Smartphone based Robust Hierarchical Framework for Activity Recognition based on Machine Learning

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***Abstract*— Human behaviors are a complex and challenging task to learn from daily life activities. Persons who are dependent can be ignored by society. Besides infants, elders are observed to have more accident rates in performing daily life activities. Alzheimer disease is the common impairment that leads to dementia in elderly people. Thus, elderly people are unable to live independent life due to forgetfulness. Continuous care and monitoring is required for Alzheimer's patients to live a healthy life, as it generally becomes difficult for the people who suffer from this progressive disease to live an independent life. To support elderly people who desire to live an independent life, performing their daily activities smoothly and need a home safety is to find out daily life activities of elderly people and provide them appropriate aid. The heuristic approach has been developed to recognize human behavior and intentions with the help of sensor events. The smart environment is created for monitoring volunteers conducting activities of daily life. This research aims to develop machine learning algorithms for identifying person's daily activities. The model proposed is flexible, adaptable, and scalable well with data.**

Keywords—Bayes Net; Naïve Bayes; dynamic; ADL; classifiers

I. Introduction

Detection and prediction of the daily life activities and the changes in the human behavior is a hot issue in social research circles in recent times [1]. The concept of modern communication has completely revolutionized the lifestyle and daily routines of most of the individuals around the globe. It has affected the work routines, daily household schedules, social relationships, leisure and how we spend our free time? Nowadays, phones serve for not only staying in touch but they help to plan trips, to organize daily activities, shop online and health care related tasks. They are smart and of small size, so it is very easy to carry them around while performing different daily life activities. Therefore they emerged as an important part of daily life activities and present at all times. This motivates us to use a mobile phone to enable independent living among the elderly people by recognizing daily life activities and proposing in-time assistance and safeguards that may help to perform different tasks independently. This can also help to recognize any change in the behavior of the Alzheimer's patients that is a key to detect the rate of functional decline in such patients.

The work in this paper is an addition to the current work that adopts machine learning techniques to infer activities and behavior change in individuals. A hierarchical approach has been adopted where a number of different machine learning techniques have been applied to obtain more accurate and scalable recognition of daily life activities and behavioral change of individuals. The idea is to identify how different machine learning classifiers perform with the context of daily life activities.

The inference of activities and behavior in this paper has been performed using object usage data and context information captured from everyday objects through a mobile phone.

Rest of the paper is organized as follows: Related work is discussed in next section. The methodology and the results are discussed after that, and then a conclusion is discussed at the end.

II. Related Work

Although there is a lot of progress recently in the field of sensing through mobile devices [2] still further advances are promises with the grow of processing capabilities of these smart devices. These devices bridge the gap between contextual information, devices themselves and the end users but still it is a challenge to recognize activities from data captured through these context aware devices. Researchers have explored different dimensions and have proposed many solutions. Marschollek et al. [3] in their work utilized the accelerometer data and measured the probability of ADL's using classification techniques. Likewise, Joao Bartolo Gomes et al. [4] demonstrated Mobile Activity Recognition System (MARS) where the model was updated on mobile service itself. The model used Naive Bayes classifier and was adaptable to user profile changes. At the same time being the system was scalable and efficient in terms of privacy and consumption of the device resources.

This can be extended and user profiles can be included to make better decisions and leading users towards a certain well-being goal. For example, smart phone's built-in sensors such as accelerometer, gyroscope and Bluetooth can be used for the recognition of physical activities and social relationships.

Ghose et al. [5] evaluated phone-based accelerometers for activity recognition. The labeled accelerometer data were collected from daily activities such as strolling, running, climbing stairs, relaxing (sitting inhaling), and relaxing (standing exhaling), and then aggregated this time series data into examples which were further used to induce a predictive model for activity recognition. This work outperformed most of the prior work in that a commercial mass marketed device was used rather than a research-only device. The user was not asked to perform additional actions for the sake of experimentation, instead normal activities were monitored with the help of single device rather than multiple wearable devices distributed across the body. C4.5 decision trees (J48), logistic regression and multilayer neural networks were the three classifiers utilized along with 10-fold cross validation. The results indicate that the multilayer perceptron performed best overall. Another mobile application development for ubiquitous monitoring and assessment of physical activities was developed by Moller et al. [6], where the quality of exercises were assessed using Kullback-Leibler divergence (KLd) and pyramidal Principal Component Breakdown Analysis (PCBA) technique. The smartphone captured acceleration data and after processing, provided immediate user feedback (calculated skill level). Participant's feedback was tremendously positive regarding usability, efficiency and reliability of trainer.

Similarly, a smart phone application was developed by Anjum et al. [7] to track user activities and report estimation of calories burned. Sensor readings were obtained in different orientations and features were extracted. Evaluation of all utilized classification algorithms was done and it was determined that C4.5 Decision Tree classifier outperformed the other classifiers on average with a true positive rate of 95.2%, false positive rate of 1.1%, the precision of 94.4% and recall rate of 94.2%.

One of the key challenges within the activity recognition domain is scalability. Top-down, goal driven approaches addressed this by hierarchical structuring activities, which are made up of execution conditions and abstract sensor mappings The hierarchical model proposed in this paper carries out a similar function, as it structures activities as a hierarchical entity.

III. Methodology

The focus of this research is elderly people with low entropy and Alzheimer's and dementia patients of the moderate and mild stage. The term low entropy is specifically used here, as patients and aged individuals have fixed routines of performing daily life activities (ADLs). Dementia patients suffer from forgetting things, and find difficulty in social interaction and performing daily life activities. Doctors give such patients some specific tasks to perform on a daily basis to check the status of their disease and improvement in health.

For instance, such schedule comprising of Morning Refresh, Making Breakfast, Prepare-Meal, Evening-Activity, performing some tasks like reading, walking, and iron clothes in the evening, etc. Such routine is followed on regular routines and sleep.

The identification of ADLs and intentions of elderly people is done using machine learning classifiers. Different algorithms are used to complete this hierarchical approach and to investigate which ADL is active.

A bottom up hierarchical approach, shown in Fig. 1, is used for ADL recognition. ADLs are high-level activities covering the higher tier. These ADLs are further composed of tasks which are forming lower tier. The bottom level comprises of sensors embedded in different objects under use to identify what tasks are being performed by individuals. Activity recognition is based on tasks which are identified by sensor events.

Dense sensing is used for gathering data which is followed by Generating Alternative sequences (GATS) algorithm [8] for recognition of tasks that are in correspondence to sensor events generated. GATS generate a different sequence of tasks from the stream of object Usage data. The object usage data is based on the conjunction of the disjunction of task possibilities from each sensor.

Similarly, frequent pattern mining algorithms have been used to find a pattern from object data stream. From the incoming input streams, we check out either this pattern belongs to existing tasks or not. ECLAT algorithm [8] is used in this research to find a pattern from the stream of sensor data. When sensors occur at an as specific frequency, a pattern is generated (Support).

The next tier is the learning layer. This layer comes after task identification and pattern mining. In this tier, the model learns to add pattern in the system or not. The pattern is significant or not is judged by the frequency of sensors objects. Here it is also determined either this pattern is introducing a new task or belongs to existing task set.

If the pattern doesn't belong to any existing task and is still considered significant by the learning tier, then the user is prompted to add it to the model. Based on user response, the system is updated by the pattern addition or it is discarded.

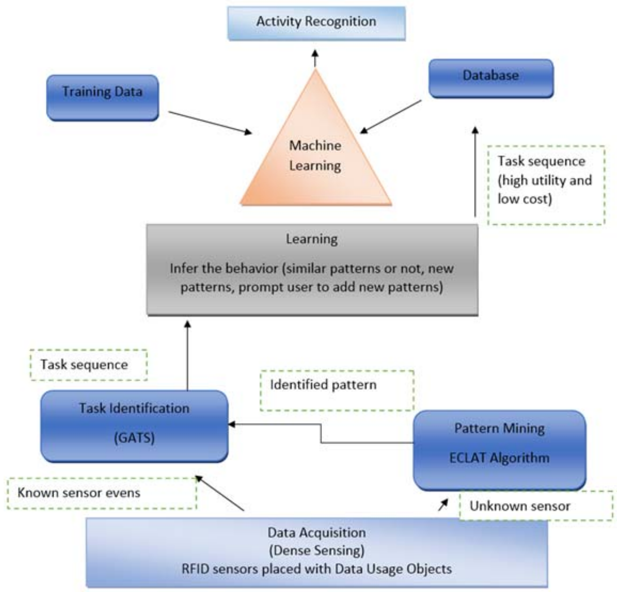

Fig. 1. The hierarchical framework of activity recognition.

The highest tier is the ADL layer. ADL plans consist of tasks. ADL at this level are complex ADLs and system needs to learn the behavior of users. Machine learning is used to fulfill this requirement. Five instances of this layer comprise of machine learning classifiers.

Different classifiers (KNN, SVM, MLP, Bayes Net, Naïve Bayes) are applied by training on ground truth and then tested to check how accurately they identify activities performed by subjects to improve diagnosis and medical treatments of dementia patients.

The purpose of classifier implementation is to make the system dynamic and intelligent dealing with all behavior changes of individuals suffering from dementia.

Classifiers learn input behavior and map them to the desired output. In our research, the lower layer tasks act as input to a higher layer. They are mapped to the desired activities by model learning.

The activities are based on tasks at a lower level. So as an example, if we consider 'Morning Refresh', it is an ADL consisting of sub-activities "Enter Wash Room", "Wash Face" and "Brush Teeth".

On the basis of machine learning, ADL recognizer is developed which takes task streams from the task recognition component and identify the current activity performed by the user. New tasks that are recognized at the task recognition level are also identified at this level.

IV. RESULTS

Activity recognition varies in terms of each classifier. Five classifiers are utilized to find the accuracy of activity recognition for an efficient dynamic framework. Table 1 shows the prediction for each activity when using separate testing and training files. KNN, Bayes Net and Naïve Bayes provide better results when data is not experimented using cross validation techniques.

TABLE I. RESULTS USING SEPARATE TESTING AND TRAINING FILES IN TERMS OF EACH ACTIVITY

Classifiers	**Morning Refresh (Correct/Total)**	**Breakfast (Correct/ Total)**	**Evening Activity (Correct/Total)**
KNN	8/8	10/10	10/11
SVM	7/8	6/10	9/10
MLP	7/8	9/10	9/11
Bayes Net	8/8	8/10	9/11
Naïve Bayes	8/8	10/10	10/11

Classifiers	**Prepare Meal (Correct/Total)**	**Iron Cloths (Correct/Total)**
KNN	8/10	4/5
SVM	3/10	5/5
MLP	8/10	5/5
Bayes Net	10/10	4/5
Naïve Bayes	10/10	4/5

Similarly, comparison of Machine Learning Classifiers on the basis of recognition rate for each of the five daily life activities over Imbalance Dataset is shown in Fig. 2. The horizontal axis represents different classifiers (KNN, SVM, MLP, Bayes Net and Naive Bayes) and the vertical axis represents recognition rate. The results show that KNN, Bayes Net and Naive Bayes performed well with all activities in the dataset.

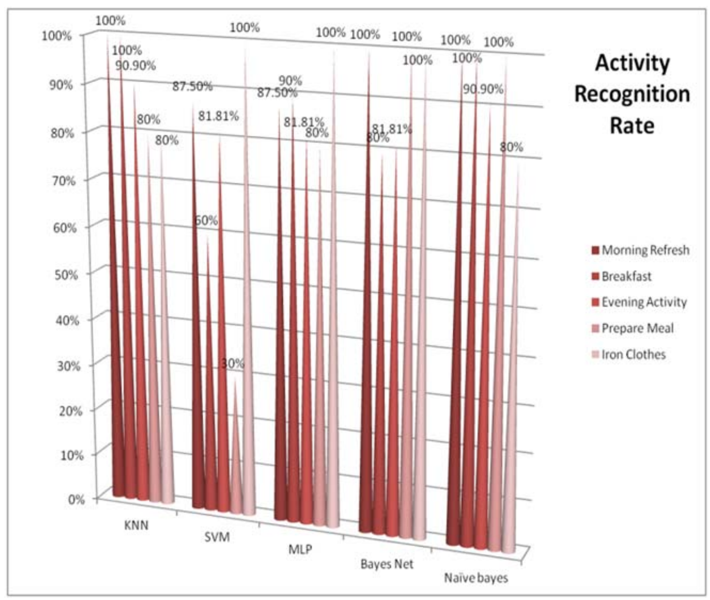

Fig. 2. Activity recognition rate.

A. *Experiments Recognition Rate*

Four types of experiments are performed for activity recognition. Experiment 1 was for a predefined sequence of activities in which MLP and Naïve Bayes outperformed. Experiment 2 was done for checking task variation results and the results were much positive with Bayes Net. The third experiment was for judging missing data; both Naïve Bayes and KNN gave 100% accuracy. The last experiment was done for additional tasks where most of the classifier gave 80% accuracy. The experimental analysis is represented in Fig. 3.

B. Comparison Of Asbru And Proposed Model

A comparison is made between Asbru model discussed previously in literature with the proposed framework and the results are found in negligible. This model provides a solution to all medical affairs regarding low entropy, utilizing Smartphone and proposing a robust, dynamic, authentic and intelligent. Table 2 presents a comparison with the existing framework.

C. Disadvantages of the Previous Model

Asbru-based Model [1], [9] is static which is one of the major issues that lead to research for a more intelligent approach to dynamic behavior. This system however, works best with the available data. It reports flaws with any up gradation. The drawbacks of the previous framework are presented in Fig. 4.

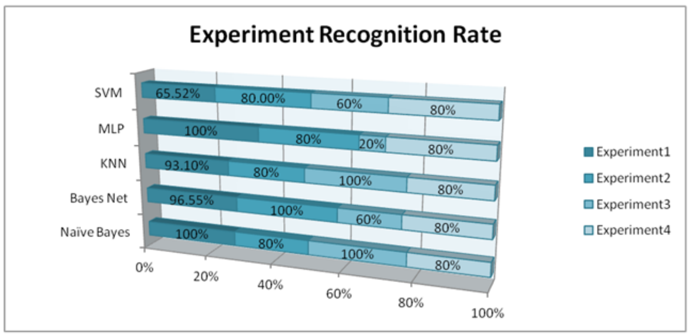

Fig. 3. Experimental recognition rate.

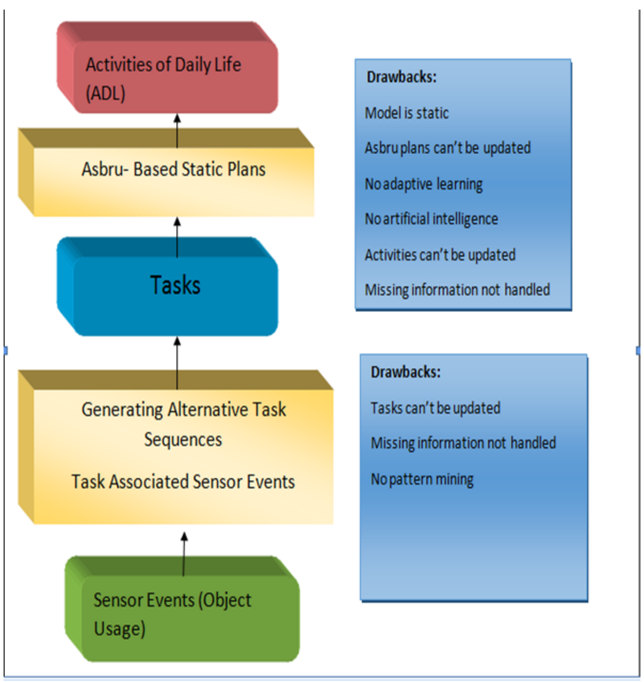

Fig. 4. Drawbacks of the previous framework.

Advantages of Proposed Model

This Dynamic framework overrules many issues reported in the Asbru-based infrastructure [1], [9]. The system is intelligent and robust, and is integrated in Smartphone, a device which is the basic need of every individual these days. This model also ensures updating additional tasks and handling missing information. The advantages of the proposed framework are shown in Fig. 5.

The recognition rate compared with the existing Asbru model [1], [9] with all classifiers utilized in this framework is shown in Table 3. The results show that Naïve Bayes performs best among all.

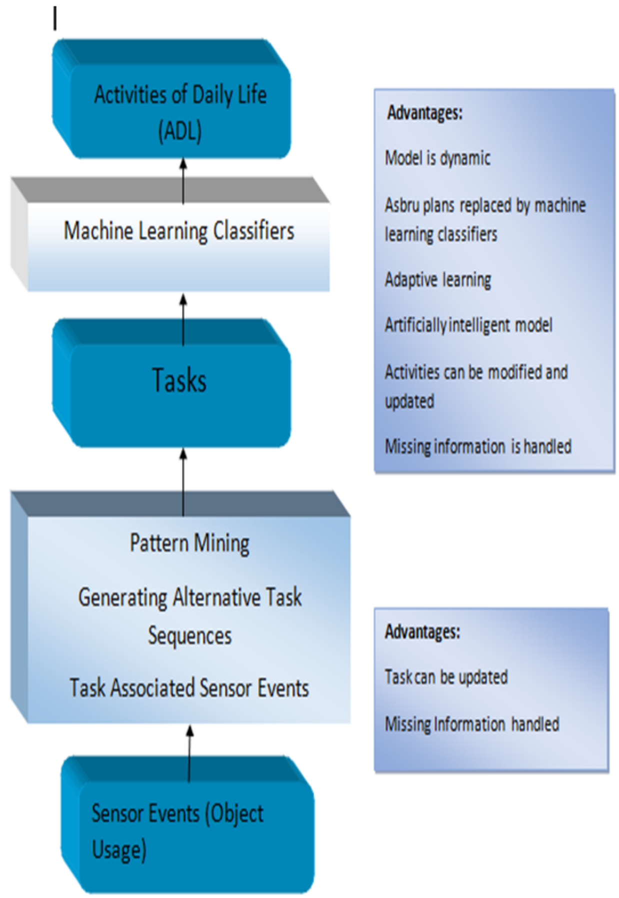

Fig. 5. Advantages of proposed framework.

D. Recognition Rate of Asbru Model and Proposed Model

The proposed model is compared in terms of recognition rate with the existing Asbru based model [1], [9] and the results of all classifiers indicate that Naïve Bayes performed efficiently among all for activity recognition framework with the imbalanced dataset.

Naïve Bayes results are based on likelihood in addition to probabilities. So, it produces good results as the independence of features is somehow correct in case of imbalance dataset.

TABLE II. COMPARISON WITH EXISTING FRAMEWORK

	Parameters	Existing Framework	Enhanced Framework
1.	**Adaptive**	Only works with fixed routines	Adapts to behavioral changes.
2.	**Disjunctive Normal Form**	Yes.	Yes
3.	**Update in activities**	No	Update tasks from which activities are created by sensor events associations.
4.	**Pattern Recognition**	No	Abnormalities detection is performed using pattern mining.
5.	**New tasks addition**	No	Addition of new tasks is supported as changes in behavior
6.	**Activity Recognition**	static	Dynamic
7.	**Classification**	Activities are recognized by matching task streams with Asbru plans	Classifier learning is performed using task streams which predict activities.
8.	**Model**	Model is developed using Asbru plans	Model is based on machine learning classifier and is intelligent
9.	**Implementation of Machine learning classifiers**	No	5 classifiers (Bayes Net, Naïve Bayes, SVM, KNN, MLP) are implemented
10.	**Asbru Plans Up gradation**	No	System proposed is dynamic and intelligent based on machine learning
11.	**Accuracy**	Static cases are predicted accurately	All new variations and modifications are predicted accurately

TABLE III. RECOGNITION RATE OF ASBRU AND PROPOSED MODEL

Recognition Rate [%]					
Asbru based model	**Activity Recognition Using Machine Learning Classifier**				
Asbru	**KNN**	**Naïve Bayes**	**MLP**	**Bayes Net**	**SVM**
67%	90.9%	95.45%	86.36%	90.91%	68.18%

V. CONCLUSION

The paper describes Smartphone based robust hierarchical framework for activity recognition based on machine learning. From low-level task recognition to activities of daily life, system recognition rates are made more flexible and efficient. Activity recognition for various medical treatments is enhanced using modern implementation of cellular devices making it more accurate and dynamic. Using standard data collected from ADLs performed on a regular basis, the system is tested based on experimentation and the results obtained are positive and efficient. The proposed framework also works well with missing and additional information.

However, the next step is to exploit the higher level recognition using unsupervised learning. Another avenue for future work is feature selection that is required in case of irrelevant (and missing) data. PCA (principle component analysis) utilization is selected for future research on this framework.

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