Anomaly Detection for Human Home Activities Using Pattern Based Sequence Classification

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Abstract. In most countries, the old-age people population continues to rise. Because young adults are busy with their work engagements, they have to let the elderly stay at home alone. This is quite dangerous, as accidents at home may happen anytime without anyone knowing. Although sending elderly relatives to an elderly care center or hiring a caregiver are good solutions, they may not be feasible since it may be too expensive over a long-term period. The behavior patterns of elderly people during daily activities can give hints about their health condition. If an abnormal behavior pattern can be detected in advance, then precautions can be taken at an early stage. Previous studies have suggested machine learning techniques for such anomaly detection but most of the techniques are complicated. In this paper, a simple model for detecting anomaly patterns in human activity sequences using Random forest (RF) and K-nearest neighbor (KNN) classifiers is presented. The model was implemented on a public dataset and it showed that the RF classifier performed better, with an accuracy of 85%, compared to the KNN classifier, which achieved 73%.

Keywords: *anomaly detection; classification; elderly; home activities; sequence patterns.*

1 Introduction

According to the *World Population Ageing Report* [1], the number of oldest-old people (over age 80) will reach 434 million in the year 2050, compared to 125 million people in the year 2015. It is necessary to find a way to take care of these elderly people, especially those who have to stay at home alone. The common solution is to hire a caregiver, which may be quite expensive over a long-term period. Thus, a cheaper and still reliable solution is needed to assist the elderly in living alone and monitoring their health regularly. Since the collection of data is required for detecting anomalous home activities through a machine learning algorithm, several researchers have focused on identifying individual activities using surveillance videos or sensors. Bourobou and Yoo in [2] proposed activity recognition in a smart home using a clustering model together with a temporal artificial neural network (ANN) algorithm. The experimental results proved that

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this combined method outperformed the clustering method used alone. Zhu and Liu [3] developed a human behavior anomaly clustering model for anomaly detection by using images captured from surveillance videos.

The model utilized a training set from the clustering algorithm, a Topic Hidden Markov Model (THMM), a Hidden Markov Model (HMM), and Laten Dirichlet Allocation (LDA). The authors claimed that the experimental results proved the robustness and effectiveness of their proposed approach. Zhu, *et al.* [4] proposed a system to detect activity recognition online by using data collected from surveillance videos. They used unsupervised learning by combining HMM with LDA (HMM-LDA) clustering, and the Likelihood Ratio Test (LRT). This system was successful in detecting anomalies with a rate of 90.62%. Wu, *et al.* [5] also used video surveillance to detect abnormalities in indoor human behavior. Their method utilizes a Gaussian Mixture model to slice the background image in the video and implements block processing to extract space-time blocks from the images. Then Fuzzy C-means is used to detect outliers in the dataset. The experimental results showed that the proposed model could achieve a satisfying practical value. Antonakaki, *et al.* [6] introduced a model to understand human behavior. The authors utilized a multi-camera framework and an HMM in the project. The proposed model is built by using a training dataset containing normal data only, while detection of the abnormal behavior is based on two distinct rules, i.e., short-term behavior and the trajectory of the individual.

Several research groups have used sensors to recognize human activities. Zohra, *et al.* [7] proposed a model using IoT and sensors with the aid of machine learning techniques to observe the health of patients who suffer from dementia. The model clustered and detected urinary tract infections (UTI) by using non-negative matrix factorization. The Isolation Forest technique was used to detect or identify changes in the pattern of activities. The proposed method was compared with Support Vector Machine (SVM) and the results showed that the accuracy of the proposed model exceeded the performance of SVM. Huang, *et al.* [8] proposed a design with triboelectric motion sensors for detecting human activities. The data are collected based on a sequence of five activities. These activities include climbing the stairs, walking, sitting, standing and running. The KNN algorithm is used to identify these activities. Experimental results showed that the proposed model achieved an accuracy of 80% for all aforementioned activities, except climbing the stairs. Chen, *et al.* [9] developed a model that uses an accelerometer to detect activities. In their model, eight activities are collected from 31,688 samples and the Convolutional Neural Network (CNN) algorithm is used to classify them. Experimental results showed that the model achieved an accuracy of 93.8%. Yin, *et al.* [10] collected data using sensors and used a cascaded model for detecting anomalies. Their model proved to be able to decrease the false positive rate. Kwon, *et al.* [11] introduced a model that utilizes an ANN algorithm along with smartwatch technology to classify human activities. The authors analyzed eleven types of activities as part of day-to-day behavior. The model achieved an accuracy of 95%. Damla, *et al.* [12] proposed an anomaly detection method that utilizes the Recurrent Neural Network (RNN) algorithm to observe and detect anomalies in human activity sequences of patients with dementia symptoms. The model maintained true positive cases at a rate of 91.43% and false-positive cases at a rate of 40.96%. Hsu and Chen [13] developed a smart system that recognizes anomalies in the human behavior of elderly people at home. The model uses Radio Frequency Identification (RFID) to collect data from an RFID reader carried by the individuals. The model is aided by a clustering algorithm to detect anomalies in human behavior. The authors stated that the results obtained were promising.

There are two important types of home activity anomalies, i.e., time interval-based anomalies and sequence pattern-based anomalies. A time interval-based anomaly is a change in the usual routine of human activities, whereas a sequence anomaly is an abnormality in a sequence of activities of an individual. A group of researchers, Poh, *et al.* [14-16], have proposed different models for detecting time interval-based anomalies and sequence pattern-based anomalies. The data instances used in their models are a mixture of normal data obtained from CASAS [17], while the abnormal data were artificially injected into the sequence of daily activities. In [14], Poh *et al.* proposed a time interval-based human activity anomaly detection model. The anomaly detector was built to find activities that occur within a time interval that are not recorded in a database. If the number of these activities exceeds a threshold value then an abnormal behavior is decided. The model achieved an accuracy of 94.44%. In [15], Poh, *et al.* proposed a sequence pattern-based anomaly detection method using a threshold to identify anomalies. The model showed an accuracy of 90.79%. In [16], Poh, *et al.* proposed a system that recognizes abnormal activities by using the Long Short-Term Memory (LSTM) method to detect anomalies in sequence patterns. The authors compared the performance of the LSTM method with an HMM. Their results showed that LSTM had a comparable performance when compared to the HMM in terms of accuracy. Other techniques have been proposed by other groups of researchers in detecting time interval-based anomalies and sequence pattern-based anomalies. Forkan, *et al.* [18] proposed a model to detect anomalies in a sequence of human activities using a HMM with an average accuracy of 90%. Tahayori, *et al.* [19] proposed a model for predicting and detecting the behavior of human activities using the Adaboost algorithm. The authors used a dataset available from the e-Health Monitoring Open Data Project. Their model achieved an accuracy of 94.48%.

Hoque, *et al.* [20] presented a comprehensive system for detecting anomalous behavior in in-home activities. They used semantic rules to define and explain any activities deviating from regular behavior. They successfully reduced false positives and false negatives by at least 46% and 27%, respectively. Carus, *et al.* [21] proposed an anomaly detection model based on an unsupervised learning technique. The model operates by detecting any decrease or increase in an individual physical activity. The model works on a time-anomaly basis by using the observed activity period as a reference. Thus, the algorithm can accurately detect anomalies at another time. The results showed precision above 75% and a recall score of 92%.

The models for anomaly detection in human activities proposed in previous works are rather complex and require a long training period and high computational power. Moreover, there are many different parameters that have to be tuned. They can still be deployed in real life applications, but this will take a longer time in comparison with simpler machine learning algorithms. In the present paper, a simple machine learning model is proposed to detect anomalous activities of an individual at home, which is faster to train and does not require high computational power. Whenever an anomalous activity is detected, a warning can be triggered to inform the next of kin as soon as possible. The rest of this paper is organized as follows. In Section 2, the methodology will be discussed. Section 3 gives the results and their discussion, and Section 4 provides the conclusions and future work.

2 Research Method

Figure 1 shows the model framework, depicting the process of constructing the designed model to detect anomalous activities. The following subsections describe each of the steps in the process, i.e., data collection, data preparation, training/testing data, building the model, and model evaluation.

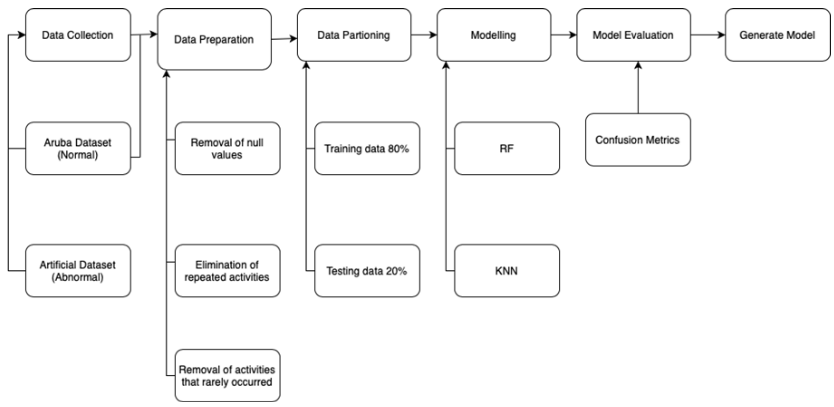

Figure 1 Framework of the model.

2.1 Data Collection

A dataset available for the public from CASAS, Washington State University [17] was used in this project. The dataset is called the Aruba dataset, and it belongs to a volunteer who kept records for 220 days. The dataset consists of date, time, activity types, state of activity type, and sensor data. The state of activity types has the labels ‘begin’ and ‘end’. An example of sensor data is that from a motion sensor with ON/OFF indicator. In total, the dataset comprises eleven types of activities, i.e., sleeping, eating, toileting, meal preparation, respirating, leaving home, entering home, working, relaxing, housekeeping, and washing dishes.

In this research, the data from the Aruba dataset were processed and labeled as ‘normal’, while the abnormal dataset was artificially generated by injecting multiple toileting and eating instances to the data. The reason behind choosing multiple toileting and feeding instances is because excessive food intake and toilet use are abnormal activities indicative of 3P diabetes symptoms, including polyuria (frequent urination) and polyphagia (increased appetite) [22].

2.2 Data Preparation

This step is essential to transforming the raw data into the appropriate format to be utilized by the classifier model. Data preparation comprises of two stages: (1) data cleaning, which involves the removal of noise, and (2) data processing.

2.2.1 Data Cleaning

Data cleaning process consists of removal of unwanted attributes such as sensor mode and type. These will be removed from the dataset. Other data that need to be eliminated are:

1. null values in the dataset;
2. identical activities that are recorded multiple times within a close interval;
3. the activity ‘Respirating’, which occurred only six times in the whole 220 days.

Table 1 shows part of the dataset after cleaning.

Table 1 Output of data after cleaning.

Date	Time	Activity	Switch
2010-11-04	00:03	Sleeping	begin
2010-11-04	05:40	Sleeping	end
2010-11-04	05:41	Bed_to_Toilet	begin
2010-11-04	05:44	Bed_to_Toilet	end
2010-11-04	05:45	Sleeping	begin

2.2.2 Data Processing

Firstly, the activities are segmented to a shorter sequence, where each activity is symbolized by a single character, that is, Relax (R), Work (W), Sleeping (S), Meal_Preparation (M), Leave_Home (L), Enter_Home (H), Wash_Dishes (D), Housekeeping (K), Bed_to_Toilet (B) and Eating (E). Secondly, the dataset (normal and abnormal) is divided into two sections based on a specific time frame (00:00-17:59), which are categorized as day-time (indicated as '0') and (18:00-23:59) for night-time (indicated as '1') in the model. Thirdly, the sequence of activities or data instances is grouped collectively for each day with the day-time or night-time indicator. Examples of grouped sequence activities are shown in Table 2.

Table 2 Examples of grouped sequence activities.

Day/Night Indicator	Activity Sequence	Label
1	RW	Normal
0	BSMRMRMRELHLHMEDRK	Normal
1	RMERS	Normal
1	BSBSWBLSBESEBM	Abnormal
0	BEBEREB	Abnormal
1	SESBSBDKBSE	Abnormal

After data cleaning and data processing are done, the whole dataset consisted of normal and abnormal data. Table 3 shows the distribution of the data, where 66 were normal and day-time data, 70 were abnormal and day-time data, 60 were normal and night-time data, and 70 were abnormal and night-time data.

Table 3 Distribution of normal/abnormal data.

	Normal	Abnormal
Day-time	66	70
Night-time	60	70

2.3 Train and Test Data

From the dataset, a random sample of 80% was used as training data and the remaining 20% were used as test data. In default random sampling, every observation in the main dataset has an equal probability to be selected. In other words, 80% was first selected as the training group, then 80% of the total data instances were randomly chosen for training. Hence, the remaining 20% of the dataset had a chance of being chosen as testing data.

2.4 Build the Model

In this research, supervised machine learning techniques were used to accomplish the main objective of building the best model to detect anomalies in human activities. The machine learning techniques chosen were RF and KNN.

The RF classifier is a type of ensemble algorithm for classification. It operates by building a profusion of decision estimator trees during the training phase and computing the average. The RF classifier will combine the estimator predictions to produce accurate results [23].

The KNN algorithm is also a classification technique. It works by calculating the distance between a query and all the examples in the dataset. This is followed by choosing a suitable number for K and then looking for the most repeated or frequent label. The number of K is chosen by trying different numbers for K and choosing the optimum result [24]. In this project, K was chosen to be 8.

Four models (as shown in Table 4) were built in this research. The first model uses a RF classifier with only one input variable, which is the sequence of activities. The second model uses a RF classifier with only two input variables, i.e., the sequence of activities and day-time/night-time. The third model uses KNN classifier with only one input variable, i.e., the sequence of activities. The last model uses a KNN classifier with two input variables, i.e., the sequence of activities and day-time/night-time.

Table 4 The proposed four models.

Input variables	RF	KNN
Sequence of activities	Model 1	Model 3
Sequence of activities and day-time/night-time	Model 2	Model 4

2.5 Model Evaluation

Confusion Matrix is an evaluation technique that can be used to evaluate the performance of classification models [25]. A confusion matrix has the format of an N x N matrix, where N is the number of target classes. The matrix will compare the target value (actual) with the values predicted by the classifier model. Since this project solves a binary classification problem, the confusion matrix is a 2 x 2 matrix as shown in Figure 2. True positive (TP), true negative (TN), false positive (FP) and false negative (FN) are defined as follows:

1. TP represents a positive value predicted by the model that matches the positive actual value;
2. TN represents a negative value predicted by the model that matches the negative actual value;

3. FP represents a positive value predicted by the model that falsely matches the actual negative value;
4. FN represents a negative value predicted by the model that falsely matches the actual value.

From the features of the confusion matrix, the accuracy, precision, recall, and F1 score can be derived. The formulas used are shown in Eqs. (1) to (4) below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ Score = \frac{2(Precision \times Recall)}{Precision + Recall} \tag{4}$$

	Actually Positive	Actually Negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

Figure 2 Confusion matrix.

3 Results and Discussion

Table 5 presents the accuracy for the four models. It shows that the models with two input variables performed better compared to those only using one input variable. A further investigation on the performance of all the models was carried out; the results are stated in Table 6.

Table 5 Accuracy of the models.

Input variables	RF	KNN
Sequence of activities	77%	62.9%
Sequence of activities and day-time/night-time	85%	73%

Table 6 Performance evaluation of models.

Model	Precision	Recall	F1
1	80%	67%	73%
2	90%	87%	88%
3	67%	33%	44%
4	81%	73%	77%

Table 6 shows that Model 1 scored 80% for precision, 67% for recall, and 73% for F1 score. On the other hand, Model 3 only obtained a precision score of 67%, 33% for recall, and 44% for F1 score. This indicates that among the one-variable models, RF performed better than KNN. Of the two-variable models, the RF algorithm (Model 2) performed better than the KNN algorithm (Model 4). Overall, the RF classifier performed better compared to the KNN classifier.

The proposed models were compared with other models that utilize HMM and LSTM algorithms [16] to detect an abnormal sequence of activities using the same dataset that was used in this paper. Table 7 shows the comparison between the proposed models with the models proposed in [16]. The comparison shows that the proposed Model 2 outperformed HMM and LSTM in terms of precision, F1 score, and accuracy.

Table 7 Comparison of the proposed models with other techniques.

Model	Precision	Recall	F1	Accuracy
HMM [16]	66.67%	60%	63.16%	65.%
LSTM [[16]	75%	90%	81.81%	80%
Proposed Model 1	80%	67%	73%	77%
Proposed Model 2	90%	87%	88%	85%
Proposed Model 3	67%	33%	44%	62.9%
Proposed Model 4	81%	73%	77%	73%

4 Conclusion

This paper proposed an anomaly detection model to detect anomalies in the sequence of human activities throughout the day, considering day-time and night-time. The model was trained and tested on normal and abnormal data. The normal dataset Aruba was collected from the CASAS website. The abnormal dataset was artificially generated by injecting multiple toileting and eating instances to reflect the 3P symptoms of diabetes. The techniques used in this paper were RF and KNN classifiers with either one input variable or two input variables. Based on overall performance, the model with the RF classifier and two input variables gave the best results. This indicates that splitting the data into day/night time is essential to adequately train the model and obtain optimal performance.

A future enhancement can be done by using a larger dataset, for example, covering a two-year period. This would allow the model to train on a greater number of combinations of sequences, which is expected lead to better results. Another enhancement is taking into consideration the use of a deep learning method integrated into a large dataset to achieve better results.

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