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Machine Learning approach applied to Human Activity Recognition – An application to the VanKasteren dataset.

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Abstract

Reminders are a core component of many assistive technology systems and are aimed specifically at helping people with dementia function more independently by compensating for cognitive deficits. These technologies are often utilized for prospective reminding, reminiscence, or within coaching-based systems. Traditionally, reminders have taken the form of nontechnology based aids, such as diaries, notebooks, cue cards and white boards. This article is based on the use of machine learning algorithms for the detection of Alzheimer's disease. In the experimentation, the LWL, SimpleLogistic, Logistic, MultiLayerPercepton and HiperPipes algorithms were used. The result showed that the LWL algorithm produced the following results: Accuracy 98.81%, Precission 100%, Recall 97.62% and F- measure 98.80%

Keywords: Machine learning, HAR, ADL, Human Activity Recognition, Activity Daily Living, VanKasteren Dataset.

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1. Introduction

Reminders can be more helpful when rich contextual information is used to present them at the most appropriate time, in an appropriate location and in the most appropriate manner [1]. For example, a shopping list reminder is more helpful while passing the supermarket enroute home from work, rather than while at work or after getting home. Mobile phones are considered as a suitable platform for the deployment of context-aware reminders. The ubiquity and unobtrusiveness of modern smart phones, equipped with various sensor technologies including GPS, accelerometer, and gyroscopes, make them well suited for use as a mobile sensing platform.

Indeed, participatory, and opportunistic sensing, leveraging the users' own mobile device, to collect social, physiological, or environmental data, is gaining popularity. Several reminding applications have utilized the user's sensed location to schedule reminders when the user is close to a place of interest, which has even made its way into commercial reminder applications, most notably Google Now. Nevertheless, fewer applications have used other contextual information, such as the user’s activity or social interactions to improve reminder delivery.

For example, reminders could be delivered to a user when they are carrying their mobile device, or prompts could be delivered when it will have the least impact on a user’s current activity. Reminder systems have attempted to improve reminder delivery by considering the physical and temporal context of the user when delivering reminders. Helal [2] described a reminder system that uses data from sensors in the home to detect the location of the user and display reminder videos on the most ideal display present. Autominder [3] is an activity-based reminder robot that uses Artificial Intelligence techniques and quantitative temporal Bayesian networks to observe and reason about ADLs which have been performed to develop a model of a user's typical daily plan. It then maintains and uses this learned model to schedule future reminders. Nevertheless, a limitation identified from this approach is the inability to manually adjust a given schedule once learned.

This article arises because of the research project entitled "Technological platform to support the early diagnosis of Alzheimer's disease through the analysis of resonance images using data mining techniques", funded by Colciencias in Colombia. This article is organized as follows; first a brief systematic review of the literature is shown. Second the algorithms and the data are described and finally the results of the experimentation are shown.

2. Brief Literature Review

NeuroPage [4] is an alphanumeric pager-based system that sends short messages to a pager, which is operated by a single button that permits a user to acknowledge receipt of the reminder. Neuropage has been evaluated with over 200 patients with a range of cognitive impairments, including dementia, and has been shown to be effective at assisting with prospective memory problems [5,6,7]. Nevertheless, such ‘low tech’ solutions have been criticized for their lack of generalizability and inability to modify the solution to suit the needs or preferences of the user [8]. More recently, technology-based approaches have focused on delivering text-based reminders to mobile platforms via email or Short Message Service (SMS) messages.

Correspondingly, studies have shown that SMS reminders can have a positive impact across the healthcare setting [9] including medication adherence [10], clinic appointment attendance [11,12] and patient self-management [13]. Mobile technology continues to progress at a staggering pace, with many users now owning smartphones. Reminder applications have begun to leverage this new technology to deliver reminders using a range of multimedia formats, in conjunction with utilizing the smartphone’s integrated sensors and wireless communications. Within the research literature several smartphone applications have been described that focus specifically on people with cognitive impairments. O’Neil [14] developed the Mobile Phone Video Streaming (MPVS) system, which provides video- based reminders for everyday activities. The application was developed through an iterative design process and evaluated with a cohort of 40 persons with dementia along with their respective caregivers.

More recently, the TAUT (Technology Adoption and Usability Testing) project [15] aimed to investigate the issues surrounding the adoption of smartphone-based reminding technologies by people with mild cognitive impairments. Described in Hartin [16], a smartphone application has been developed for the Android platform and is designed to provide the user with an interface to schedule and acknowledge reminders for a range of daily activities.

In addition to providing scheduled reminders, the application also records details of the user’s interactions, such as when the reminder is acknowledged, the type of reminder and how many reminders the person has missed. These details are subsequently used to assess how well the user is engaging with the application and to provide insight into details regarding how the application is used. Initial results obtained from a study of 30 users over a 6-month period have indicated low rates of acknowledgment of reminders, with 70% of all reminders set being missed and only 15% of missed reminders being attributed to the smartphone being switched off [17]. Consequently, research into the effectiveness of reminders and how acknowledgement rates and compliance with reminders can be improved are essential for realizing the full potential of such technology-based reminding systems. Traditional approaches to computing are based on numerical values, crisp logic or binary logic, and are characterized by accuracy. In contrast, soft computing approaches are based on techniques, such as fuzzy logic, fuzzy reasoning, computing with words, etc., that are characterized by approximation, yet can be utilized to adequately model uncertainty [18]. Such uncertainty occurs in multiple situations when designing reminders for a smart environment, including the uncertainty found in human behavior and the uncertainty found in the data collected from a range of sensors, which can present noise, imprecision, and inconsistency. Consequently, the use of soft computing techniques provides a promising approach for handling uncertainty when designing reminding systems for smart environments, as they improve and enrich the knowledge within smart environments, thereby yielding the most successful solutions in terms of flexibility and offering realistic adaptable models.

3. Materials and Methods

For experimentation it was used the VanKasteren dataset, defines a scenario in which the individual occupation of a man in the apartment is analyzed. This apartment was equipped with a total of 14 sensors that received the interaction of the individual for 28 days. This interaction allowed identifying a set of 2,120 sensor-associated events with 245 activity instances, see table 1.

Table 1. Description of the characteristics of the Preprocessed dataset.

Activity	Description
Bed	Sensors that allow us to identify if the person is performing the action of using the bed to sleep
Toilet	It allows identifying when a person is using the bathroom for a period.
Breakfast	It can identify that the person is doing the breakfast activity for a certain time
Shower	Using this type of sensor, the time it takes to bathe can be determined
Leave	A sensor is activated on the apartment door that identifies when the person leaves the apartment
Dinner	It allows to determine when an individual is eating
Drink	Allows the identification of the duration of the individual taking a drink

For the development of this experimentation, different algorithms based on classification were taken, which can be grouped according to the following typologies: based on distance (LWL), based on logistic analysis (SimpleLogistic, Logistic), based on neural networks (MultiLayerPerceptron) and based on clustering (HiperPipes).

4. Results

To carry out this experimentation, the following phases of data discovery and analysis were carried out:

Phase 1- Preprocessing of the data: Different techniques of data ordering were applied, considering the time of identification of the activities by means of the sensors.

Phase 2 - Selection of data preprocessing techniques: The SMOTE technique was used to balance the data considering the different classes.

Phase 3 - Implementation of classification algorithms: Different data mining techniques were selected to apply in the data set, among which the following stand out: LWL, SimpleLogistic, Logistic, MultiLayerPercepton and HiperPipes.

Phase 4- Application of quality metrics, among which we can highlight: Accuracy, Precision, Recall y Fmeasure.

$$Accuracy = \frac{(true\ positive + true\ negative)}{total} \quad [1]$$

$$Precision = \frac{true\ positive}{(true\ positive + false\ negative)} \quad [2]$$

$$Recall = \frac{true\ negative}{(true\ positive + false\ positive)} \quad [3]$$

$$F - measure = \frac{2 * precision * recall}{precision + recall} \quad [4]$$

The results of the implementation can be seen in Table 2 and in Figures 1 to 3.

Table 2 . Algorithms results.

Algorithm	Accuracy	Precision	Recall	F-measure
LWL	98,81%	100,00%	97,62%	98,80%
SimpleLogistic	97,62%	100,00%	95,24%	97,56%
Logistic	96,43%	100,00%	92,86%	96,30%
MultilayerPrecepton	95,24%	100,00%	90,48%	95,00%
HiperPipes	92,86%	87,50%	100,00%	93,33%

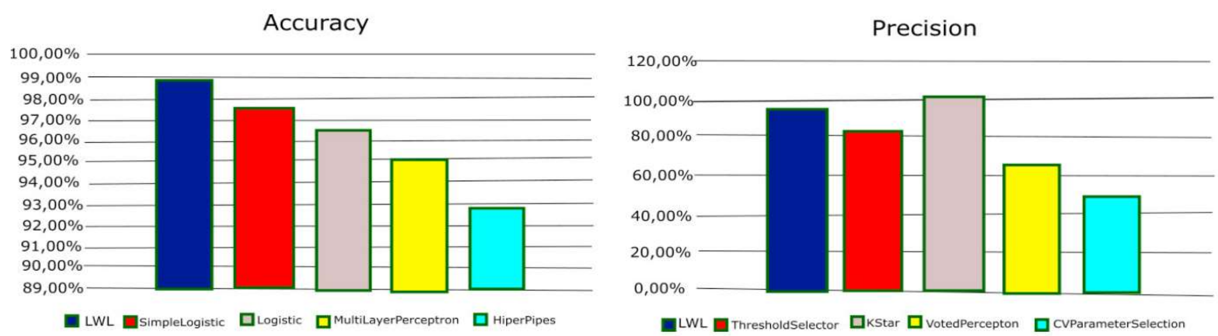


Fig 1. (a) Accuracy Results (b) Precission Results.

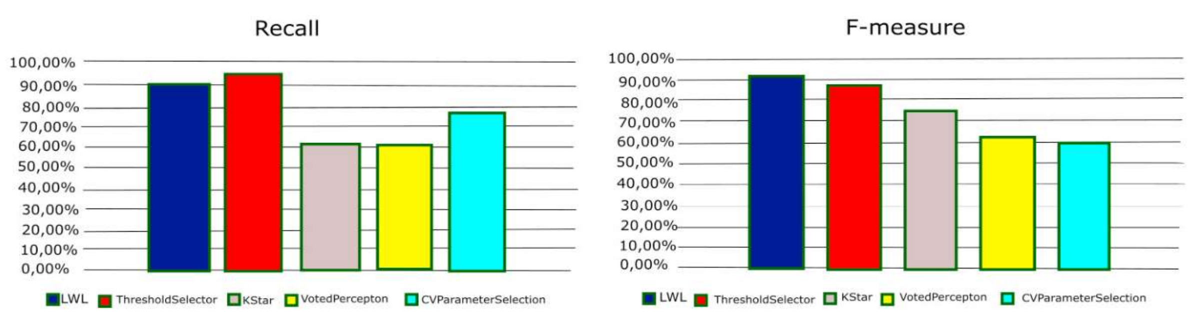
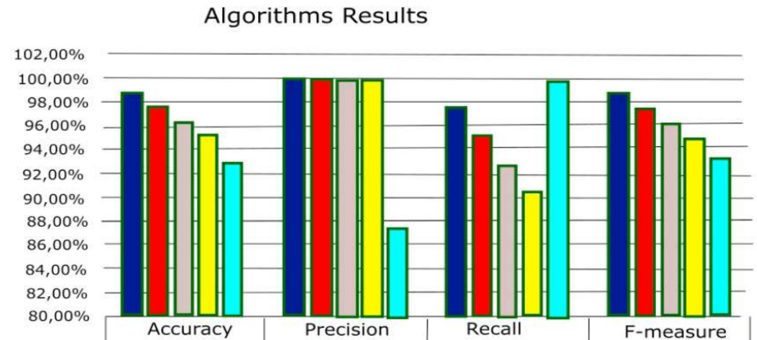


Fig 2. (a) Recall Results (b) F-measure Results.



	Accuracy	Precision	Recall	F-measure
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SimpleLogistic	97.62%	100,00%	95.24%	97.56%
Logistic	96.43%	100,00%	92.85%	96.30%
MultiLayerPerceptron	95.24%	100,00%	90.48%	95.00%
HiperPipes	92.86%	87,50%	100,00%	93.33%

Fig . 3 Algorithms Results

5. Conclusions

Through the implementation of these techniques, the effectiveness of automatic learning in the processes of detection of recognition of human activities can be evidenced. The high performance of classifiers can be denoted as LWL with good accuracy results above 98%, , although the other classifiers such as SimpleLogistic, Logistic, MultiLayerPerceptron and HiperPipes also show good performance. In general, it is observed that the algorithms based on clustering punctually HiperPipes obtains the lowest score. That is why it is chosen to select the LWL algorithm

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