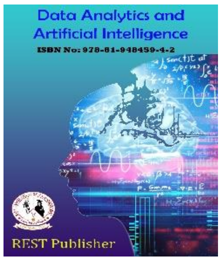
Data Analytics and Artificial Intelligence

Vol: 3(3), 2023

REST Publisher; ISBN: 978-81-948459-4-2

Website: http://restpublisher.com/book-series/daai/



Human Activity Detection

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Abstract: *Human activity detection has become a vital necessity in many countries because most elderly people live alone and are vulnerable. Thus, more research to advance the monitoring systems used to recognize the activities of elderly people is required. Many researchers have proposed different monitoring systems for activity recognition using wired and wireless wearable sensing devices. However, the activity classification accuracy achieved so far should be improved to meet the challenges of more precise activity monitoring. Our study proposes a smart Human Activity detection system architecture utilizing an open-source dataset generated by wireless, battery-less sensors used by 14 healthy aged persons and unsupervised and supervised machine learning algorithms. In this paper, we also propose using a smart grid for checking regularly the wearable sensing device's operational status to address the well-known reliability challenges of these devices, such as wireless charging and data trustworthiness. As the data from the sensing device is very noisy, we employ the K-means++ clustering to identify outliers and use advanced ensemble classification techniques, such as the stacking classifier for which a meta-model built using the random forest algorithm gave better results than all other base models considered. We also employ a bagging classifier, which is an ensemble meta-estimator fitting the prediction outputs of the base classifiers and aggregating them to produce the ensemble output. The best classification accuracy of 99.81 was achieved by the stacking classifier in training and 99.78% in testing, respectively. Comparisons for finding the best model were conducted using the recall, F1 score, and precision values.*
Keywords: *Human activity, Detections, Recognition, Open-cv, Dataset, HAD systems, Clusters algorithms.*

1. INTRODUCTION

Several countries in the world currently have a vast elderly population. This situation entails additional challenges in providing this demographic with quality healthcare services and facilities. Elderly people require more physical and psychological support and assistance. Most elderly people currently live on their own as their children work in different geographic locations. This leads to a lesser likelihood of children taking care of their parents. This makes the elderly parents very vulnerable to risks with no immediate assistance available. However, this problem can be mitigated with technological advancements in activity monitoring systems for elderly people. Data required by these systems are acquired by wearable sensing devices and then analyzed to understand and forecast the individual's health condition and required support. These monitoring systems are referred to as Human Activity Recognition (HAD) systems. HAD systems play important roles in several domains such as healthcare, security, and smart environment deployment. The operation of these systems involves five major steps, which are illustrated in figure 1.1 (human activity detection) for four basic activities such as sleeping, walking, standing, and sitting. However, to successfully implement these steps, appropriate devices and sensors are required to ensure the efficiency of the entire system. Hence, the development of such a system relies on wireless networks, machine learning (ML), data processing, and classification methods. A HAD system can detect and monitor the activities as well as the hazards that can affect elderly people. Since the devices connected to users can generate huge amounts of data while monitoring their activities, ML algorithms can help to discover the patterns in the activity logs and make necessary predictions of future trends to assist in adequately supporting elderly persons.

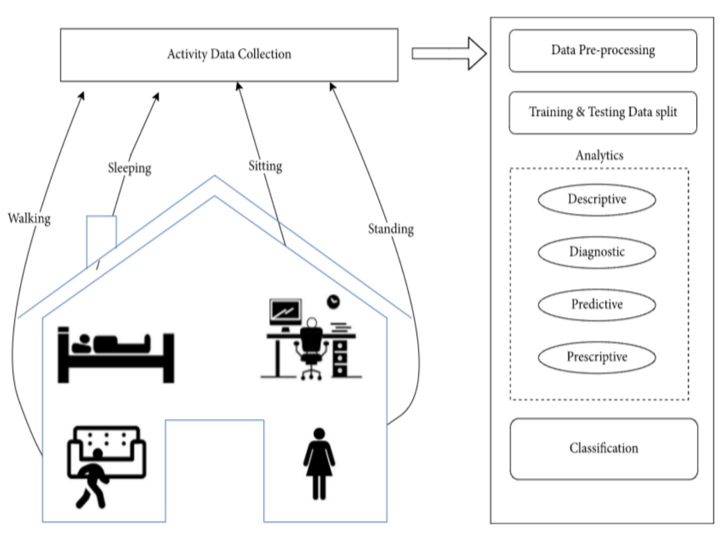

Figure 1.1 Human activity detections

2. OVERVIEW OF HUMAN ACTIVITY DETECTION

The HAD systems can be considered a type of Cyber-Physical System). A CPS is an integrated ensemble of hardware and software components that can run a given process effectively and safely. Nowadays in Smart Homes (SHs), CPSs effectively perform the following tasks:

(1) Monitoring human activities
(2) Learning inhabitant preferences or needs
(3) Providing the required assistance for activity determination, localization, and scheduling.

Thus, the HAD systems adopting machine or deep learning offer very efficient health and safety monitoring methods, especially for elderly people. In these systems, data are collected by sensors, wearable devices, and cameras, and transmitted using wireless networks, to be later analyzed to detect activity changes, behavioral patterns, social interactions, and sleep patterns. These types of systems can even help in assessing several health risk factors such as depression, loneliness, and fall risk, as well as unexpected changes in the behavior of healthy people. Many researchers have implemented various CPSs for these purposes. Mohsen et all proposed a TensorFlow-based model for classifying human activities. However, deep learning models require substantial computation power. Hence, other approaches using ML algorithms with good classification and prediction accuracy have been proposed. Examined the performance of several supervised learning algorithms for classifying the daily activities of dementia patients using data collected by smartwatch Another article, demonstrated the detection of Parkinson's disease from inertial sensor data using unsupervised standardized gait tests. Although developing more accurate monitoring models to recognize human activities and detect problems using HAD systems or CPSs is challenging, these challenges must be overcome to enhance the effectiveness of the HAD systems. The existing literature works indicate that HAD systems can be generally based on either sensors or computer vision. In the latter, the system gathers data in form of images or videos with cameras deployed in the monitored environment. proposed a Markov recognition model using maximum entropy utilizing depth camera data. However, their method may infringe on users' privacy as cameras capture their every motion in videos or images. Hence, the methods which use wearable sensors to gather data are efficient and are strongly preferred. Therefore, in this study, we used a dataset gathered using sensors worn by healthy elderly people.

3. EXISTING SYSTEM

HAR systems are typical representatives of pattern recognition systems. They work in two stages: (1) training and (2) recognition. Both stages consist of almost identical steps. The training stage involves gathering prior knowledge of the activities which must be recognized. The recognition stage uses the information collected in the training stage to accurately recognize those activities. In other words, the second stage strongly depends on the success of the first stage. The training stage includes steps such as data collection, feature selection, and learning from the selected features. Data can be collected from different types of sensors employed by the system. However, data are often noisy and must be preprocessed to clean them before further analyses. This preprocessing occurs during the feature selection process. The collected data can be classified into structural and statistical features in the feature selection process. Structural features are those which indicate correlations between data points. Statistical features result from applying statistical methods directly to the data or after they have been transformed, including the mean, variance, and others. The most widely used transformations are the Fourier and wavelet transforms. Following feature selection, the learning process is executed as the final step in the training phase of a HAD system. In this step, a recognition model is trained from the data gathered by sensors. Several algorithms can be used for creating a best-fit model for recognition. All these three steps are again performed in the recognition stage. After the recognition stage, the most accurate, fastest, and resource-efficient recognition model is chosen. We propose a smart HAD system with the most accurate recognition model for elderly people's activity monitoring and prompt assistance. To enhance the effectiveness and reliability of the HAD system in smart environments, we use an SG monitoring system in the proposed system.

4. PROPOSED SYSTEM

The detailed structure of the proposed smart HAD system is shown in Figure 5. The system performs the following five major processes:

(1) Data collection

(2) Setting up a smart environment

(3) Data management

(4) Computational modeling

(5) Activity recognition or alert notification.

5. SETTING UP A SMART ENVIRONMENT

In this process, a smart environment for data collection from the wearable sensing devices, monitoring, and issuing alerts to caretakers, is set up. Here, we deployed an SG monitoring system with appropriate sensors, such as PMUs, to monitor the device's operational status and the system data transmission status. An activity data log is collected using RFID reader antennas, whares used for recognizing physical activities. However, use the of appropriate sensors and wireless networks assists in accurately monitoring physical activities and recording a proper log of data in the cloud or on servers. But, the raw sensor data is likely very noisy; the data management process must also include data cleaning.

6. DATA COLLECTIONS

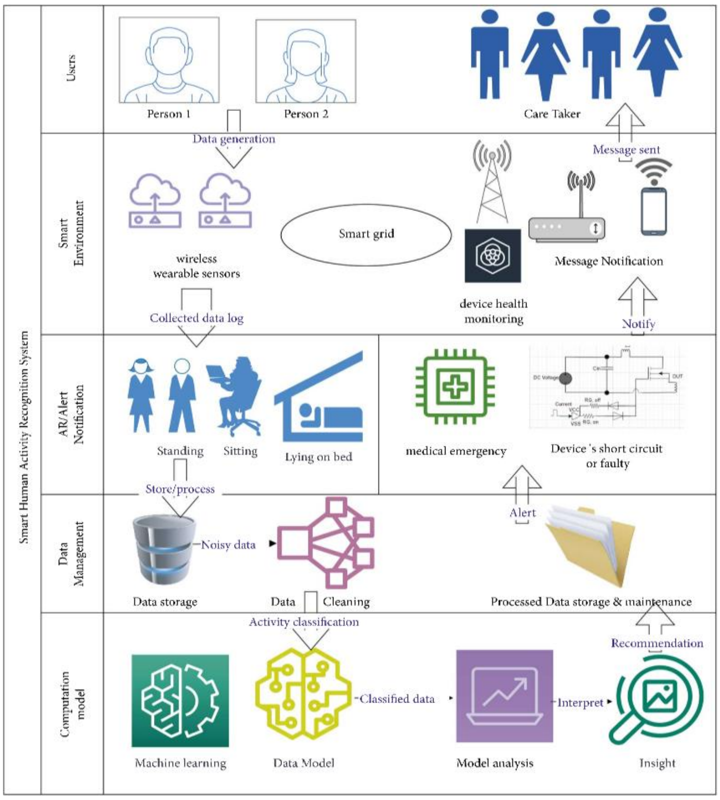

Figure 6.1 Data collections

This process is concerned with the generation of data from the users of the smart HAD system. The data is collected by wearable sensors. In our study, we used the data gathered from elderly people using wearable battery-less sensor devices because we aimed to propose this smart system for elderly people who need immediate assistance in emergencies. However, setting up a smarter environment ensures the efficiency of this process and the overall quality of this proposed system which is dependent entirely on the data collected.

7. DATA MANAGEMENT

There are three main tasks involved in the data management process. Firstly, the data which is collected has to be properly stored for future retrieval. Then, the collected data are likely to require transformation into a suitable format for creating a more accurate recognition model. Later, there is an increased likelihood of noise in the sensor-based data; therefore we have to perform data cleaning. In our study, we used data clustering for data cleaning as it is very efficient. In our experiment, we considered four activities typically performed by elderly people who live alone in their homes. We selected an appropriate dataset and applied the K-means++ clustering algorithm to group the data for these four activities. The clustering algorithm produced four clean clusters, which were fed as inputs into the activity classification model as a part of the HAR system training. Once the model is adequately trained using the ensemble classification method, it can be tested to recognize all the activity data that is generated from the sensors during the HAR system recognition stage. This process also takes care of the management of process data.

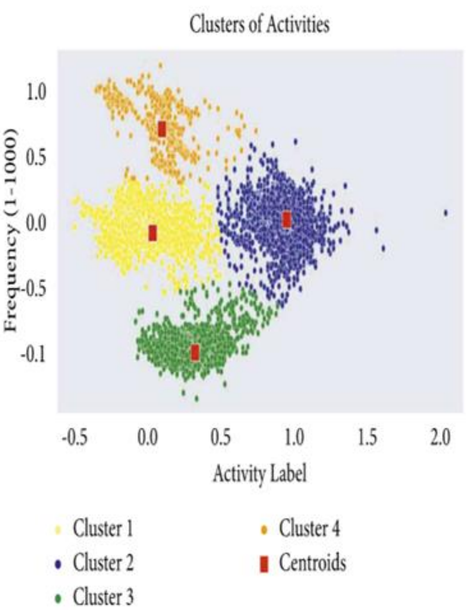

Figure 7.1 Data management

8. COMPUTATIONAL MODELING

In this process, the clustered output is fed to the ensemble classification model so that it can learn and formulate a hypothesis about the activities to be recognized during the training phase and ensure that those activities are accurately identified during the recognition phase. In our study, we used the stacking and bagging classifiers as the ensemble algorithms. We designed these models using four base models, including the logistic regression (LR), support vector machine (SVM), RF, and decision tree (DT) classifiers and modified the meta-classifier or evaluation classification model using the outputs of the base models. However, the obtained models must be compared and evaluated to find the best one. Hence, we compared the models using several statistical metrics. So, whenever there is abnormal activity identified by the model, the corresponding classification results are visualized. And, based on the classification result, the alert notification process is initiated.

9. RESULTS

Using the publicly available dataset taken from the UCI repository, we experimented using our proposed system with the hardware and software specifications listed in Table 2. We started the experiment with data cleaning using the K-means++ clustering algorithm for the four labeled activity classes (sitting on the bed, sitting in the chair, lying on the bed, and ambulating (walking and standing in the room)). An important feature of the K-means++ algorithm is the intelligent initialization of centroids that produce better clusters. The steps to find such centroids are as follows:

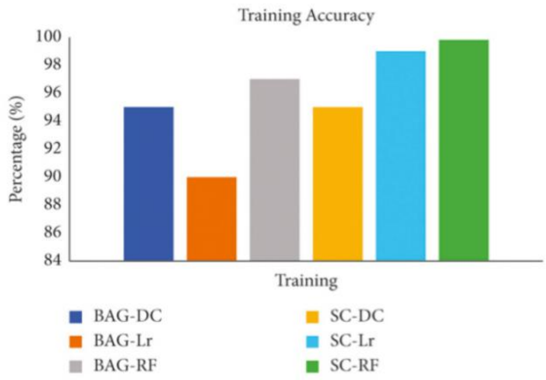

FIGURE 9. 12 Results

(1) Select a random centroid point from the given dataset

(2) For each instance "i" in the dataset, find the distance *x* from that instance "i" to the closest, earlier chosen centroid

(3) Select the subsequent centroid from the dataset with the termination goal that the probability of selecting a point as a centroid corresponds to the distance from the closest, recently selected centroid

(4) Repeat Steps 2 and 3 until we find the K centroid points.

10. CONCLUSION

proposed a smart HAD system to identify the physical activities performed by elderly people and an SG monitoring system to track the wearable sensing device operational status for ensuring the data quality and sensing device as well as the entire system reliability. A major challenge in the development of the HAD system was the creation of a more accurate activity recognition model. In this study, we used a combination of clustering and ensemble classification algorithms to increase the efficiency of the recognition model and provide accurate classification of predefined and abnormal activities, so that elderly people can be assisted promptly in emergencies.

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