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Activity recognition and anomaly detection in smart homes

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ABSTRACT

Physical and cognitive impairments decline the ability of elderly in execution of daily activities, such as eating, sleeping or taking medication. The proposed approach recognizes the activities performed in a smart home, and separates the normal from the anomalous activities. Moreover, we identify the anomalous days based on the number of activities performed in a day. We perform activity recognition by applying probabilistic neural network on the pre-segmented activity-data obtained from the sensors deployed at different locations in a smart home. We use H2O autoencoder to identify the anomalous from the normal instances of activities. We further categorize the anomalies based on the criteria such as missing or extra subevents, and unusual duration of activity. Since the ground truth of the anomalies is unavailable, we generate the ground truth using the boxplots of the duration, and the number of subevents in an activity. We provide the quantified results of activity recognition and anomaly detection that can be further used by the research community. A comprehensive evaluation of the proposed approach on two publicly available CASAS smart home datasets demonstrates its ability in the activity recognition and the correct identification of anomalies.

1. Introduction

Smart homes can be used to unobtrusively recognize the human activities, such as meal preparation, eating, sleeping and using toilet [1,2]. Besides activity recognition, another aspect is the anomaly detection. Anomalies are the incorrect execution of activities, which can be identified by detecting irregular durations, and deviated patterns of activities [3]. The recognition of the performed activities and related anomalies can provide important information to health providers about their patient's medical condition, which can be useful in timely prevention of many health-related risks. People suffering from Dementia [4], such as Alzheimer disease, tend to forget the sub-tasks within an activity or can take unusual duration to perform an activity. Let us take an example of 'preparing meal' activity. A Dementia patient may forget an event, such as switching on/off the stove, required to complete an activity, which can result in an anomaly. Another important application of anomaly detection would be in remote health monitoring. Let us consider the recent scenario of Covid-19. A Covid-19 patient requires isolation so that the spread of disease could be minimized [5], though patient needs to be under keen observation of the health providers. Automated remote health monitoring can effectively treat patients, with mild to moderate level severity, without hospitalization, which can reduce the burden on the hospitals and quarantine centers.

Multiple non-intrusive ambient sensors are deployed at multiple locations and objects in a smart home [6]. The obtained sensor data is partitioned into multiple segments, where each segment is a sequence of consecutive time intervals during which an activity is performed [7]. Existing activity classification approaches use the segmented information for activity recognition by exploiting different learning techniques, such as Hidden Markov Model (HMM) [8], Conditional Random Fields (CRF) [9], Support Vector Machine (SVM) [10], Neural Networks [11,12] and Decision Tree (DT) [13]. In [14], activities are recognized by converting a multiclass into a binary class problem, and a confidence score is attached with every assignment to improve the recognition accuracy. A large variation exists in the number of instances per activity class resulting in a class imbalance problem. In addition, only a few sensors remain active in an activity, resulting in a sparse representation of data. However, these existing classifiers ignore the class imbalance and the data sparsity aspects, which are considered in the proposed approach.

Identification of anomalies in general activities of daily living is an important step to predict the cognitive health decline. However, most of the existing anomaly detection techniques emphasize on

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physical activities of sitting, standing, walking or fall detection [15]. In [16], activity recognition is considered solved while anomalies in general activities are identified using density-based clustering on the two features i.e. irregular features and unusual duration. Four clusters are formed per activity class, where three are anomalous; however, quantitative results are not provided. Anomaly detection becomes more challenging in the case of general activities because of the intra-class variations, since these variations can be the representative of the individuals' preferences and not the anomalies [17,18]. Anomaly detection techniques that exist for the general activities rely only on the average performance of the overall system, while the performance in the case of individual activities is ignored in most of the cases [19–21]. The proposed approach on the other hand presents a detailed analysis of anomaly detection for each activity class separately.

We propose an activity recognition and anomaly detection approach that assigns the labels to the activity instances and identifies the anomalies. First, we extract features from the pre-segmented activity instances. We apply Probabilistic Neural Network (PNN) on the extracted features, since PNN performs well on sparse and noisy sensor data. In the next step, we identify the anomalies within each activity class. We define an activity instance to be anomalous if it has unusual duration of execution or involves irregular number of subevents. Since the ground truth for such anomalies are not available, we determine the ground truth from the boxplots of number of subevents in an activity, and the time duration of an activity. We then apply the H2O autoencoder for the anomaly detection. Finally, we identify the anomalous days based on the number of activities performed in a day. In [6], daily routine of a smart home resident is monitored by applying K-mean clustering to the frequency of activities per day. K = 3 is applied to categorize the activities as normal, suspicious and anomalous. In contrast the proposed approach exploits both the mean as well as the median of the number of activities per day to monitor the daily routine of a smart home resident. The curve fitting on the histogram, of the number of activities per day, identifies the variations from the mean, while the boxplot provides us the variations from the median in the same data. The proposed approach presents a detailed analysis of anomaly detection for each activity class separately. A comprehensive evaluation of the proposed approach using two publicly available smart-homes datasets from CASAS project [22] shows the improved performance of the proposed approach in correct recognition of activities and identification of anomalies within each activity class. .

The rest of the paper is organized as follows: Section 2 describes the state-of-the-art activity recognition and anomaly detection approaches. Section 3 presents the proposed methodology to recognize the anomalous activity instance and their further categorization. Section 4 shows the extensive experimental evaluation on two publicly available smart home CASAS datasets and shows its effectiveness in correct identification of anomalies. Section 5 concludes the proposed approach.

2. Related work

The activities can be categorized into physical and general activities. Physical activities, such as walking, jogging and running, can be recognized through the accelerometer and gyroscope wearable or mobile sensors [23]. In contrast to physical activities, complex general activities, such as eating, drinking and taking medication, are recognized through ambient switch state sensors [24,6,14,10,25]. The data collected through multiple sensors is used to unobtrusively monitor these general activities to learn the behavior of a smart-home resident [24]. Identification of changes in the daily routine of the resident can be helpful in an early detection of health decline. Through a combination of sensors, such as accelerometer, altimeter and temperature, accuracy of an activity recognition system can be improved [26]. Motion sensors and locational context information is used to find spatial, time duration and sequential anomalies in the behavior of a smart-home resident [27]. The frequency of appliances usage along with activity duration is also exploited to monitor the behavior of a smart-home resident [19]. Fahad et al. [6] recognize the pre-segmented activities of daily living using Probabilistic Neural Network (PNN) and then analyze the daily routine using K-means clustering. Fleury et al. in [28,10] used multi-class one-vs-one Support Vector Machine (SVM) along with temporal information to recognize the daily activities such as sleeping or eating.

In addition to activity recognition approaches [17,29], advances in intelligent context aware systems and widespread availability of sensors have resulted in solving a number of different types of applications such as sensor data fusion [30], reduction of electrical pollution [31], text classification [32,33], cancer detection [34], facial age estimation [35], effect of climate on COVID-19 [36], forecasting economical growth [37] and feature selection in constrained environments [38]. Next, we discuss the existing anomaly detection approach that focus on identification of deviated patterns from the normal activities.

In [16], DBSCAN clustering algorithm is used to detect anomaly. Fatima et al. [39] make use of kernel fusion method for accurate and precise activity recognition and then identify the behaviors of smart-home occupants from the recognized activities. Dynamic Bayesian Network is used for detection of anomalies, while parameters are optimized through maximum-likelihood estimation algorithm and laplace smoothing. Hidden Markov Model (HMM) can be used to model the repeatable patterns in the data [40], while anomalies are identified by fitting a distribution model. Normal and anomalous patterns in the activities of a smart-home resident can be identified using Support Vector Data Descriptors (SVDD) [3]. In [41], normal activities are identified using One Class Support Vector Machine (OCSVM), while anomalies in the activities are separated by Kernel Non-linear regression models. Also in [20], anomalous activity patterns are separated using OCSVM.

A windowing technique is introduced in [42,43] to quantify the changes in the activity patterns of a smart-home resident. An elderly monitoring system is developed using the semantic web rules and context information [44], where the deviations in the activities of a smart-home resident are identified by learning the normal routine. A hybrid anomaly detection approach combines the probabilistic and knowledge based reasoning model to achieve adaptability and better generalization [45,46]. In [47], an adaptive and personalized anomaly detection approach is developed by learning the temporal, spatial and sequential activity patterns. Statistical techniques such as Modified Thompson tau test can be used for identification of deviated trends in the activities of a smart-home resident [48]. An activity prompting approach is presented in [49], where automated prompts are generated for the smart-home resident to complete an activity successfully, and in the case of an activity error identified by one class classification. Association rule mining can also be applied for detection of anomalies in the daily activities [50].

Existing approaches focus on separating the anomalies from the entire dataset through learning the regular activity patterns, whereas contribution of the proposed approach lies in detection of anomalies at fine grained level within each activity class. Three levels of anomalies are identified: activity instances with irregular features, unusual duration of an activity, irregular frequencies of activities executed in a day. We further quantify the obtained results.

3. Proposed approach

Let A be a set of K activity classes $\{A_k\}_{k=1}^{K}$ and $\{I_{jk}\}_{j=1}^{J}$ be the set of J activity instances of A_k. Each I_{jk} is observed through ambient sensors deployed in the smart-home. The proposed approach consists of three major steps: feature extraction, activity recognition and anomaly detection (Fig. 1).

3.1. Feature set

Given a set of pre-segmented activities, first, we perform feature extraction. A feature set F_{jk} of R features is extracted from I_{jk} such that:

$$F_{jk} = \{f_{jk}^{r}\}_{r=1}^{R}. \tag{1}$$

F_{jk} represents the *duration* – the total time spent to complete an activity; the *sensor count* – the number of times each sensor remains active during an activity; and the *activities per day* – the number of times each activity is performed in a day. Next, we select the discriminative features of each activity class. In order to identify the discriminative features of each activity class, we compare multiple feature selection methods including Principle Component Analysis (PCA), Information Gain (IG) and H2O autoencoder, where the H2O autoencoder shows the best performance.

3.2. Activity recognition

We use the learning algorithm PNN for activity recognition, which performs better in the case of sparse data [51,52]. The training of PNN is performed on the training set containing selected features of activity instances of each activity class (Fig. 2). PNN has four layers namely: input layer, pattern layer, summation layer and decision layer. The *input* layer spreads the feature set F_{jk} of the training sample among the pattern layer neurons $x_{j'k'}$. The neurons in the *pattern* layer are equal to the training samples, while each neuron belongs to a class A_k. The feature vector F_{jk} is given as input to each pattern neuron to compute the output $\phi_{j'k'}(F_{jk})$ given as

$$\phi_{j'k'}(F_{jk}|A_k) = \frac{1}{(2\pi)^{R/2}\sigma^R} exp\left[-\frac{(F_{jk}-x_{j'k'})^T(F_{jk}-x_{j'k'})}{2\sigma^2}\right], \tag{2}$$

where $x_{j'k'}$ is the neuron vector, R is the dimension of the pattern vectors F_{jk}, and σ is the smoothing parameter. The *summation* layer summarizes and averages the output of the neurons of pattern layer belonging to the same class to compute the maximum likelihood of the pattern to be classified.

$$p_k(F_{jk}|A_k) = \frac{1}{(2\pi)^{R/2}\sigma^R}\frac{1}{J}\sum_{j=1}^{J} exp\left[-\frac{(F_{jk}-x_{j'k'})^T(F_{jk}-x_{j'k'})}{2\sigma^2}\right], \tag{3}$$

where J is the total number of activity instances in A_k. In *decision* layer, F_{jk} is assigned to the activity class using the Bayesian decision rule, assuming an equal a priori probability of each activity class A_k and an equal losses associated with every incorrect decision for each activity class A_k, given as

$$C^{F_{jk}} = \arg\max_k\{p_k(F_{jk})\}, \quad k = 1, 2, \cdots, K, \tag{4}$$

where $C^{F_{jk}}$ is the estimated class of F_{jk} and K is the total number of activity classes in the training samples. PNN is considered as a

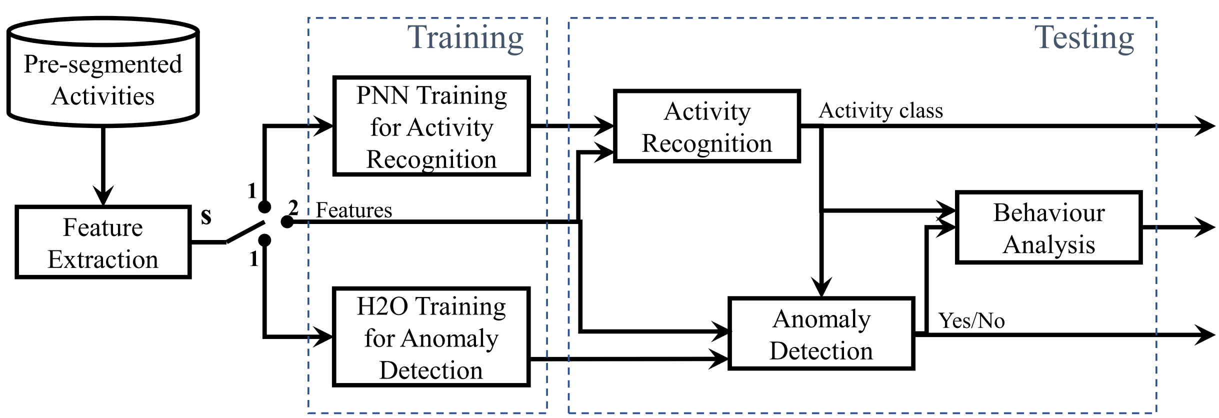


Fig. 1. Block diagram of the proposed approach. Switch $s = 1$ is training and $s = 2$ is testing.

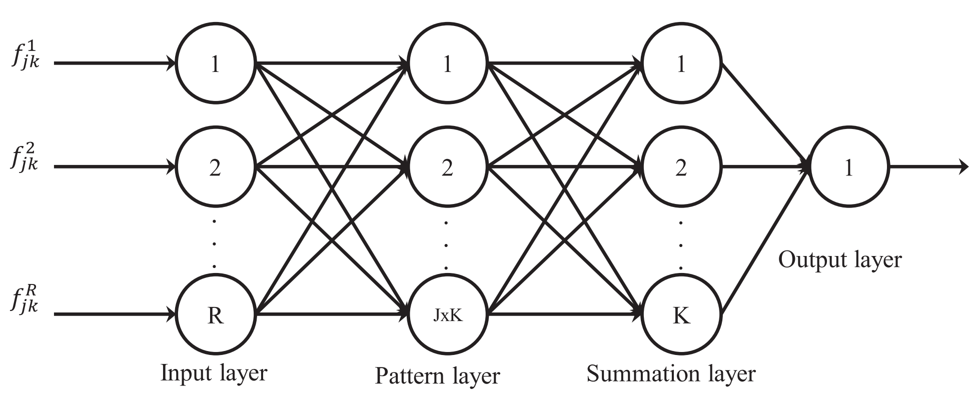


Fig. 2. Architecture of Probabilistic Neural Network [51] used in the proposed approach, wheref_{jk}^{r} is the r^{th} feature of the j^{th} instance of the k^{th} activity class and R is the total number of features. Total number activity classes are K, and the total number of instances per activ.ity are J.

Table 1
The description of the two smart-home datasets used in the evaluation of the proposed approach.

S.no	Datasets	Description	Participants	Activities	Instances	Activities (Instances)
1	Aruba	Daily life activities Apr. 11, 2010 - Jun. 11, 2011	1	11	6467	Bed to Toilet (157), Eating (257), Enter Home (431), House Keeping (33), Leave Home (431), Resperate (5), Meal Preparation (1606), Relax (2910), Sleeping (401), Wash Dishes (65), and Work (171).
2	Milan	Daily life activities Oct. 16, 2009 - Jan. 6, 2010	1 + pet	15	2310	Bed to Toilet (122), Chores (89), Desk Activity (21), Dining Room Activity (54), Evening Medication (22), Guest Bathroom (19), Kitchen Activity (330), Read (96), Leave Home (554), Master Bathroom (213), Sleep (314), Master Bedroom Activity (304), Meditate (17), Morning Medication, (114), and Watch TV (41).

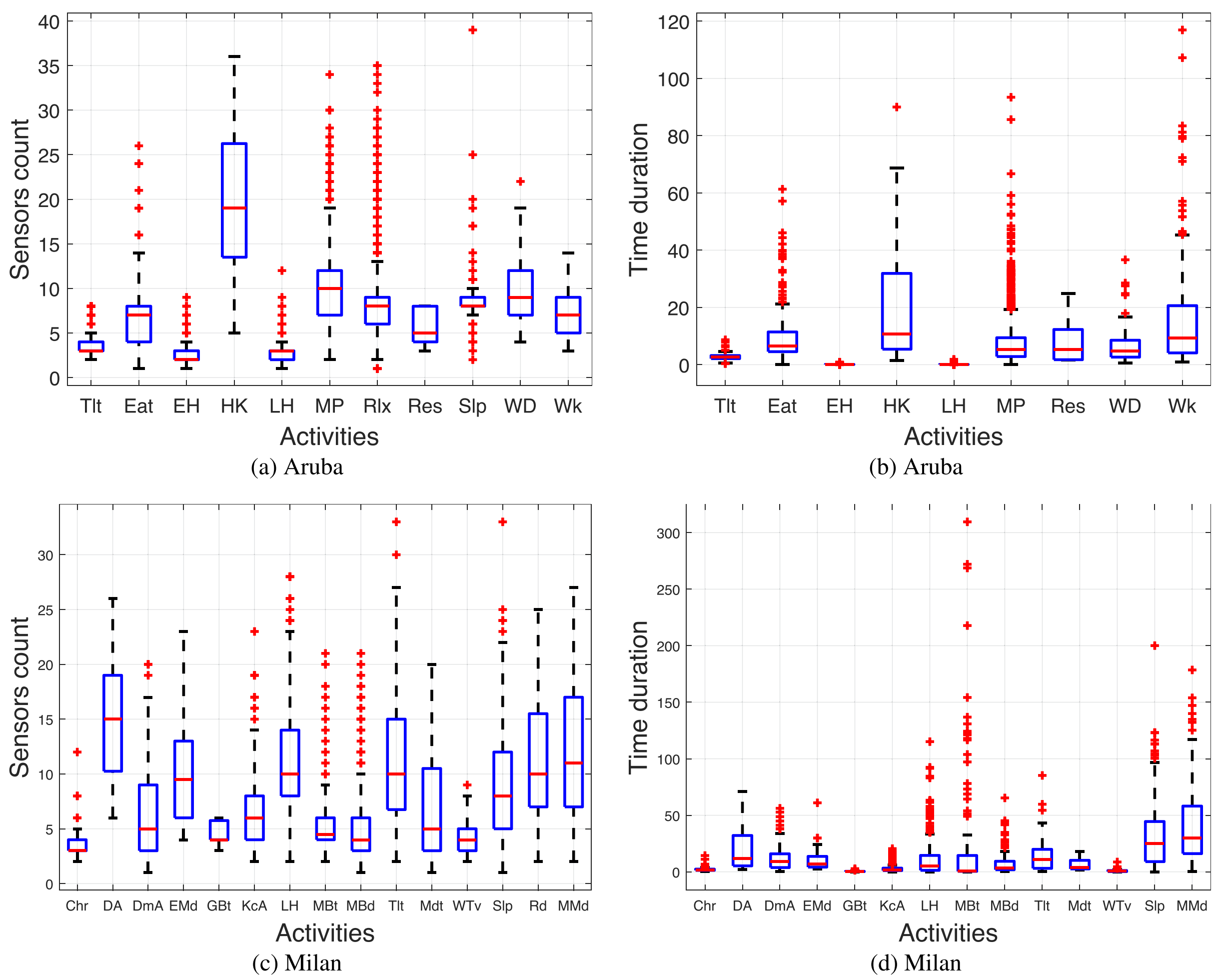


Fig. 3. Boxplots representing (a, c) number of events and (b, d) time durations, per activity class in Aruba and Milan smart-home datasets [22]. Key: (Aruba) – > MP - Meal Preparation, Rlx – Relax, Eat – Eating, Wk - Work, Slp - Sleeping, WD - Wash Dishes, Tlt - Bed to Toilet, EH - Enter Home, LH - Leave Home, HK - House Keeping, Res - Resperate; (Milan) – > Chr - Chores, DA - Desk Activity, DmA - Dining Room Activity, EMd - Evening Medicine, GBt - Guest Bathroom, KcA - Kitchen Activity, LH - Leave Home, MBt - Master Bathroom, MBd - Master Bedroom Activity, Mdt - Meditate, MMd - Morning Medication, Rd - Reading activity, Slp - Sleep, WTv - Watch TV, Tlt – Bed to Toilet.

memory-based classification approach. Based on the number of neurons and the layers of PNN the time complexity is calculated as $O(R.M.K) => O(R.J.K^2)$, where R is the number of neurons in the input layer equal to the size of the feature set; $M = J.K$ is the number of neurons in the pattern layer equal to the total number of datapoints; and K is the number of neurons in the summation layer equal to the number of activity classes. The trained PNN can be used for the recognition of the new activity instances.

3.3. Anomaly detection

The recognized activities are analyzed to identify the anomalies, where an anomaly refers to the rare and unexpected deviations from standard patterns. In the case of smart homes, anomalous instances are deviated from the normal trend in terms of irregular number of events and unusual duration. We apply the learning algorithm H2O autoencoder for the identification of anomalies. H2O is a fast and scalable predictive analytic method.

H2O follows the multi-layer, feedforward neural network architecture. For a Network of N layers, the objective is to minimize a loss function $L(W, B|j)$, where j is the training sample, $W = \{W_i\}_{i=1}^{N-1}, W_i$ is the weight matrix connecting layers i and $i+1$ for a Network of N layers, and $B = \{B_i\}_{i=1}^{N-1}, B_i$ is a vector of biases for layer $i+1$. A typical loss function based on the mean square error is defined as

$$L(W, B|j) = \frac{1}{2}||t^{(j)} - o^{(j)}||_2, \tag{5}$$

where $t^{(j)}$ is the actual target and $o^{(j)}$ is the predicted output of the network. The output α of each neuron at the i^{th} layer is the weighted combination of input values x_i, weights w_i and the bias b given as

$$\alpha = \sum_i w_i x_i + b. \tag{6}$$

The activation function for each neuron based on α is given as

$$f(\alpha) = \frac{e^{\alpha} - e^{-\alpha}}{e^{\alpha} + e^{-\alpha}}, \tag{7}$$

where $f(\alpha)\epsilon[-1, 1]$ is the non-linear logistic activation function *tanh*. H2O performs a regularization technique to avoid overfitting based on l_1 and l_2 norms. The loss function is modified as

$$L'(W, B|j) = L(W, B|j) + \lambda_1 R_1(W, B|j) + \lambda_2 R_2(W, B|j), \tag{8}$$

where the l_1 regularization, $R_1(W, B|j)$, is the sum of all l_1 norms for the weights and biases in the network, and l_2 regularization, $R_2(W, B|j)$, is the sum of squares of all the weights and biases in the network. The λ_1 and λ_2 are kept in the range of $1 * 10^{-5}$.

In order to perform training we define a binary class problem based on normal and anomalous activity instances. The instances of each activity class within the whiskers of the boxplot representations are considered as normal and the remaining are labeled as anomalous, where whiskers are $Q3 + 1.5(Q_3 - Q_1)$ and $Q_1 - 1.5(Q_3 - Q_1)$, and Q_s is the s^{th} quartile. We consider two cases of abnormality, which are based on irregular number of features representing missing or extra subevents in an activity; and unusual duration of the activity. The trained H2O model is tested for anomaly detection in the new recognized activities.

Table 2
Activity level performance analysis of the proposed approach for activity recognition using (a, c) Performance Evaluation Metrics and (b, d) confusion matrices in Aruba, and Milan smart-home datasets [22] using training to test ratio of 70 : 30. Key: Acts - Activities, TP - True positive, FP - False positive, TN - True Negative, FN - False Negative; (Aruba) $->$ MP - Meal Preparation, Rlx – Relax, Eat – Eating, Wk - Work, Slp - Sleeping, WD - Wash Dishes, Tlt - Bed to Toilet, EH - Enter Home, LH - Leave Home, HK - House Keeping, Res - Resperate; (Milan) $->$ Chr - Chores, DA - Desk Activity, DmA - Dining Room Activity, EMd - Evening Medicine, GBt - Guest Bathroom, KcA - Kitchen Activity, LH - Leave Home, MBt - Master Bathroom, MBd - Master Bedroom Activity, Mdt - Meditate, MMd - Morning Medication, Rd - Reading activity, Slp - Sleep, WTv - Watch TV, Tlt – Bed to Toilet.

Acts	TP	FP	TN	FN	Accuracy	Precision	Recall	F1score
Tlt	47	37	1854	0	1.00	0.55	1.00	0.71
Eat	69	3	1858	8	0.89	0.95	0.89	0.92
EH	59	18	1791	70	0.45	0.76	0.45	0.57
HK	7	0	1 929	2	0.77	1	0.77	0.87
LH	110	73	1736	19	0.85	0.60	0.85	0.70
MP	448	23	1434	33	0.93	0.95	0.93	0.94
Rlx	849	16	1047	26	0.97	0.98	0.97	0.97
Res	1	2	1935	0	1.00	0.33	1.00	0.50
Slp	116	1	1817	4	0.96	0.99	0.96	0.97
WD	1	8	1911	18	0.05	0.11	0.05	0.07
Wk	49	1	1886	2	0.96	0.98	0.96	0.97
All	-	-	-	-	**0.90**	**0.74**	**0.80**	**0.74**

(a) Aruba

Groundtruth

	Tlt	Eat	EH	HK	LH	MP	Rlx	Res	Slp	WD	Wk
Tlt	47	0	0	0	0	0	0	0	0	0	0
Eat	1	69	0	0	0	3	4	0	0	0	0
EH	0	0	59	0	70	0	0	0	0	0	0
HK	1	0	0	7	0	0	1	0	0	0	0
LH	0	0	17	0	110	0	2	0	0	0	0
MP	14	0	1	0	0	448	9	0	0	8	1
Rlx	16	3	0	0	2	3	849	1	1	0	0
Res	0	0	0	0	0	0	0	1	0	0	0
Slp	4	0	0	0	0	0	0	0	116	0	0
WD	1	0	0	0	0	17	0	0	0	1	0
Wk	0	0	0	0	1	0	0	1	0	0	49

Predicted

(b) Aruba

Acts	TP	FP	TN	FN	Accuracy	Precision	Recall	F1score
Chr	3	5	656	23	0.11	0.37	0.11	0.17
DA	1	4	677	5	0.16	0.20	0.16	0.18
DmA	12	0	671	4	0.75	1.00	0.75	0.85
EMd	2	3	678	4	0.33	0.40	0.33	0.36
GBt	2	9	673	3	0.40	0.18	0.40	0.25
KcA	96	11	577	3	0.96	0.89	0.96	0.93
LH	142	23	498	24	0.85	0.86	0.85	0.85
MBt	62	8	615	2	0.96	0.88	0.96	0.92
MBd	78	38	558	13	0.85	0.67	0.85	0.75
Tlt	15	637	20	0.42	0.50	0.42	0.46	0.80
Mdt	5	1	681	0	1.00	0.83	1.00	0.90
WTv	5	7	668	7	0.41	0.41	0.41	0.41
Slp	87	5	588	7	0.92	0.94	0.92	0.93
Rd	21	2	657	7	0.75	0.91	0.75	0.82
MMd	24	1	652	10	0.70	0.96	0.70	0.81
All	-	-	-	-	**0.80**	**0.66**	**0.64**	**0.64**

(c) Milan

Groundtruth

	Chr	DA	DmA	EMd	GBt	KcA	LH	MBt	MBd	Tlt	Mdt	WTv	Slp	Rd	MMd
Chr	3	0	0	0	0	1	0	0	22	0	0	0	0	0	0
DA	0	1	0	1	0	0	2	0	0	2	0	0	0	0	0
DmA	1	0	12	0	0	0	1	0	0	2	0	0	0	0	0
EMd	0	0	0	2	0	0	1	1	0	1	0	0	1	0	0
GBt	0	0	0	0	2	0	0	0	0	0	0	3	0	0	0
KcA	0	0	0	0	0	96	3	0	0	0	0	0	0	0	0
LH	0	0	0	0	5	5	142	5	2	0	1	4	1	0	1
MBt	1	0	0	0	0	0	1	62	0	0	0	0	0	0	0
MBd	3	1	0	0	0	2	0	0	78	7	0	0	0	0	0
Tlt	0	3	0	0	0	1	2	1	11	15	0	0	0	2	0
Mdt	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0
WTv	0	0	0	0	4	0	3	0	0	0	0	5	0	0	0
Slp	0	0	0	2	0	1	4	0	0	0	0	0	87	0	0
Rd	0	0	0	0	0	0	2	0	1	3	0	0	1	21	0
MMd	0	0	0	0	0	1	4	1	2	0	0	0	2	0	24

Predicted

(d) Milan

4. Evaluation and discussion

We evaluate the proposed approach for activity recognition, anomaly detection and daily routine analysis using a comprehensive evaluation metrics. Two publicly available smart-home datasets from CASAS project [22] namely: Aruba and Milan, are used in the evaluation. We split the data in training and testing with the ratio of 70 : 30.

The performance evaluation metrics comprise of True Positives (TPs), False Positives (FPs), True Negatives (TNs), False Negatives (FNs), Precision, Recall, F1score and Accuracy given as

$$Precision = \frac{TP}{TP + FP}, \tag{9}$$

$$Recall = \frac{TP}{TP + FN}, \tag{10}$$

$$F1score = \frac{2 \times Precision \times Recall}{Precision + Recall}, \tag{11}$$

and

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}. \tag{12}$$

In the activity recognition, TPs and FNs represent the activity instances belonging to the same class, while TPs and FNs are the anomalous instances in the case of anomaly detection.

4.1. Datasets and ground truth

Table 1 shows the list of activities performed in each of the two publicly available challenging datasets from CASAS smart-home project [22]. *Aruba* includes 6477 instances of 11 activities performed by a single resident in a smart-home over a period of one year. *Milan* contains 2310 instances of 15 activities performed by a single resident living with a pet for a period of three months.

Datasets are selected based on the challenges that include similar events in the instances of different activities, addition of noise in the datasets because of the presence of non-participating agents such as pets in the home, and the sensor errors affecting the inputs during an activity instance. Another factor is the number of instances per activity class, since fewer instances make it challenging for the learning methods to be trained while large number of instances increases the computational cost of a system. The binary sensors used in these datasets are motion sensors, contact switch sensors, absent/present status of item sensors and door open/close

Table 3
Activity level anomaly detection comparison of existing approaches: SVM, OCSVM and K-means clustering with the proposed approach in Aruba smart-home dataset using training to test ratio of 70 : 30. Key: Acts - Activities, TP - True positive, FP - False positive, TN - True Negative, FN - False Negative; (Aruba) – > MP - Meal Preparation, Rlx – Relax, Eat – Eating, Wk - Work, Slp - Sleeping, WD - Wash Dishes, Tlt - Bed to Toilet, EH - Enter Home, LH - Leave Home, HK - House Keeping, Res - Resperate.

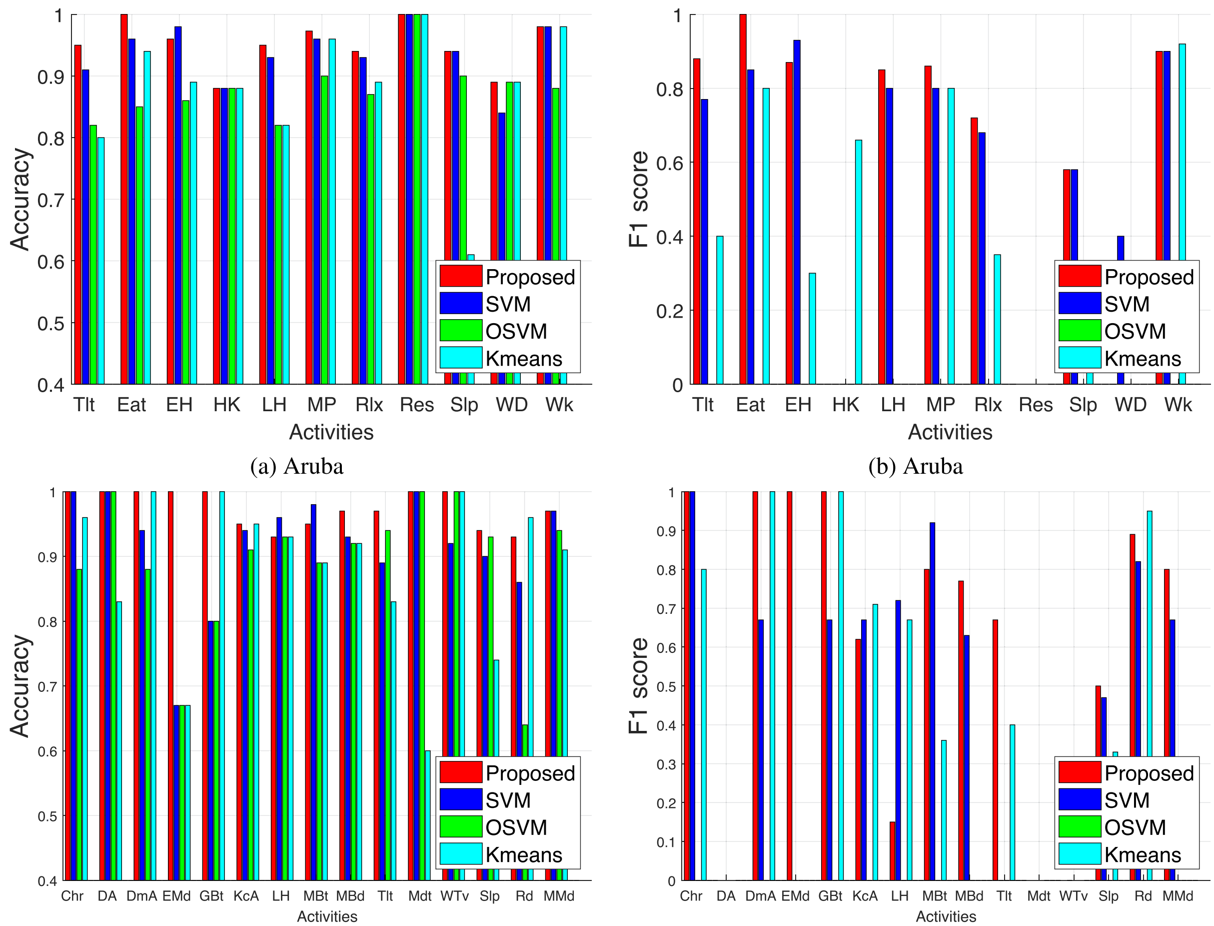
Acts	Classifiers	TP	FP	TN	FN	Accuracy	Precision	Recall	F1-score
Tlt	Proposed	8	2	37	0	0.95	0.80	1	0.88
	SVM	7	3	36	1	0.91	0.70	0.87	0.77
(47)	OSVM	0	0	39	8	0.82	–	0	0
	K-means	3	4	35	5	0.80	0.42	0.37	0.40
Eat1	Proposed	11	0	66	0	1	1	1	1
	SVM	9	1	65	2	0.96	0.9	0.81	0.85
(77)	OSVM	0	0	66	11	0.85	–	0	0
	K-means	8	1	65	3	0.94	0.88	0.72	0.80
EH	Proposed	14	1	111	3	0.96	0.93	0.82	0.87
	SVM	15	0	112	2	0.98	1	0.88	0.93
(129)	OSVM	0	0	112	17	0.86	–	0	0
	K-means	3	0	112	14	0.89	1	0.17	0.30
HK	Proposed	0	0	8	1	0.88	–	0	0
	SVM	0	0	8	1	0.88	–	0	0
(9)	OSVM	0	0	8	1	0.88	–	0	0
	K-means	1	1	7	0	0.88	0.5	1	0.67
LH	Proposed	17	1	106	5	0.95	0.94	0.77	0.85
	SVM	16	2	105	6	0.93	0.88	0.72	0.80
(129)	OSVM	0	0	107	22	0.82	–	0	0
	K-means	0	0	107	22	0.82	–	0	0
MP	Proposed	40	7	428	6	0.97	0.85	0.87	0.86
	SVM	35	6	429	11	0.96	0.85	0.76	0.80
(481)	OSVM	0	0	435	46	0.90	–	0	0
	K-means	38	10	425	8	0.96	0.79	0.82	0.80
Rlx	Proposed	64	1	762	48	0.94	0.98	0.57	0.72
	SVM	59	2	761	53	0.93	0.96	0.52	0.68
(875)	OSVM	0	0	763	112	0.87	–	0	0
	K-means	24	0	763	88	0.89	1	0.21	0.35
Res	Proposed	0	0	1	0	1	–	–	–
	SVM	0	0	1	0	1	–	–	–
(1)	OSVM	0	0	1	0	1	–	–	–
	K-means	0	0	1	0	1	–	–	–
Slp	Proposed	5	0	108	7	0.94	1	0.41	0.58
	SVM	5	0	108	7	0.94	1	0.41	0.58
(120)	OSVM	0	0	108	12	0.90	–	0	0
	K-means	1	35	73	11	0.61	0.02	0.08	0.04
WD	Proposed	0	0	17	2	0.89	–	0	0
	SVM	1	2	15	1	0.84	0.33	0.55	0.40
(19)	OSVM	0	0	17	2	0.89	–	0	0
	K-means	0	0	17	2	0.89	–	0	0
Wk	Proposed	5	0	45	1	0.98	1	0.83	0.90
	SVM	5	0	45	1	0.98	1	0.83	0.90
(51)	OSVM	0	0	45	6	0.88	–	0	0
	K-means	6	1	44	0	0.98	0.85	1	0.92

Table 4
Activity level anomaly detection comparison of existing approaches: SVM, OCSVM and K-means clustering with the proposed approach in Milan smart-home dataset using training to test ratio of 70 : 30. Key: Acts - Activities, TP - True positive, FP - False positive, TN - True Negative, FN - False Negative; (Milan) $->$ Chr - Chores, DA - Desk Activity, DmA - Dining Room Activity, EMd - Evening Medicine, GBt - Guest Bathroom, KcA - Kitchen Activity, LH - Leave Home, MBt - Master Bathroom, MBd - Master Bedroom Activity, Mdt - Meditate, MMd - Morning Medication, Rd – Reading activity, Slp - Sleep, WTv - Watch TV, Tlt – Bed to Toilet.

Acts	Classifiers	TP	FP	TN	FN	Accuracy	Precision	Recall	F1-score
Chr	Proposed	3	0	23	0	1	1	1	1
	SVM	3	0	23	0	1	1	1	1
(26)	OSVM	0	0	23	3	0.88	–	0	0
	K-means	2	0	23	1	0.96	1	0.67	0.80
DA	Proposed	0	0	6	0	1	–	–	–
	SVM	0	0	6	0	1	–	–	–
(6)	OSVM	0	0	6	0	1	–	–	–
	K-means	0	1	5	0	0.83	0	–	0
DmA	Proposed	2	0	14	0	1	1	1	1
	SVM	1	0	14	1	0.94	1	0.50	0.67
(16)	OSVM	0	0	14	2	0.88	–	0	0
	K-means	2	0	14	0	1	1	1	1
EMd	Proposed	2	0	4	0	1	1	1	1
	SVM	0	0	4	2	0.67	–	0	0
(6)	OSVM	0	0	4	2	0.67	–	0	0
	K-means	0	0	4	2	0.67	–	0	0
GBt	Proposed	1	0	4	0	1	1	1	1
	SVM	1	1	3	0	0.80	0.50	1	0.67
(5)	OSVM	0	0	4	1	0.80	–	0	0
	K-means	1	0	4	0	1	1	1	1
KA	Proposed	4	0	90	5	0.95	1	0.44	0.62
	SVM	6	3	87	3	0.94	0.67	0.67	0.67
(99)	OSVM	0	0	90	9	0.91	–	0	0
	K-means	6	2	88	3	0.95	0.75	0.67	0.71
LH	Proposed	1	0	154	11	0.93	1	0.08	0.15
	SVM	9	4	150	3	0.96	0.69	0.75	0.72
(166)	OSVM	0	0	154	12	0.93	–	0	0
	K-means	11	10	144	1	0.93	0.52	0.92	0.67
MBt	Proposed	6	2	55	1	0.95	0.75	0.86	0.80
& SVM	6	0	57	1	0.98	1	0.86	0.92	
(64)	OSVM	0	0	57	7	0.89	–	0	0
	K-means	2	2	55	5	0.89	0.50	0.29	0.36
MBd	Proposed	5	1	83	2	0.97	0.83	0.71	0.77
	SVM	5	4	80	2	0.93	0.56	0.71	0.63
(91)	OSVM	0	0	84	7	0.92	–	0	0
	K-means	0	0	84	7	0.92	–	0	0
Tlt	Proposed	1	0	33	1	0.97	1	0.50	0.67
	SVM	0	2	31	2	0.89	0	0	0
(35)	OSVM	0	0	33	2	0.94	–	0	0
	K-means	2	6	27	0	0.83	0.25	1	0.40
Mdt	Proposed	0	0	5	0	1	–	–	–
	SVM	0	0	5	0	1	–	–	–
(5)	OSVM	0	0	5	0	1	–	–	–
	K-means	0	2	3	0	0.60	0	–	0
WTv	Proposed	0	0	12	0	1	–	–	–
	SVM	0	1	11	0	0.92	0	–	0
(12)	OSVM	0	0	12	0	1	–	–	–
	K-means	0	0	12	0	1	–	–	–
Slp	Proposed	3	2	85	4	0.94	0.60	0.43	0.50
	SVM	4	6	81	3	0.90	0.40	0.57	0.47
(94)	OSVM	0	0	87	7	0.93	–	0	0
	K-means	6	23	64	1	0.74	0.21	0.86	0.33
Rd	Proposed	8	0	18	2	0.93	1	0.80	0.89
	SVM	9	3	15	1	0.86	0.75	0.90	0.82
(28)	OSVM	0	0	18	10	0.64	–	0	0
	K-means	9	0	18	1	0.96	1	0.90	0.95
MMd	Proposed	2	1	31	0	0.97	0.67	1	0.80
	SVM	1	0	32	1	0.97	1	0.50	0.67
(34)	OSVM	0	0	32	2	0.94	–	0	0
	K-means	0	1	31	2	0.91	0	0	0

status of cabinet sensors. In addition, the analog sensors are used to measure the temperature and the status of water and burner.

The datasets provide the ground truth for the activity recognition; however, the ground truth for the anomaly detection does not exist. we generate the ground truth by defining two criteria for anomalous events. The first criterion is the time duration of an activity, while the second is the number of subevents in an activity, represented by the number of active sensors, assuming each sensor captures a subevent. Fig. 3 shows the boxplots of the distribution of activities based on the two defined criteria, where the box represents the data between first and the third quartile, and the length of whiskers is $1.5(Q_3 - Q_1)$. We consider an activity instance as anomalous if it is outside the whiskers of the box plot of either the time duration or the number of subevents.



(a) Aruba (b) Aruba

(c) Milan (d) Milan

Fig. 4. Anomaly detection comparison of existing approaches using: SVM, OCSVM and K-means clustering with the proposed approach using (a, c) Accuracy and (b, d) F1score in Aruba and Milan smart-home datasets [22]. Key: (Aruba) – > MP - Meal Preparation, Rlx – Relax, Eat – Eating, Wk - Work, Slp - Sleeping, WD - Wash Dishes, Tlt - Bed to Toilet, EH - Enter Home, LH - Leave Home, HK - House Keeping, Res - Resperate; (Milan) – > Chr - Chores, DA - Desk Activity, DmA - Dining Room Activity, EMd - Evening Medicine, GBt - Guest Bathroom, KcA - Kitchen Activity, LH - Leave Home, MBt - Master Bathroom, MBd - Master Bedroom Activity, Mdt - Meditate, MMd - Morning Medication, Rd - Reading activity, Slp - Sleep, WTv - Watch TV, Tlt – Bed to Toilet.

4.2. Activity recognition

Table 2 shows the performance evaluation of the proposed approach for activity recognition in the two datasets Aruba and Milan. The extracted feature set is given as input to the PNN for activity recognition. We perform the comprehensive evaluation of the proposed approach at the activity level as well as for the whole system, using the evaluation measures Accuracy, Precision, Recall and F1score.

In Aruba, it can be noted that a large variation exists in the number of instances per activity class ranging from only 1 in 'Resperate' to 875 in 'Relax' activities. The proposed approach is able to recognize majority of the activities with an overall accuracy of 90% and F1score of 74%. A few activities have less recognition accuracy such as 'Enter Home' and 'Wash Dishes' with accuracy of 45% and 5%. From the confusion matrix it can be noted that all the 70 FNs of 'Enter Home' activity are recognized as 'Leave Home' and the 17 FNs of 'Leave Home' activity are recognized as 'Enter Home'. The two activities are confused with each other because the entry and exit of the house involve the same main door and thus the same sensors are involve in capturing their events. Similarly, 'Wash Dishes' is confused with the 'Meal Preparation' activity, since both are performed in the same location (kitchen), and thus share similar events. Also the activity of 'Wash Dishes' can be executed during 'Meal Preparation', therefore can be considered as its sub-activity.

In Milan, two challenges are similar to Aruba that include the smaller number of activity instances available for training, and the different activities sharing common features. In addition, the presence of a pet in Milan dataset makes it more challenging. The proposed approach achieves an overall accuracy of 80% in Milan dataset. The activities not performing well include 'Chores', 'Desk activity','Evening Medicine' and 'Watch TV'. From the confusion matrix it can be noted that 'Desk Activity' and 'Evening Medicine', both have less number of activity instances available for training. The FNs of 'Chores' can be seen in the 'Master Bedroom activity'. Since chores stands for household activities, hence it represents the case of less inter-class variations, sharing similar features with the other class. Some activities are mis-classified due to the presence of pet. An example of such activity could be 'Bed to Toilet', as its 11 instances are wrongly recognized as 'Master Bedroom' activity and represent the noise because of the pet.

4.3. Anomaly detection

The proposed approach identifies activity instances with abnormal duration or number of events, within each activity class. Aruba and Milan datasets are used with the training to test ratio of 70 : 30 per activity class. TPs represent the anomalies correctly identified by the proposed approach. The results are compared with the

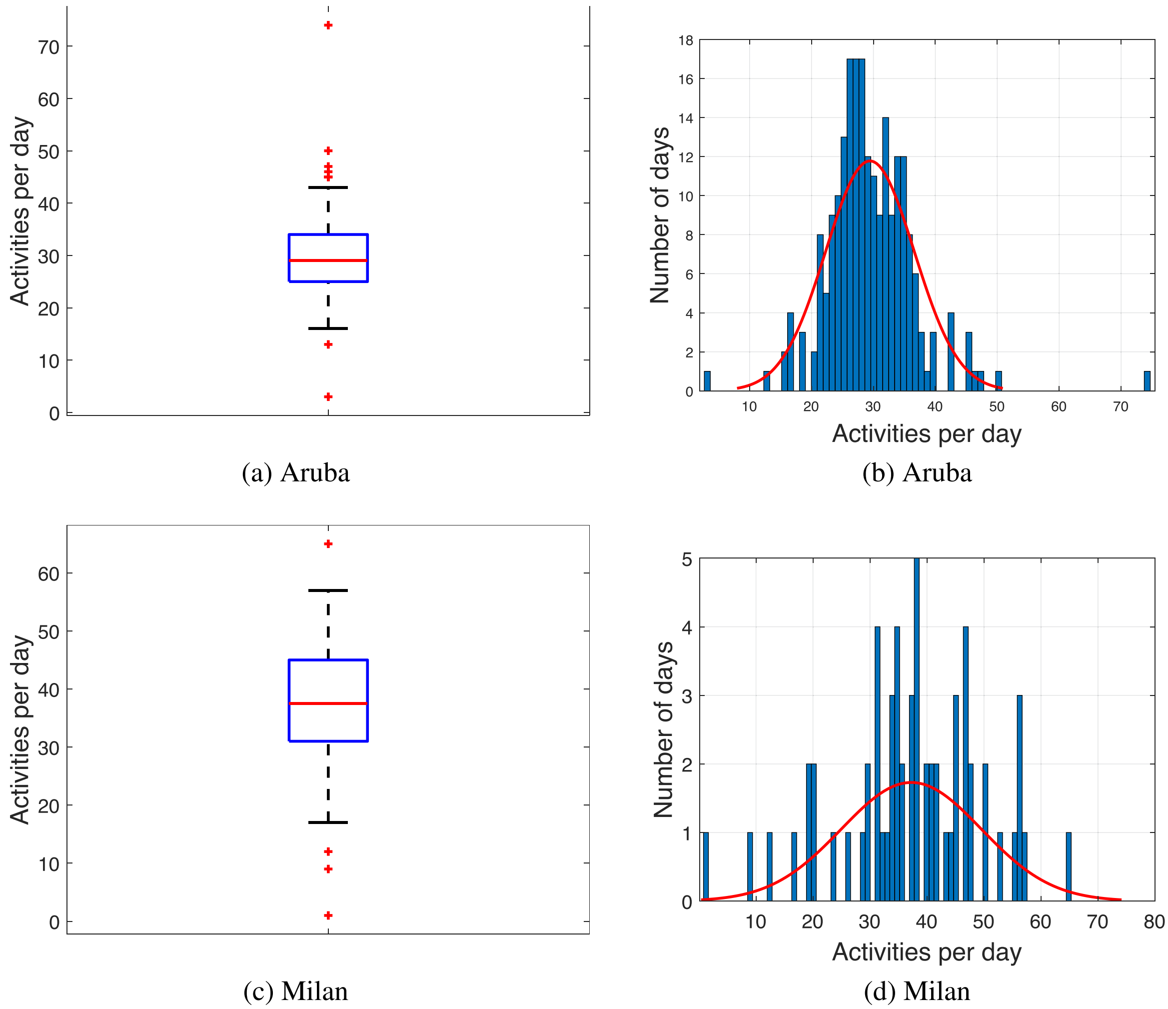


Fig. 5. Anomalous days recognition using the box plot as well as the curve fitting on the number of activities performed per day in (a, b) Aruba and (c, d) Milan smart-home datasets [22].

existing classification based approaches using: binary class SVM [3], OCSVM [20], and K-means clustering [53].

Table 3 shows the performance evaluation of the proposed approach for anomaly detection in Aruba dataset. It can be noted that maximum number of TPs (anomalies) and the minimum number of FNs are identified by the proposed approach with more than 90% accuracy in 9 out of 11 activities. In the remaining two activities 'House Keeping' and 'Wash Dishes', only 1 and 2 anomalous instances exist, respectively. Table 4 shows the performance evaluation of the proposed approach for anomaly detection in Milan dataset. The total number of anomalous instances are very few, only 64 exists in the testing data. Since H20 autoencoder shows good results in the case of sparse data, the proposed approach is able to achieve highest accuracy even in the case of activity classes without anomalous instances. An interesting case of 'Evening Medication' activity with only two anomalous instances can be observed, where the proposed approach is able to correctly identify both the instances, while rest of the three approaches of SVM, OCSVM and K-means remains unsuccessful in the correct recognition of any anomalous instance.

Fig. 4 shows the comparison of proposed approach with SVM [3], OCSVM [20], and k-means clustering [53] using Accuracy and F1score. In Aruba, the proposed approach achieves the highest accuracy and F1-score in all the eleven activities. Similar trends can also be observed for activities in Milan. The proposed approach achieves 100% of accuracy and F1-score in those activity instances where the compared methods were unable to detect any anomalies.

The proposed approach achieves significantly better performance, with $p < 0.05$ at 95% confidence interval in the t-test, for both activity recognition and anomaly detection. Hence, the proposed approach proves to be a more reliable in automated healthcare systems that require high accuracy in outputs for automated decisions, such as in medical diagnostic systems.

4.4. Daily routine analysis

Fig. 5 shows the number of activities performed per day in a smart home, which determines the daily routine of the resident. Daily routine analysis helps in determining whether a smart-home resident is able to execute the daily activities independently or needs an intervention. A day can be declared as anomalous if the number of activities performed in that day deviates from a normal pattern. We identify the anomalous days by two closely related approaches. First is the boxplot of the number of activities in a day, where the days outside the whiskers are declared as anomalous. In the second approach, we perform the curve fitting on the distribution of activities per day. The data within three-standard deviations (3σ) from the mean is declared as normal, which accounts for the 99.7% of the data. The rest of the days are declared as anomalous. The former method is based on the median of the data while the latter is on mean. In Aruba, 7 days are identified as anomalous, while in Milan, only 4 days come out as anomalous based on the number of activities performed per day.

5. Conclusion

We proposed an activity recognition and anomaly detection approach for the daily activities performed in a smart-home. Probabilistic neural network is used for the classification of pre-segmented activity instances, while H2O autoencoder detects the anomalies within each activity class. Further, we identify the anomalous days based on the number of activities performed per day. The ground truth for the anomalous activities is generated for the evaluation using the boxplots of the number of features and the duration of activities. We perform a comprehensive activity level evaluation of the proposed approach on two smart-home datasets. The future work includes the recognition and identification of anomalies in multi-resident activities.

CRediT authorship contribution statement

Labiba Gillani Fahad: Data curation, Conceptualization, Methodology, Software, Validation, Writing - original draft. **Syed Fahad Tahir:** Formal analysis, Visualization, Investigation, Methodology, Supervision, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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