ORIGINAL PAPER

Utilizing Machine Learning to Recognize Human Activities for Elderly and Homecare

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ABSTRACT

Introduction: Dementia is a progressive disorder associated with age, which is characterized by deterioration of individuals' cognitive functions such as the ability to perform routine tasks. With the increase of human life expectancy, the prevalence of dementia patients will reach 152 million in 2050. Unfortunately, there is no treatment available to cure dementia or alter the course of its progression. However, there is an area of support for patients and caregivers to assist daily living. Technological devices and applications are increasingly advancing, exploiting sensory data for dementia patients and homecare using smartphones to permit monitoring of their activities. **Aim:** This paper uses the labeled dataset besides comparing the 3-classification algorithm to evaluate whether or not the algorithms deployed can classify the activities with high accuracy. **Results:** A public data is used to classify human activities into one of the six activities, BigML platform is used to build machine learning models. Results show that machine learning algorithms can achieve high accuracy. The activity recognition algorithms are highly accurate using ridged regression and deep neural networks, with almost all activities being recognized correctly over 98% of the time. **Conclusion:** An application of smartphones can be utilized for human activities monitoring by proposing a high level for dementia patients and homecare monitoring services. Using this service, the patients only need to carry the smartphone, and their caregivers simply need to use the application that monitors their patients' activities.

Keywords: Dementia; HAR; Machine Learning; BigML; Smartphone.

1. INTRODUCTION

Dementia is a progressive disorder associated with age, which is characterized by deterioration of individuals' cognitive functions such as the ability to perform routine tasks (i.e., speaking, walking, sitting down, standing up). Forgetfulness is part of human nature, and it affects people, especially among adults. However, dementia determined by gradual impairment of individuals' abilities to perform daily tasks beyond what is expected from normal aging. Dementia impact is different for one person to another, depending on the stage and progression of the disease resulting in dependency and disabilities among elders. According to the World Health Organization (WHO), the total number of people with dementia worldwide is estimated to reach 82 million in 2030 and 152 million in 2050 (1). According to the General Authority of Statistics in Saudi Arabia, a statistical report posted in 2016 indicated that the number of people over the age of 60 years old was 1.3 million (6.5%) of the Saudi population (2). The percentage of elderly people would increase by 2050 to be 25% of the population, as the life expectancy will move from 74 to 82 years old (3).

A retrospective cohort study conducted at King Faisal Specialist Hospital and Research Centre (KFSH-RC) between the years 1995 and 2010 found out the percentage of patients diagnosed with dementia over the age of 65 is 63.41% with a total sample size of 418 patients (4). In addition, the study reviewed the type of caregiver per patients; 50.24% of those patients were taken care by family members, 1.44% of patients had housemaid, 1.44% patients had private nurses, 16.27% were in Home Health Care (HHC), and 30.62% of patients not documented who took care of them. From these numbers, we can conclude that there is an urgent need for national strategies to help elderly patients who suffer from cognitive diseases and to establish assistive solutions.

The need for smart systems to assist the patients and caregivers increases each year. Unfortunately, there is no treatment available to cure dementia or alter the course of its progression. However, there is an area of support for patients and caregivers to assist daily living. One field applied for such disorder is Human Activity Recognition (HAR) technologies, which is a machine learning field focusing on identifying human movements and actions utilizing sensory devices. HAR is an evolving field that uses minimally invasive devices to monitor individuals' activities. Devices used vary from the wristband to smartphones to intelligent systems such as robotics.

This paper intent to classify activities into one of the six activities performed based on a labeled sample of the Human Activity Recognition database which was built from the recordings of 30 study participants performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors (10-14).

The dataset contains a total of 10299 records. According to the UCI machine learning repository's description of the dataset, the experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments have been video-recorded to label the data manually.

Various applications of intelligent systems have been constructed to study human activity recognition methods on smartphones or portable devices (11-16). Such as to assess the movement of patients after stroke (5) or for postoperative patients assessment (6) or for obesity and wellbeing (7) or for sports activities (8) and for detecting falls (9).

Several studies utilized machine learning algorithms to predict HAR using accelerometer sensor data. Kwapisz *et al.* (17) applied a C4.5 decision tree, Logistic Regression, Multi-Layer Perceptron (MLP), on HAR data gathered from 29 users with 43 attributes. They achieved an accuracy of 90% with the MLP algorithm while Wang *et al.* (16) achieved an accuracy of 94.8% by applying the Hidden Markov Model (HMM). On the other hand, Wu and Song (18) utilized Random forest and AdaBoost algorithms to classify HAR activities using smartphones. They reported that AdaBoost achieved a better result than the Random Forest model.

2. AIM

This paper uses the labeled dataset besides comparing the 3-classification algorithm to evaluate whether or not the algorithms deployed can classify the activities with high accuracy. The paper investigates the possibility of the utilization of HAR technologies within Saudi Arabia using mobile applications and Saudi telecommunication infrastructure.

3. METHODS

In this section, the methodology of this research article was explained - the description of how the data sets and features. The remaining segments of this research article are arranged as follows: Section 2 presents the literature review on the utilization of machine learning-based models in predicting HAR. Section 3 explains the methodology, while Section 4 presents the results and analysis. The utilization of HAR technology is discussed in Section 5. Finally, Section 6 includes the conclusion and future work.

3.1. Dataset and Processing

According to the UCI machine learning repository's description of the dataset, the experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, the researchers captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments had been video-recorded, and the data had been labeled manually (10).

The sensor signals (accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity. The gravitational force is assumed to have only low-frequency components. Therefore a filter with 0.3 Hz cut-off frequencies was used. From each window, a vector of features was obtained by calculating variables from the time and frequency domain.

3.2. Features and Algorithms

For each of the 10299 records in the dataset the following information is provided: 561 numeric features summarizing sensor signals. An identifier of the subject who carried out the experiment.

Its activity label (a factor variable having the following levels: LAYING, SITTING, STANDING, WALKING, WALKING_DOWNSTAIRS, WALKING_UPSTAIRS)

As the dataset does not have any demographic/anthropometric characteristics of subjects subject identifier is not relevant for our analysis. The activity label is our dependent variable, while the rest of 561 features are predictors. The dataset is split into a 70% training set and a 30% testing set.

	LAYING	SITTING	STANDING	WALKING	WALKING_ DOWNSTAIRS	WALKING_ UPSTAIRS	ACTUAL	RECALL
LAYING	370	0	0	0	0	0	370	100.00%
SITTING	0	338	14	0	0	0	352	96.02%
STANDING	0	20	382	0	0	0	402	95.02%
WALKING	0	1	0	346	0	0	347	99.71%
WALKING_DOWNSTAIRS	0	2	1	0	269	0	272	98.90%
WALKING_UPSTAIRS	0	0	0	0	0	317	317	100.00%
PREDICTED	370	361	397	346	269	317	2060	98.28%
PRECISION	100.00%	93.63%	96.22%	100.00%	100.00%	100.00%	98.31%	98.16%

Table 1. Ridges Regression Algorithm Result

	LAYING	SITTING	STANDING	WALKING	WALKING_ DOWNSTAIRS	WALKING_ UPSTAIRS	ACTUAL	RECALL
LAYING	377	0	0	0	0	0	377	100.00%
SITTING	0	319	20	0	0	0	339	94.10%
STANDING	0	11	371	0	0	0	382	97.12%
WALKING	0	0	0	358	0	0	358	100.00%
WALKING_DOWNSTAIRS	0	0	0	2	282	0	284	99.30%
WALKING_UPSTAIRS	0	0	0	4	1	315	320	98.44%
PREDICTED	377	330	391	364	283	315	2060	98.16%
PRECISION	100.00%	96.67%	94.88%	98.35%	99.65%	100.00%	98.26%	98.16%

Table 2. Deep Neural Network Algorithm Results.

	LAYING	SITTING	STANDING	WALKING	WALKING_ DOWNSTAIRS	WALKING_ UPSTAIRS	ACTUAL	RECALL
LAYING	388	0	0	0	1	0	389	99.74%
SITTING	0	325	35	0	0	0	360	90.28%
STANDING	0	18	363	0	0	0	381	95.28%
WALKING	0	0	0	338	6	9	353	95.75%
WALKING_DOWNSTAIRS	0	0	0	14	261	11	286	91.26%
WALKING_UPSTAIRS	0	0	0	13	9	269	291	92.44%
PREDICTED	388	343	398	365	277	289	2060	94.12%
PRECISION	100.00%	94.75%	91.21%	92.60%	94.22%	93.08%	94.31%	94.37%

Table 3. Decision Tree Algorithm Results.

In this report, BigML (15) platform is used to build the machine learning models. BigML is a machine-learning platform founded in 2011 to enable the adoption of advanced analytics by automating it end-to-end. The choice of algorithms was driven primarily by their ability to handle a large number of features without serious over-fitting and without requiring any subjective preliminary dimensionality reduction procedures and without serious overtraining. Three machine learning algorithms were deployed, namely Ridge Regression, Deep Neural Network, and Decision tree.

4. RESULTS

To pick up the best mode, many models were built. The model with an accuracy of at least 96% was chosen. The best model per algorithm is listed below:

Ridge Regression is a machine-learning algorithm used to analyze a dataset with inter-associated, inter-correlated independent variables. It is used to reduce model over-fitting, making a better prediction.

Deep Neural Network: is a complex neural network with multiple layers. The data is processed through multiple layers between the input and output layer; the model is optimized to handle a variety of data types (i.e. numeric, images, categorical).

Decision tree: is a supervised machine learning model simulates trees with each node represents a class label, used for classification tasks.

The models achieved high accuracy prediction for Human Activity Recognition data; the accuracy was especially high in the case of the ridge regression algorithm. The result implies that this technique should be widely used by researchers in the field of activity recognition. “Sitting” was relatively often mistakenly predicted as “standing” by all algorithms. Therefore, feature-engineering efforts should be directed to find features that distinguish between these two activities better. Predictions for other activities were excellent,

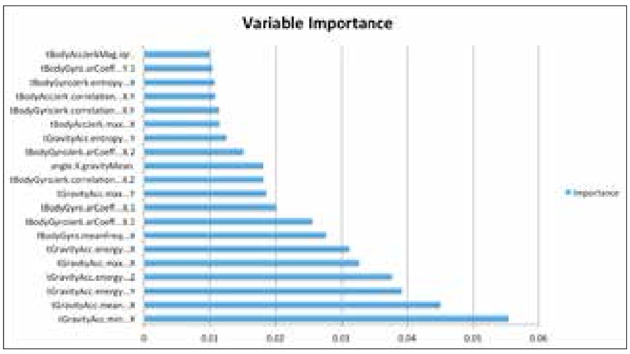

Figure 1. Feature Importance.

Feature	Importance	Percentage
tGravityAcc.min...X	0.05535	5.54%
tGravityAcc.mean...X	0.04504	4.50%
tGravityAcc.energy...Y	0.03919	3.29%
tGravityAcc.energy...Z	0.03762	3.76%
tGravityAcc.max...X	0.03268	3.27%
tGravityAcc.energy...X	0.03119	3.12%
fBodyGyro.meanFreq...X	0.02767	2.77%
tBodyGyroJerk.arCoeff...X.1	0.02558	2.56%
tBodyGyro.arCoeff...X.1	0.02002	2%
tGravityAcc.max...Y	0.01859	1.86%
tBodyGyroJerk.correlation...X.Z	0.01806	1.86%
angle.X.gravityMean.	0.01802	1.81%
tBodyGyroJerk.arCoeff...X.2	0.01511	1.80%
tGravityAcc.entropy...Y	0.01249	1.51%
tBodyAccJerk.max...X	0.01147	1.25%
tBodyGyroJerk.correlation...X.Y	0.01142	1.15%
tBodyAccJerk.correlation...X.Y	0.01079	1.14%
tBodyGyroJerk.entropy...X	0.0107	1.08%
tBodyGyro.arCoeff...Y.1	0.01033	1.07%
tBodyAccJerkMag.iqr..	0.00994	1.03%
tBodyGyroJerk.arCoeff...X.3	0.00969	1.03%
tGravityAcc.sma..	0.00967	0.99%
tGravityAccMag.arCoeff..3	0.00946	0.97%
fBodyGyro.bandsEnergy...41.48	0.00932	0.97%
tGravityAcc.entropy...X	0.00868	0.95%
fBodyGyro.bandsEnergy...1.16.1	0.00851	0.93%
fBodyBodyAccJerkMag.energy..	0.00819	0.86%
tBodyAccJerkMag.max..	0.00809	0.85%
fBodyBodyGyroJerkMag.skewness..	0.00772	0.82%
fBodyAcc.bandsEnergy...9.16.1	0.00759	0.81%

Table 4. Feature Importance Percentage.

no matter which algorithm were used. Feature importance was assessed based on the Deep Neural Network model obtained in our study. Top-20 most important variables are presented in Figure 1. The most commonly mentioned most important variables were gravity accelerometer and body accelerometer features.

The top-30 features are presented in Table 4. Interestingly, top-15 features account for 40% of the overall explanatory power of the model. This information can potentially be useful for selecting a minimally acceptable set of sensors that need to be used when a full set of sensors is not feasible for some reason.

5. DISCUSSION ABOUT SERVICE ARCHITECTURE FOR DEMENTIA PATIENT

Mobile smartphones nowadays have very highly functional and reliable wearable sensors; these devices can be carried while people go about their daily lives. The choice of sensory device used to collect data was a smartphone (Samsung Galaxy S II) on the waist. Samsung Galaxy S II is a screen-touch enabled Android device with dual-core CPU and expandable memory with 10-12 hours average battery life. Such a mobile device is widely accessible and available in Saudi Arabia. This device was released in 2011; however, currently, more compact and powerful portable devices with greater battery life could be utilized, permitting the same results. Since the focus group for this study are dementia individuals and homecare, to ensure utilization of the device, it is suggested that the portable sensory device be strapped on the waist or wrist. The study models could be used to develop and deploy a cloud-based assistive care service for dementia individuals utilizing the advance information and communications technology infrastructure (ICT) in Saudi Arabia and the widespread on mobile phones.

Dementia is a disease with many progression stages; in some of its stage's individuals could wander around not knowing where they are; some even forgot how to walk or do basic routine activities. An assistive care service could help caregivers detect wandering patients in real-time using a mobile application installed on the patient strapped phone or a strap-on smart watch. The application automatically takes actions by notifying caregivers about the patient's current location using the GPS, Google Maps, and Navigation API that are built inside the android device to monitor the location of patients and alerts caregivers when a patient has fallen. Service Architecture can be developed in 4 main tiers, as shown in Figure 2.

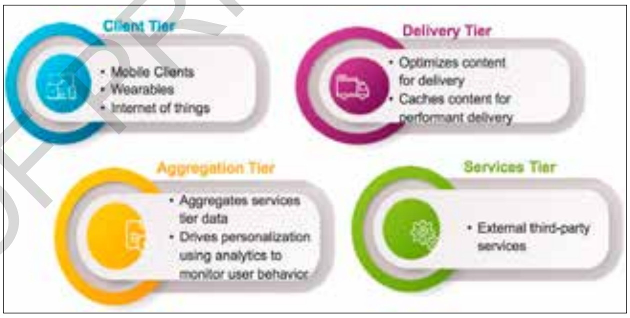

Figure 2. Proposed Service Architecture Tiers

5.1 Client Tier

This will consist of the android/IOS based mobile application used to monitor targeted patient groups and transmit data and alerts over the cloud to caretakers and health personal using this application, as shown in Figure 3. The application can work on the background, thus not being interrupted by other applications executed on the device. The application can utilize the build-in sensors (Gyro, Acc, Bar). Patient activity information will be collected and processed by the application and then sent to the aggregation tier for further analysis by the Machine Learning model.

Figure 3. Client Tier Components

Figure 4. 3G/4G Coverage by Service Providers in Saudi Arabia. [19]

5.2 Delivery Tier

The client tier will transfer all application data over the delivery tier using Transmission Control Protocol/ Internet Protocol (TCP/IP). This tier will utilize the 3G/4G infrastructure, which covers most urban areas in Saudi Arabia, as shown in Figure 4. The 4G Internet communications will provide real-time alerting and data gathering that will increase the efficiency and reliability of this service.

5.3 Aggregation Tier

This is the cloud tier where application and storage servers are hosted. Most data processing will take place in this tier. Integration with external service providers will take place in this tier. Any integration will utilize the application APIs. External service providers can integrate their system with cloud tier using APIs, allowing them to receive alerts regarding patients and monitor their wellbeing.

5.4 Service Tier

This Tier includes External Service providers such as "Health monitoring centers, Emergency Centers" such services can be established to monitor and receive alerts regarding the targeted patient group. These alerts can vary from "wondering patient outside the normal or set area, critical falls, stationary for a prolonged period of time, ...etc." The Health monitoring center will receive such alerts and can dispatch health personal nurses or specialists to assets and help patients in need. Health monitoring centers can also assist caretakers in locating wandering patients as well as shown in Figure 5.

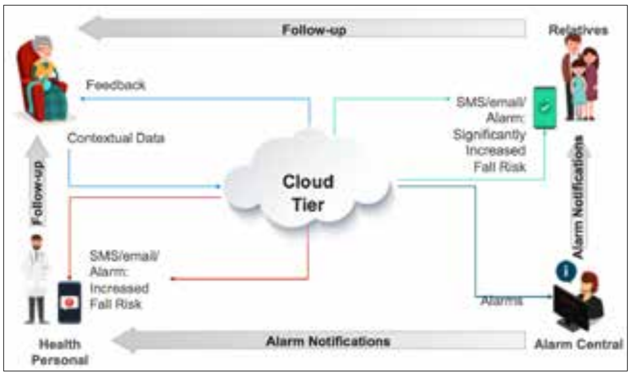

Figure 5: High-level design for the proposed service.

6. CONCLUSION

This paper used a public dataset for HAR generated by the use of smartphones and enabled the BigML platform to analyze dataset activities. Ridged Regression and Deep Neural Network algorithms have shown high accuracy; these techniques should be widely used by researchers in the field of activity recognition. "Sitting" was relatively often mistakenly predicted as "standing" by all algorithms. Therefore, feature-engineering efforts should be directed to find features that distinguish between these two activities better. Predictions for other activities were excellent, no matter which algorithm were used.

An application of smartphones can be utilized for human activities monitoring by proposing a high level for dementia patients and homecare monitoring services. Using this service, the patients only need to carry the smartphone, and their caregivers simply need to use the application that monitors their patients' activities. The activity recognition algorithms are highly accurate using ridged regression and deep neural networks, with almost all activities being recognized correctly over 98% of the time.

List of abbreviations

HAR -Human Activity Recognition.
ADL-Activities Of Daily Living.
UCI-The University Of California, Irvine.
CPU-Central Processing Unit.
ICT-Information And Communication Technology
GPS-Global Positioning System.
API-Application Programming Interface.
TCP/IP-Transmission Control Protocol/ Internet Protocol.

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