in daily routine activities in an IoT-based smart home environment consists of the following steps:

1. Develop a database of user interactions in the context of day to day activities and ADLs in a smart and connected IoT-based environment
2. Identify specific characteristics of complex activities by analyzing their atomic activities and context attributes
3. Use CARALGO to infer about the start of any given complex activity
4. For each atomic activity performed on its associated context attribute
    a. Capture the users facial image on completion of the atomic activity
    b. Analyze the emotion conveyed by the facial image
    c. Record the information
5. Use CARALGO to infer about the end or completion of the given complex activity
6. Infer the overall emotion conveyed by the user by analyzing the above recorded information
7. Relate the emotion to the mood using specific set of rules obtained by a learning approach
8. Develop a learning approach to predict the user experience of activities based on this emotion and mood

To evaluate the efficacy of this proposed framework, it was implemented in RapidMiner [25]. RapidMiner is a data science software platform that provides an integrated development environment for implementing data science, machine learning, deep learning and natural language processing algorithms. The GUI of RapidMiner enables its users to develop these algorithms using the inbuilt “processes” in the desired manner. These “processes” can be developed by connecting the various “operators” that are provided by the software. An “operator” in RapidMiner is like a predefined method or function that consists of the general outline of a given task and can be modified by the user as per the requirement. A number of “operators” can be connected together to implement a specific functionality in the given “process”. There are currently two versions of RapidMiner which are available – the free version and the commercial version. For implementation of this framework, the free version of RapidMiner was used.

Implementation of the above framework can be broadly summarized into three major subtasks once the dataset of user interactions consisting of ADLs in a smart home has been developed. The first subtask involves using CARALGO for activity recognition, identification of complex activities, determination of atomic activities and context attributes associated to all the given ADLs in the dataset. The second subtask involves analyzing the facial expressions for each of these atomic activities and identifying the emotional response as a whole, for the given complex activity. Thereafter the third task involves using a learning approach to relate the emotional response of the user to the mood to predict the user experience of any activity to be performed by the user next. These are discussed in the three sub sections that follow.

3.1 Using CARALGO to Analyze Complex Activities

For implementing CARALGO for activity recognition and activity analysis, a dataset was created which was a subset of the dataset developed by Sztyler et al. [20]. This dataset was developed during research on activity recognition at the University of Mannheim by Sztyler et al. [20]. The dataset consisted of tracking ADLs performed by seven individuals in an IoT-based smart home environment over a period of 14 days. The individuals were males and were aged around 23 years at the time of the experiment.

Multiple occurrences of the different ADLs performed by these individuals were captured using a host of wireless and wearable sensors as described in [20]. The specific subset of this dataset chosen for this work, consisted of details of one individual performing the different complex activities of grooming, deskwork, socializing, eating, drinking, going out for shopping, playing indoor sports and making meals. Multiple occurrences of these complex activities over a typical 24-hour period is shown in Figure 2.

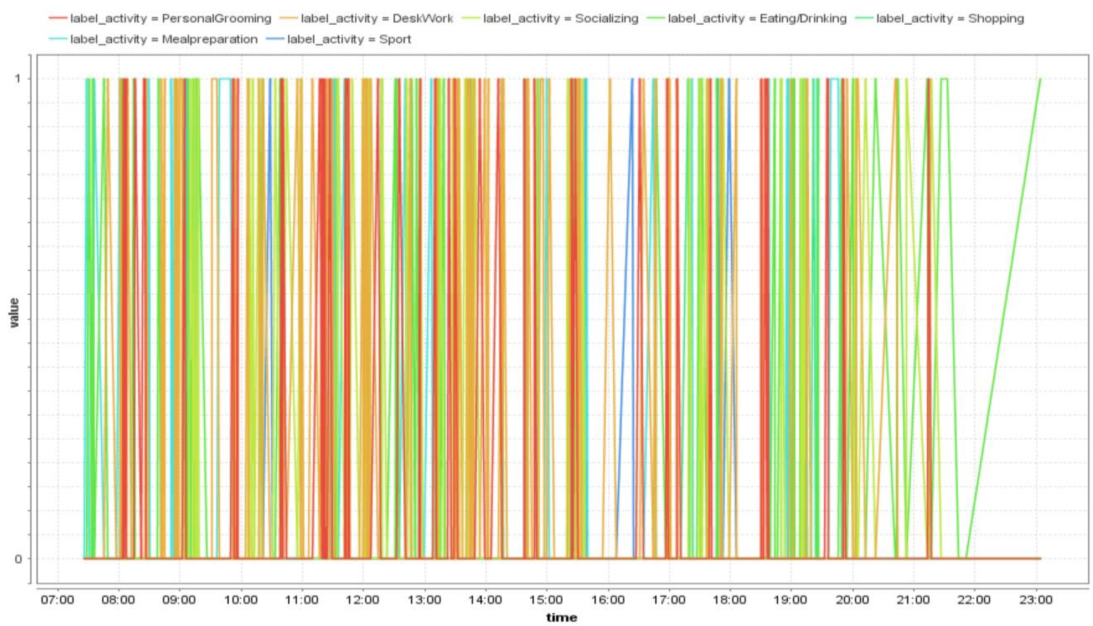

FIGURE 2: Analysis of multiple complex activities performed by one of the subjects in [20]. These different complex activities involve activities of grooming, deskwork, socializing, eating, drinking, going out for shopping, playing indoor sports and making meals.

Analysis by CARALGO for identification of all atomic activities and all context attributes, start atomic activities and start context attributes, end atomic activities and end context attributes, core atomic activities and core context attributes associated with these respective complex activities is shown in Tables 1-7. For each of these activities, the user is first assumed to be seated on a chair, after which the user initiates the given complex activity.

This analysis by CARALGO involved identifying all the small actions or tasks that the user performed towards reaching the end goal of completing the given activity. It also involved analyzing the context parameters on which these tasks were performed in the given IoT environment. These small actions or tasks are referred to as atomic activities and the context parameters on which these atomic activities were performed are called context attributes. Based on the relevance of these tasks and their associated context parameters, they were assigned weights by probabilistic reasoning principles.

For instance, Table 5 represents the CARALGO analysis of the complex activity of Going out for Shopping. The respective atomic activities are At1: Standing, At2: Putting on dress to go out, At3: Carrying bag, At4: Walking towards door, At5: Going out of door and their associated weights are At1: 0.12, At2: 0.32, At3: 0.30, At4: 0.13 and At5: 0.13. The context attributes associated with these respective atomic activities are Ct1: Lights on, Ct2: Dress Present, Ct3: Bag present, Ct4: Exit Door and Ct5: Door working and their associated weights are Ct1: 0.12, Ct2: 0.32, Ct3: 0.30, Ct4: 0.13 and Ct5: 0.13. As observed from this analysis the atomic activities At1 and At2 describe the user starting the complex activity and therefore they are identified as start atomic activities and their associated context attributes Ct1 and Ct2 are identified as start context attributes. Similarly, At4 and At5 describe the user completing the activity so they are identified as the end atomic activities and end context attributes respectively. Also, as the atomic activities At2 and At3 have the highest weights, they are identified as the core atomic activities and their associated context parameters are identified as core context attributes for this complex activity.

TABLE 1: Analysis by CARALGO of the Complex Activity of Grooming (AG).

Complex Activity WCAtk (WT Atk) - AG (0.67)	
Weightof Atomic Activities WtAti	At1: Standing (0.14) At2: Walking towards Mirror (0.16) At3: Picking up grooming kit (0.25) At4: Taking out grooming instrument (0.15) At5: Sitting Down to groom (0.08) At6: Putting back grooming kit (0.12) At7: Coming back to seat (0.10)
Weightof Context Attributes WtCti	Ct1: Lights on (0.14) Ct2: Mirror present (0.16) Ct3: Presence of grooming kit (0.25) Ct4: Grooming instruments present (0.15) Ct5: Sitting Area (0.08) Ct6: Presence of space for kit (0.12) Ct7: Seating area (0.10)
Core γAt and ρCt	At2,At3,At4 and Ct2,Ct3,Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6, At7 and Ct5, Ct6, Ct7

TABLE 2: Analysis by CARALGO of the Complex Activity of Working on a Desk (WD).

Complex Activity WCAtk (WT Atk) - UL (0.82)	
Weightof Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Desk (0.23) At3: Taking out Laptop (0.28) At4: Typing log in password (0.15) At5: Sitting Down near Laptop (0.06) At6: Opening Required Application (0.10) At7: Connecting any peripheral devices like mouse, keyboard etc. (0.08)
Weightof Context Attributes WtCti	Ct1: Lights on (0.10) Ct2: Desk Area (0.23) Ct3: Laptop Present (0.28) Ct4: Log-in feature working (0.15) Ct5: Sitting Area (0.06) Ct6: Required Application Present (0.10) Ct7: Peripheral devices (0.08)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2, and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 3: Analysis by CARALGO of the Complex Activity of Socializing with Friends (SF).

Complex Activity WCAtk (WT Atk) - LTS (0.70)	
Weight of Atomic Activities WtAti	At1: Standing (0.16) At2: Walking Towards Main Door (0.18) At3: Welcoming Friends (0.23) At4: Going to Entertainment Area (0.13) At5: Seating Down (0.11) At6: Starting a discussion (0.11) At7: Serving food (0.08)
Weight of Context Attributes WtCti	Ct1: Lights on (0.16) Ct2: Main Door Area (0.18), Ct3: Friends Present (0.23) Ct4: Entertainment Area (0.13) Ct5: Seating Space Available (0.11) Ct6: Discussion Topic (0.11) Ct7: Food Present (0.08)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

TABLE 4: Analysis by CARALGO of the Complex Activity of Enjoying Drinks (ED).

Complex Activity WCAtk (WT Atk) – EL (0.72)	
Weightof Atomic Activities WtAti	At1: Standing (0.08) At2: Walking towards drinking area (0.20) At3: Taking out the drink to be poured (0.25) At4: Preparing the drink (0.20) At5: Sitting down (0.08) At6: Starting to drink (0.19)
Weightof Context Attributes WtCti	Ct1: Lights on (0.08) Ct2: Drinking Area (0.20) Ct3: Drink present (0.25) Ct4: Drinking cup present (0.20) Ct5: Sitting options available (0.08) Ct6: Drink taste (0.19)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6 and Ct5, Ct6

TABLE 5: Analysis by CARALGO of the Complex Activity of Going out for Shopping (GS).

Complex Activity WCAtk (WT Atk) - GS (0.68)	
Weightof Atomic Activities WtAti	At1: Standing (0.12) At2: Putting on dress to go out (0.32) At3: Carrying bag (0.30) At4: Walking towards door (0.13) At5: Going out of door (0.13)
Weightof Context Attributes WtCti	Ct1: Lights on (0.12), Ct2: Dress Present (0.32), Ct3: Bag present (0.30), Ct4: Exit Door (0.13), Ct5: Door working (0.13)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At4, At5 and Ct4, Ct5

TABLE 6: Analysis by CARALGO of the Complex Activity of Playing Indoor Games (PIG).

Complex Activity WCAtk (WT Atk) - LV (0.68)	
Weight of Atomic Activities WtAti	At1: Standing (0.12) At2: Going to playing area (0.32) At3: Taking out playing equipment’s (0.30) At4: Inviting others to play (0.13) At5: Starting to play (0.13)
Weightof Context Attributes WtCti	Ct1: Lights on (0.12), Ct2: Playing Area (0.32), Ct3: Playing equipment’s present (0.30), Ct4: Other players present (0.13), Ct5: Game knowledge (0.13)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At4, At5 and Ct4, Ct5

TABLE 7: Analysis by CARALGO of the Complex Activity of Making Meals (MM).

Complex Activity WCAtk (WT Atk) - MB (0.73)	
Weight Of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Kitchen (0.12) At3: Loading Food In Microwave (0.14) At4: Turning on Microwave (0.25) At5: Setting The Time (0.15) At6: Taking out prepared meal (0.18) At7: Sitting down to eat (0.06)
Weight Of Context Attributes WtCti	Ct1: Lights on (0.10), Ct2: Kitchen Area (0.12), Ct3: Microwavable food Present (0.14), Ct4: Time settings (0.15), Ct5: Microwave Present (0.25), Ct6: Microwave Working (0.18), Ct7: Sitting down to eat (0.06)
Core γAt and ρCt	At4, At5, At6 and Ct4, Ct5, Ct6
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7

3.2 Facial Emotion Analysis for Atomic Activities

For implementation of this framework to analyze the emotional response of each atomic activity and its associated context attribute for a given complex activity, the following steps need to be implemented:

1. Capture the facial image of the user after completion of each atomic activity.
2. Represent the facial image by a fixed number of feature points and record muscle movements at each of these feature points.
3. Develop a database of these images and use methodology of Facial Action Coding System (FACS) to associate each of them with one of the seven basic emotional states Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral.
4. Train a learning model based on this data to enable it to classify new facial images into the various emotional states.
5. Capture the facial images during a given complex activity by identifying the start and end of the complex activity with CARALGO.
6. Use this learning model to analyze these facial images and evaluate the overall emotional state during the complex activity occurence.
7. Relate the emotional state to the mood using a specific set of rules.
8. Develop a learning model that can predict user experiences based on mood, emotional response and the outcome of the given activity.

To evaluate the efficacy of the framework in implementing the above functionality, a dataset was developed based on the dataset which was a result of the work of Goodfellow et al. in [21]. This work by Goodfellow et al. [21] consists of facial images of users captured while they performed different activities. The respective images in this dataset also provide information about the muscle movements and outline the associated emotional state using Facial Action Coding System (FACS). Using this information, a learning model was developed in RapidMiner that can analyze this information and classify images into the seven basic emotional states - Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral. The system first consisted of using operators in RapidMiner to preprocess the data, detect and remove outliers, spilt the data into training set and test set, which was followed by training the model. 80% of the data was used for training the model and 20% of the data was used as the test data. This system is shown in Figure 3.

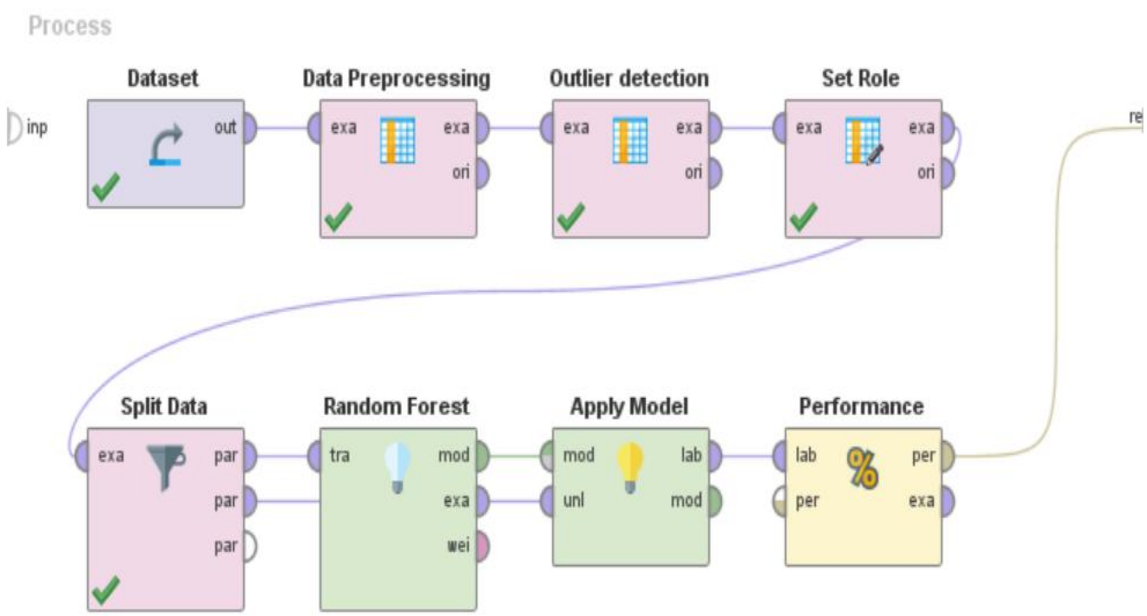

FIGURE 3: System developed in RapidMiner for analyzing emotions from facial images.

Different learning approaches were built in RapidMiner and their respective performance accuracies were compared to choose the learning approach that had the highest performance accuracy. Some of the major learning approaches – neural networks, decision tree learning, random forest, naïve bayes, deep learning and K-NN classifier were implemented as shown in Table 8. The seven different emotional states were considered as seven classes and the highest-class precision, lowest class precision and overall performance accuracies of these learning methods for this chosen dataset were compared.

These performance characteristics were obtained by analyzing the working of these learning methods through confusion matrices. Table 8 shows the comparison of the performance characteristics of these learning methods, details about their respective performance accuracies are presented in Figures 4-9 in the form of confusion matrices.

TABLE 8: Comparison of Different Learning Methods for Analyzing Emotions from Facial Images from this Dataset.

Learning Method Name	Overall Performance Accuracy	Lowest Class Precision	Highest Class Precision
Artificial Neural Networks	34.69%	29.28%	42.12%
Decision Tree Learning	77.50%	33.03%	100.00%
Random Forest	79.53%	49.55%	100.00%
Naïve Bayes	69.30%	47.29%	100.00%
Deep Learning	38.78%	11.13%	50.06%
K-NN Classifier	69.37%	46.63%	83.30%

accuracy: 34.69%

	true angry	true disgust	true sad	true neutral	true happy	true fear	true surprise	class precision
pred. angry	0	0	0	0	0	0	0	0.00%
pred. disgust	0	0	0	0	0	0	0	0.00%
pred. sad	0	0	0	0	0	0	0	0.00%
pred. neutral	0	0	0	0	0	0	0	0.00%
pred. happy	0	112	893	112	893	0	110	42.12%
pred. fear	1117	0	0	670	112	1005	448	29.98%
pred. surprise	0	0	0	0	0	0	0	0.00%
class recall	0.00%	0.00%	0.00%	0.00%	88.86%	100.00%	0.00%	

FIGURE 4: Performance Characteristics in the form of a confusion matrix for the learning system (Artificial Neural Networks) developed for analyzing emotions from facial images from this dataset.

accuracy: 77.50%

	true angry	true disgust	true sad	true neutral	true happy	true fear	true surprise	class precision
pred. angry	1005	0	0	0	0	0	112	89.97%
pred. disgust	0	0	0	0	0	0	0	0.00%
pred. sad	0	0	669	0	0	0	0	100.00%
pred. neutral	0	112	112	782	112	0	0	69.95%
pred. happy	0	0	112	0	670	0	0	85.68%
pred. fear	112	0	0	0	0	1005	336	69.17%
pred. surprise	0	0	0	0	223	0	110	33.03%
class recall	89.97%	0.00%	74.92%	100.00%	66.67%	100.00%	19.71%	

FIGURE 5: Performance Characteristics in the form of a confusion matrix for the learning system (Decision Tree Learning) developed for analyzing emotions from facial images from this dataset.

accuracy: 79.53%

	true angry	true disgust	true sad	true neutral	true happy	true fear	true surprise	class precision
pred. angry	1005	0	0	0	0	0	112	89.97%
pred. disgust	0	0	0	0	0	0	0	0.00%
pred. sad	0	0	669	0	0	0	0	100.00%
pred. neutral	0	112	112	782	112	0	0	69.95%
pred. happy	0	0	112	0	781	0	0	87.46%
pred. fear	112	0	0	0	0	1005	336	69.17%
pred. surprise	0	0	0	0	112	0	110	49.55%
class recall	89.97%	0.00%	74.92%	100.00%	77.71%	100.00%	19.71%	

FIGURE 6: Performance Characteristics in the form of a confusion matrix for the learning system (Random Forest) developed for analyzing emotions from facial images from this dataset.

accuracy: 69.30%

	true angry	true disgust	true sad	true neutral	true happy	true fear	true surprise	class precision
pred. angry	333	0	0	0	0	0	112	74.83%
pred. disgust	0	0	0	0	0	0	0	0.00%
pred. sad	0	0	669	0	0	0	0	100.00%
pred. neutral	0	112	112	782	112	0	0	69.95%
pred. happy	0	0	112	0	893	0	0	88.86%
pred. fear	784	0	0	0	0	1005	336	47.29%
pred. surprise	0	0	0	0	0	0	110	100.00%
class recall	29.81%	0.00%	74.92%	100.00%	88.86%	100.00%	19.71%	

FIGURE 7: Performance Characteristics in the form of a confusion matrix for the learning system (Naïve Bayes) developed for analyzing emotions from facial images from this dataset.

accuracy: 38.78%

	true angry	true disgust	true sad	true neutral	true happy	true fear	true surprise	class precision
pred. angry	1117	0	0	223	0	1005	448	39.99%
pred. disgust	0	0	0	0	0	0	0	0.00%
pred. sad	0	112	112	559	112	0	0	12.51%
pred. neutral	0	0	0	0	0	0	0	0.00%
pred. happy	0	0	781	0	893	0	110	50.06%
pred. fear	0	0	0	0	0	0	0	0.00%
pred. surprise	0	0	0	0	0	0	0	0.00%
class recall	100.00%	0.00%	12.54%	0.00%	88.86%	0.00%	0.00%	

FIGURE 8: Performance Characteristics in the form of a confusion matrix for the learning system (Deep Learning) developed for analyzing emotions from facial images from this dataset.

accuracy: 69.37%

	true angry	true disgust	true sad	true neutral	true happy	true fear	true surprise	class precision
pred. angry	1117	0	0	112	0	0	112	83.30%
pred. disgust	0	0	0	0	0	0	0	0.00%
pred. sad	0	112	781	670	112	0	0	46.63%
pred. neutral	0	0	0	0	0	0	0	0.00%
pred. happy	0	0	112	0	893	0	110	80.09%
pred. fear	0	0	0	0	0	1005	336	74.94%
pred. surprise	0	0	0	0	0	0	0	0.00%
class recall	100.00%	0.00%	87.46%	0.00%	88.86%	100.00%	0.00%	

FIGURE 9: Performance Characteristics in the form of a confusion matrix for the learning system (K NN Classifier) developed for analyzing emotions from facial images from this dataset.

As observed from Table 8 and from Figures 4-9, the Random Forest learning approach has the highest-class precision as well as the highest overall performance accuracy for this given dataset. Therefore, it was chosen to associate facial expressions with emotional states for development of this framework. The system implementing this Random Forest learning approach is shown in Figure 3 and its performance characteristics are shown in Figure 6.

3.3 Predicting User Experience of Complex Activities

This learning approach can therefore be used to classify the emotional response associated to different atomic activities and evaluate the overall emotional response of the complex activity. The overall emotional response of a given complex activity is inferred based on the overall emotional state associated with the given complex activity as per the following algorithm based on CARALGO:

```
while (WCAtk >= WTAtk)
{
while (AtS!=AtE)
{
Capture Facial Image
Analyze Emotional Response = E
if (E == Angry) -> nAngry++
else if (E == Disgust) ->nDisgust++
else if (E == Fear) -> nFear++
else if (E== Happy) -> nHappy++
else if (E== Sad) -> nSad++
else if (E== Surprise) -> nSurpise++
else if (E== Neutral) ->nNeutral++
}
If ((nAngry> nDisgust) && (nAngry> nFear) && (nAngry> nHappy)
  && (nAngry>nSad) && (nAngry> nSurprise) && (nAngry> nNeutral))
        {OE = Angry}
else if ((nDisgust>nAngry) && (nDisgust > nFear) && (nDisgust > nHappy)
       && (nDisgust>nSad) && (nDisgust> nSurprise) && (nDisgust> nNeutral))
        {OE = Disgust}
else if ((nFear>nAngry) && (nFear>nDisgust) && (nFear> nHappy)
       && (nFear>nSad) && (nFear> nSurprise) && (nFear> nNeutral))
        {OE = Fear}
else if ((nHappy>nAngry) && (nHappy>nDisgust) && (nHappy>nFear)
       && (nHappy>nSad) && (nHappy> nSurprise) && (nHappy> nNeutral))
        {OE = Happy}
else if ((nSad>nAngry) && (nSad>nDisgust) && (nSad>nFear)
```

```
        && (nSad>nHappy) && (nSad> nSurprise) && (nSad> nNeutral))
          {OE = Sad}
else if ((nSurprise>nAngry) && (nSurprise>nDisgust) && (nSurprise>nFear)
        && (nSurprise>nHappy) && (nSurprise>nSad) && (nSurprise> nNeutral))
          {OE = Surprise}
else if ((nNeutral>nAngry) && (nNeutral>nDisgust) && (nNeutral>nFear)
        && (nNeutral>nHappy) && (nNeutral>nSad) && (nNeutral>nSurprise))
          {OE = Neutral}
}
```

where
WCAtk = Weight of Complex Activity
WTAtk = Threshold Weight of Complex Activity
AtS = Start Atomic Activity
CtS = Start Context Attribute
AtE = End Atomic Activity
CtE = End Context Attribute
E = Emotional Response of the given atomic activity
nAngry = Number of atomic activities showing angry emotion
nDisgust = Number of atomic activities showing disgust emotion
nFear = Number of atomic activities showing fear emotion
nNeutral = Number of atomic activities showing neutral emotion
nHappy = Number of atomic activities showing happy emotion
nSurprise = Number of atomic activities showing surprise emotion
nSad = Number of atomic activities showing sad emotion
OE = Overall emotional response of the Complex Activity

This algorithm based on CARALGO initially checks for the condition for the occurrence of the complex activity by checking whether the weight associated to the complex activity exceeds its threshold weight. Thereafter, for each atomic activity, the emotion associated with the same is analyzed. Seven counter variables are used to store the number of times each of these seven respective emotions are recorded from facial images during the course of the entire complex activity. This information is thereafter used to identify that counter variable which has the greatest value as compared to all the other counter variables. The emotion associated to this counter variable is considered as the overall emotion associated to the complex activity.

The emotional response associated to the overall activity and the subsequent emotional responses as a result of performing different complex activities can be analyzed to evaluate the overall mood of the person as discussed in [18]. This involves analyzing the respective complex activities through CARALGO, evaluating their emotional response and then analyzing the emotional response of each activity to infer the overall mood of the user. A set of specific complex activities were analyzed from the UK Domestic Appliance Level Electricity (DALE) dataset [22] for implementation of this framework. The UK DALE data set consists of details of appliance usage patterns recorded over a time resolution of six seconds in five smart homes in Southern England over a span of three years from 2012-2015. A related work [23] is referred to relate these appliance usage patterns with complex activities. A specific set of complex activities from a typical day from this dataset, as shown in Table 9 were analyzed to validate the working of this framework. These activities included the complex activities of Cooking in Kitchen, Using Washing Machine, Doing office work, Watching TV and Making Breakfast which were performed on this typical day in between 10:00 AM and 12:30PM. The CARALGO [19] analysis of these complex activities is shown in Tables 10-14 along with their respective emotional responses [24], which is summarized in Table 15.

TABLE 9: A Typical Set of Activities between 10:00 AM to 12:30PM on a typical day obtained from the UK DALE Dataset for this Analysis.

Time of day	Complex Activity Details
10:00 AM to 10:30 AM	Cooking in Kitchen
10:30 AM to 11:00 AM	Using Washing Machine
11:00 AM to 11:30 AM	Doing office work
11:30 AM to 12:00 PM	Watching TV
12:00 PM to 12:30 PM	Making Breakfast

TABLE 10: Analysis by CARALGO of the Complex Activity of Cooking in Kitchen (CFWK).

Complex Activity WCAtk (WT Atk) - CFWK (0.60)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Kitchen Area (0.16) At3: Loading Food Into Container (0.19) At4: Turning On Burner (0.12) At5: Adjusting Heat (0.09) At6: Adding spices in Food (0.11) At7: Stirring (0.07) At8: Turning Off burner (0.12) At9: Sitting Back (0.04)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10) Ct2: Kitchen Area (0.16) Ct3: Food to be cooked (0.19) Ct4: Burner Turning On (0.12) Ct5: Heat Settings (0.09) Ct6: Food spices (0.11) Ct7: Stirrer (0.07) Ct8: Burner Turning off (0.12) Ct9: Sitting Area (0.04)
Core γAt and ρCt	At2, At3 and Ct2, Ct3
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At8, At9 and Ct8, Ct9
Emotional Response	Negative

TABLE 11: Analysis by CARALGO of the Complex Activity of Using Washing Machine (UWM).

Complex Activity WCAtk (WT Atk) - UWM (0.72)	
Weight of Atomic Activities WtAti	At1: Standing (0.08) At2: Walking Towards Machine (0.20) At3: Turning On Machine (0.25) At4: Pouring Detergent (0.08) At5: Loading Clothes (0.20) At6: Adjusting Timer (0.12) At7: Sitting Down (0.07)
Weight of Context Attributes WtCti	Ct1: Lights on (0.08) Ct2: Laundry Area (0.20) Ct3: Washing Machine present (0.25) Ct4: Detergent Available (0.08) Ct5: Presence of clothes (0.20) Ct6: Timer settings working (0.12) Ct7: Sitting Area (0.07)
Core γAt and ρCt	At2, At3, At5 and Ct2, Ct3, Ct5
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7
Emotional Response	Negative

TABLE 12: Analysis by CARALGO of the Complex Activity of Doing Office Work (DOW).

Complex Activity WCAtk (WT Atk) - UL (0.82)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Office Desk (0.15) At3: Turning on Laptop (0.28) At4: Typing log in password (0.23) At5: Sitting Down near Laptop (0.06) At6: Opening Required Application (0.10) At7: Connecting any peripheral devices like mouse, keyboard etc. (0.08)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10) Ct2: Office Desk Area (0.15) Ct3: Laptop Present (0.28) Ct4: Log-in feature working (0.23) Ct5: Sitting Area (0.06) Ct6: Required Application Present (0.10) Ct7: Peripheral devices (0.08)
Core γAt and ρCt	At2, At3, At4 and Ct2, Ct3, Ct4
Start AtS and CtS	At1, At2, and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7
Emotional Response	Negative

TABLE 13: Analysis by CARALGO of the Complex Activity of Watching TV (WT).

Complex Activity WCAtk (WT Atk) - WT (0.67)	
Weight of Atomic Activities WtAti	At1: Standing (0.15) At2: Walking towards TV (0.15) At3: Turning on the TV (0.25) At4: Fetching the remote control (0.15) At5: Sitting Down (0.08) At6: Tuning Proper Channel (0.12) At7: Adjusting Display and Audio (0.10)
Weight of Context Attributes WtCti	Ct1: Lights on (0.15) Ct2: Entertainment Area (0.15) Ct3: Presence of TV (0.25) Ct4: Remote Control Available (0.15) Ct5: Sitting Area (0.08) Ct6: Channel Present (0.12) Ct7: Settings working (0.10)
Core γAt and ρCt	At2,At3,At4 and Ct2,Ct3,Ct4
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At5, At6, At7 and Ct5, Ct6, Ct7
Emotional Response	Positive

TABLE 14: Analysis by CARALGO of the Complex Activity of Making Breakfast (MB).

Complex Activity WCAtk (WT Atk) - MBUT (0.73)	
Weight of Atomic Activities WtAti	At1: Standing (0.10) At2: Walking Towards Toaster (0.12) At3: Putting bread into Toaster (0.15) At4: Setting the Time (0.15) At5: Turning off toaster (0.25) At6: Taking out bread (0.18) At7: Sitting Back (0.05)
Weight of Context Attributes WtCti	Ct1: Lights on (0.10), Ct2: Kitchen Area (0.12), Ct3: Bread Present (0.15), Ct4: Time settings working (0.15), Ct5: Toaster Present (0.25), Ct6: Bread cool (0.18), Ct7: Sitting Area (0.05)
Core γAt and ρCt	At3, At4, At5 and Ct3, Ct4, Ct5
Start AtS and CtS	At1, At2 and Ct1, Ct2
End AtE and CtE	At6, At7 and Ct6, Ct7
Emotional Response	Negative

TABLE 15: Comparison of Emotional Response of Different Complex Activities Performed Between 10AM TO 12:30PM on a Typical Day from the UK DALE dataset considered here.

Time of day	Complex Activity Details	Emotional Response
10:00 AM to 10:30 AM	Cooking in Kitchen	Negative
10:30 AM to 11:00 AM	Using Washing Machine	Negative
11:00 AM to 11:30 AM	Doing office work	Negative
11:30 AM to 12:00 PM	Watching TV	Positive
12:00 PM to 12:30 PM	Making Breakfast	Negative

According to [18] as the mood of the user is the aggregate of the emotional responses shown by the user while performing some of the most recent complex activities, it can be concluded that as a result of this specific sequence of complex activities with their respective emotional responses, the overall mood of the user starting the next complex activity would be negative. This relationship between emotion and mood is very similar to the analogy between weather and climate. The intensity of these respective emotions also plays a significant role in having an impact on the overall mood and this relationship can be determined by assigning weights with the respective emotions. These weights would specify the intensity of the given emotion and analysis of the same would help in determining the overall mood of the user as well the intensity of the same.

Thereafter, the general rules [18] for relating the mood with the outcome of a given activity to predict the user experience of the same are used to develop a learning model. The outcome in this context refers to the condition of whether the user was able to complete the given activity, or the user failed to do so. Analysis of the same is done through CARALGO [19]. These rules are presented in Table 15.

TABLE 16: Relationship Between Mood and User Experience in Terms of Activity Outcome.

Mood	Outcome	User Experience
Positive	Positive	Positive
Positive	Negative	Negative
Negative	Positive	Positive
Negative	Negative	Negative

A number of complex activities from the UK DALE dataset [22] were analyzed using this framework to obtain their associated emotional responses in different contexts. Then the above rules as mentioned in Table 16 were used to train a learning model that could predict the user experience of these activities based on the users mood and outcome of the given activity. To evaluate the actual user experience of these respective complex activities, CABERA – A Complex Activity Based Emotion Recognition Algorithm proposed by Thakur et al. [24] was used. These results were compared to analyze the performance accuracy of the system. As per Table 8, Random Forest learning approach was chosen to develop this predictive model. The system as developed in RapidMiner is shown in Figure 10.

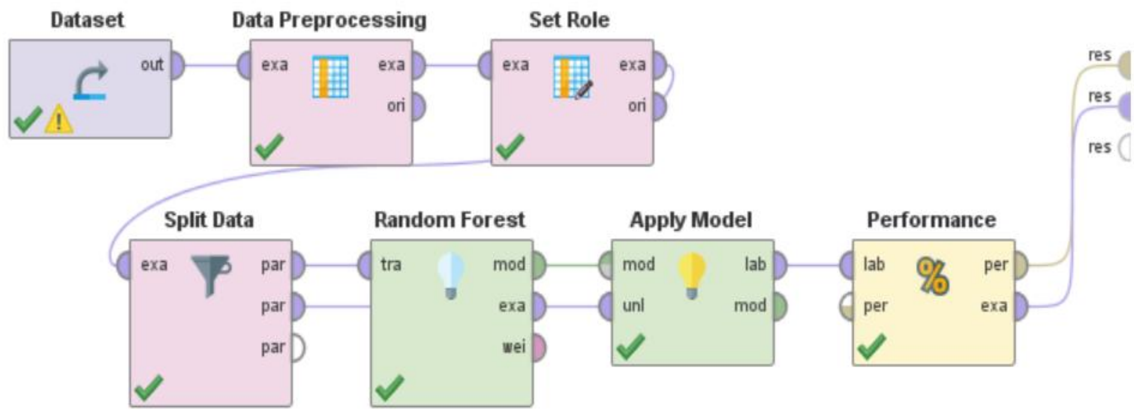

FIGURE 10: System developed in RapidMiner for predicting user experience based on nature of user interactions in complex activities.

The output of this system displayed the confidence value related to each prediction of the User Experience based on the values of mood and outcome. For simplicity of implementation just positive and negative values for each of the attributes – Mood, Outcome and User Experience, were used to develop this predictive model. The highest confidence valued attribute was used to make the prediction for a given condition to predict the User Experience. A screenshot of the output of this system showing these different attributes is shown in Figure 11. Figure 12 shows the performance characteristics of this system in the form of a confusion matrix.

Row No.	UX	prediction(UX)	confidence(Positive)	confidence(Negative)	Mood	Outcome
1	Positive	Positive	0.620	0.380	Negative	Positive
2	Positive	Positive	0.727	0.273	Positive	Positive
3	Positive	Positive	0.727	0.273	Positive	Positive
4	Negative	Negative	0.183	0.817	Positive	Negative
5	Positive	Negative	0.356	0.644	Negative	Negative
6	Positive	Positive	0.727	0.273	Positive	Positive
7	Negative	Positive	0.727	0.273	Positive	Positive
8	Negative	Negative	0.356	0.644	Negative	Negative
9	Negative	Negative	0.183	0.817	Positive	Negative
10	Negative	Positive	0.620	0.380	Negative	Positive
11	Negative	Negative	0.183	0.817	Positive	Negative
12	Positive	Positive	0.727	0.273	Positive	Positive
13	Negative	Negative	0.183	0.817	Positive	Negative
14	Positive	Positive	0.727	0.273	Positive	Positive
15	Negative	Positive	0.620	0.380	Negative	Positive

FIGURE 11: Screenshot of the output when the system shown in Figure 10 was implemented in RapidMiner.

accuracy: 73.13%

	true Positive	true Negative	class precision
pred. Positive	68	26	72.34%
pred. Negative	28	79	73.83%
class recall	70.83%	75.24%	

FIGURE 12: Performance Characteristics, represented as a confusion matrix, of the system shown in Figure 10, when implemented in RapidMiner.

The performance characteristics of this learning model as shown in Figure 12, shows that the overall performance accuracy achieved by the model is 73.13%. The respective class accuracies for predicting positive and negative user experiences are 72.34% and 73.83% respectively.

4. DISCUSSION OF RESULTS

This proposed framework extends a work done by Thakur et al. [18] and address its limitations in multiple ways. Firstly, this work discusses the efficacy of the proposed framework by validating it on three datasets as compared to the work done in [18] which is more of a proof-of-concept and involved analysis of the proposed methodology on a small dataset which had limited number of training samples and test data.

Secondly, unlike [18] where just one learning approach is discussed, multiple learning approaches were implemented to infer about the best performing learning model for the given datasets and their performance characteristics have been compared in detail. This comparison shows that for the given datasets, Random Forest learning approach achieves the highest performance accuracy as compared to neural networks, decision tree learning, random forest, naïve bayes, deep learning and K-NN classifier. Therefore, the use of this learning approach is justified and thus being proposed for implementation of this framework.

Thirdly, a greater number of training samples are used from multiple datasets, and proper data pre-processing, outlier detection and outlier elimination are performed, which helps the proposed predictive model for forecasting user experiences to achieve an overall accuracy of 73.13%. This is much higher than the overall performance accuracy of 67% as discussed in [18].

Finally, this framework also introduces a novel approach of analyzing the emotional response associated to different atomic activities and their context attributes based on emotion analysis from facial images. Such an approach would help to identify the emotional states after every task or sub-task related to the given activity and their respective impacts towards shaping the overall emotional response of the user as a result of performing the given complex activity. This method would give a better idea of the emotional states of the user as compared to the methodology of deducing emotional state of the user, after completing the given complex activity, based on probabilistic reasoning as discussed in [18].

5. CONCLUSION AND FUTURE SCOPE OF WORK

For the world to be able to sustain and support the ever-increasing population of elderly people, which has been one of the primary characteristics of this century, advanced and forward-looking development policies and sound infrastructures implemented with assistive and intelligent technologies, such as smart homes, are necessary to address their increasing needs and enhance their quality of life. The future of smart homes would involve elderly people interacting with smart systems in every aspect of their day to day living. It is essential to develop intelligent technologies that would be able to make the future of smart homes “smarter” and possess the functionality to analyze multimodal aspects of user interactions to be able to interact with users for enhancing their user experience in a technology laden environment.

With the decreasing number of caregivers and constantly increasing burden caused to the world's economy for supporting elderly people in smart homes, it is essential to develop technology-based solutions that can adapt and assist with respect to the nature of interactions performed by them to ensure a congenial living experience. In the context of IoT-based smart home environments for supporting elderly people, Affect Aware Systems possess immense potential for improving their quality of life. The essence of improving the quality of life experienced by elderly people in smart homes, lies in the effectiveness of technology-based solutions to enhance their user experience in the context of their day to day goals. Therefore, this paper proposes a framework that can predict user experiences in an Affect Aware Smart Home environment in the context of ADLs performed by elderly people. Such a predictive model would allow forecasting of user experiences even before the user engages in an activity, which would provide scope for enhancing the user experience and thus improving the quality of life of elderly people.

The proposed framework has been tested on three datasets to uphold its relevance and efficacy. The results presented uphold the relevance of this framework for predicting user experiences in the context of ADLs in a smart home for creating a smart, adaptive and assistive environment for elderly care. As per the best knowledge of the authors, no prior work has been done in this field featuring a similar approach.

Future work would involve deploying a host of wireless and wearable sensors to establish a smart and connected IoT environment for real time implementation of this proposed framework for predicting user experience in the context of ADLs performed by elderly people in the given IoT environment.

6. REFERENCES

[1] United Nations 2018 Report on Ageing, Available at: http://www.un.org/en/sections/issues-depth/ageing/.

[2] Wan He, Daniel Goodkind, and Paul Kowal, "An Aging World: 2015", International Population Reports, Issued in March 2016 by United States Census Bureau.

[3] Details of World Population Data, by the World Bank, Available: https://data.worldbank.org/indicator/SP.POP.65UP.TO.ZS.

[4] Tommy Bengtsson and Kirk Scott, "The Ageing Population", 2nd Chapter in Population Ageing - A Threat to the Welfare State?, ISBN 978-3-642-12611-6, eISBN 978-3-642-12612-3.

[5] The United Nations Principles for Older Persons, Resolution adopted by United Nations General Assembly 1991, Available: https://www.ohchr.org/en/professionalinterest/pages/olderpersons.aspx.

[6] Bethany Kon, Alex Lam and Jonathan Chan, "Evolution of Smart Homes for the Elderly" Proceedings of the 2017 International World Wide Web Conference Committee (IW3C2), April 3-7, 2017, Perth, Australia.

[7] Julio Abascal, Borja Bonail, Alvaro Marco, Jose Luis Sevillano, "AmbienNet: An Intelligent Environment to Support People with Disabilities and Elderly People" Proceedings of ASSETS'08, October 13–15, 2008, Halifax, Nova Scotia, Canada.

[8] M. Chan, E. Campo, W. Bourennane, F. Bettahar, Y. Charlon, "Mobility Behavior Assessment Using a Smart-Monitoring System to Care for the Elderly in a Hospital Environment", Proceedings of PETRA '14, May 27 - 30 2014, Island of Rhodes, Greece.

[9] Rami Yared, Bessam Abdulrazak, Thomas Tessier, Philippe Mabilleau, “Cooking risk analysis to enhance safety of elderly people in smart kitchen” Proceedings of PETRA '15, July 01 - 03, 2015, Corfu, Greece.

[10] Soo-Cheol Kim, Young-Sik Jeong, Sang-Oh Park, “RFID-based indoor location tracking to ensure the safety of the elderly in smart home environments” Personal and Ubiquitous Computing (2013) 17:1699–1707.

[11] M. Jamal Deen, “Information and communications technologies for elderly ubiquitous healthcare in a smart home”, Personal Ubiquitous Computing (2015) 19:573–599.

[12] Gabriele Civitarese, Claudio Bettini, Stefano Belfiore, “Let the Objects Tell What You are Doing”, Proceedings of Ubicomp/ISWC’16 Adjunct , September 12-16, 2016, Heidelberg, Germany.

[13] Rosa Iglesias, Nuria Gomez de Segura, Miren Iturburu, “The Elderly Interacting with a Digital Agenda through an RFID Pen and a Touch Screen”, Proceedings of MSIADU’09, October 23, 2009, Beijing, China.

[14] Leonardo Angelini, Nathalie Nyffeler, Maurizio Caon, Mélanie Jean-Mairet, Stefano Carrino, Elena Mugellini, Luc Bergeron, “Designing a Desirable Smart Bracelet for Older Adults”, Proceedings of UbiComp’13, September 8–12, 2013, Zurich, Switzerland.

[15] Rajiv Khosla, Mei-Tai Chu, Reza Kachouie, Keiji Yamada , Fujita Yoshihiro, Tomoharu Yamaguchi, “Interactive Multimodal Social Robot for Improving Quality of Care of Elderly in Australian Nursing Homes”, Proceedings of MM’12, October 29–November 2, 2012, Nara, Japan.

[16] Mohamed Tarik, Abdenour Bouzouane, Bruno Bouchard, “Sensors activation time predictions in smart home”, Proceedings of PETRA '15, July 01 - 03, 2015, Corfu, Greece.

[17] Dibya Prokash Sarkar, “A Nurse Bot for Elderly People”, Proceedings of UbiComp/ISWC'18 Adjunct, October 8–12, 2018, Singapore.

[18] Nirmalya Thakur, Chia Y. Han, “Methodology for Forecasting User Experience for Smart and Assisted Living in Affect Aware Systems”, Proceedings of IOT '18, October 15–18, 2018, Santa Barbara, CA, USA.

[19] Saguna, Arkady Zaslavsky and Dipanjan Chakraborty, “Complex Activity Recognition Using Context Driven Activity Theory and Activity Signatures”, ACM Transactions on Computer-Human Interaction, Vol. 20, No.6, Article 32, Dec. 2013.

[20] Timo Sztyler, Heiner Stuckenschmidt, Wolfgang Petrich, “Position-aware activity recognition with wearable devices”, Pervasive and Mobile Computing Volume 38, Part 2, July 2017, Pages 281-295.

[21] I Goodfellow, D Erhan, PL Carrier, A Courville, M Mirza, B Hamner, W Cukierski, Y Tang, DH Lee, Y Zhou, C Ramaiah, F Feng, R Li, X Wang, D Athanasakis, J Shawe-Taylor, M Milakov, J Park, R Ionescu, M Popescu, C Grozea, J Bergstra, J Xie, L Romaszko, B Xu, Z Chuang, “Challenges in Representation Learning: A report on three machine learning contests”, Proceedings of the ICML 2013 Workshop on Challenges in Representation Learning, Cornell University 2013.

[22] K. Jack and K. William, ``The UK-DALE dataset, domestic appliance-level electricity demand and whole house demand from five UK homes,'' Sci. Data, vol. 2, p. 150007, Sep. 2.

[23] Abdulsalam Yassine, Shailendra Singh, And Atif Alamri “Mining Human Activity Patterns From Smart Home Big Data for Health Care Applications” IEEE Special Section On

Advances Of Multisensory Services And Technologies For Healthcare In Smart Cities, June 2017.

[24] Nirmalya Thakur and Chia Y. Han, “A Complex Activity Based Emotion Recognition Algorithm For Affect Aware Systems”, Proceedings of the IEEE-CCWC 2018 Conference, 08-10 January, 2018, Las Vegas, USA.

[25] O. Ritthoff, R. Klinkenberg, S. Fisher, I. Mierswa, S. Felske. YALE: Yet Another Learning Environment. LLWA’01 – Tagungsband der GI-Workshop-Woche Lernen– Lehren – Wissen Adaptivitat. University of Dortmund, Dortmund, Germany. Technical Report 763. 2001: 84-92.

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