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# SmartWall: Novel RFID-Enabled Ambient Human Activity Recognition Using Machine Learning for Unobtrusive Health Monitoring

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**ABSTRACT** Human activity recognition (HAR) from sensor readings has proved to be an effective approach in pervasive computing for smart healthcare. Recent approaches in ambient assisted living (AAL) within the home or community setting offers people the prospect of independent care and improved quality of living. However, most of the available AAL systems are limited by several factors including the system complexity and computational cost. In this paper, a simple, the novel ambient HAR framework using the multivariate Gaussian is proposed. The classification framework augments prior information from passive RFID tags to obtain more detailed activity profiling. The proposed algorithm based on the multivariate Gaussian via maximum likelihood estimation is used to learn the features of the human activity model. The twelve sequential and concurrent experimental evaluations are conducted in a mock apartment environment. The sampled activities are predicted using a new dataset of the same activity and high prediction accuracy established. The proposed framework suits well for the single and multi-dwelling environment and offers pervasive sensing environment for elderly, disabled, and carers.

**INDEX TERMS** Ambient assisted living, human activity recognition, machine learning, multivariate Gaussian, pervasive computing.

## I. INTRODUCTION

Recent times have witnessed increasing growth in the number of elderly. It is reported that the number of elderly is expected to rise to nearly two billion by 2050 [1]. Medical reports also indicate that the prevalence of various degenerative ailments in the elderly and younger generation is on the rise [2]. These degenerative diseases including cancer, Alzheimer, dementia, osteoporosis, stroke, visual impairment, attention deficit hyperactivity disorder and asthma affect the cognitive skills of affected people, rendering them vulnerable and often incapable of performing basic activities of daily living (ADL) [3], [4]. Nonetheless, the demand by most elderly and affected people to live independently with minimal assistance makes ambient and assisted living (AAL) an interesting research subject.

The rapid advancement of the wireless sensor network and the Internet of Things (IoT) to recognize human activity is an improved possibility using different sensor readings [5], [6]. For most applications, the sensor is worn by users as wearable devices or embedded into household wares. The readings from the sensor are then collected, interpreted for possible activity recognition. One key purpose of activity recognition is change detection via identifying sudden change in metrics such as mean and covariance which represents a change in time series data within an indoor environment [7].

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Accurate manipulation of these metrics using a robust algorithm would define the class of activity performed within a timeframe. In general, activity recognition is a critical component of context-aware systems which allows smart home applications to understand user requirement and adapt to the various circumstance of the user. Human activity recognition (HAR) is crucial to assist different emergency-related healthcare and wellbeing services. This is achieved by monitoring different physical activities for reliable real-time first responder and nursing services within care homes and domestic environments [8], [9]. However, developing a robust, scalable, real-time indoor HAR system in a real environment often presents a daunting research task due to the complexity of indoor environments.

Therefore, several interesting solutions have been proposed in the literature to recognize human activities for AAL. Traditional HAR systems are based on cameras and computer vision. These approaches are useful for large coverage and pedestrian activity recognition. However, camera and computer vision approaches are often limited by potential privacy issues because of their invasive nature. To overcome this limitation, recent HAR solutions are based on wearable approach using wearable sensors or devices including smartphones [10]–[12]. However, wearable solutions are sometimes unobtrusive as they are often associated with target inconvenience since users need to always remember to equip the sensing devices. Moreover, wearable solutions depend on the target to determine where the wearable device is worn and the device position with respect to the performed activity. This implies that the transition between positions has to be detected. Furthermore, several wearable solutions rely on subject-specific approach, where the target must collect the data and characterize them. These requirements present potential limitations to wearable HAR solutions, particularly to sensitive elderly and vulnerable.

RFID is identified as a potentially viable candidate for truly pervasive computing applications. With overcoming the traditional limitations of RFID including universally accessible infrastructure and complication in its use, RFID has found its use in a wider variety of applications. Moreover, with the increasing use for automatic target and location identification, RFID is popular as an open, scalable and shared technology capable to automatically identify and collect information about entities and interactions between them in a completely transparent manner to end users [13]. Furthermore, recent desirable improvements in RFID technology has facilitated the development of cheap, high sensitivity and high read range ($\geq$ 10m) passive tags that support innovative, cost-effective emerging pervasive and IoT-based healthcare solutions [14]–[17].

To this end, the present work is motivated from previous investigations [18], [19]. The motivation is to provide a robust, cost-effective solution that meets the clinical requirement of ambient patient activity profiling with guaranteed freedom of movement. To achieve such solution, a novel ambient approach using SmartWall is proposed. The SmartWall is used to sample sequential and concurrent activities. Human activity in the present work is formulated as a multivariate classification problem. The proposed activity classification framework augments *a prior* information from RSSI of passive RFID tags to obtain more detailed activity profiling. For patients with chronic diseases, position, orientation, mobility and degree of activities are key indices for guiding reliable clinical management decisions, and as such, different real-life indoor case scenario of activity hinging on these indices is sampled on four subjects in the present work.

The major contributions of the present paper include:

- We propose the SmartWall; a novel RFID-enabled approach that implements the pervasive nature of UHF passive RFID tags to recognize sequential and concurrent activities.
- We develop machine learning via multivariate Gaussian algorithm using maximum likelihood estimation to classify and predict the sampled activities.
- We conduct comprehensive experiments of various real-life physical activities via ambient sensing for data collection, evaluation and classification.

The paper is structured as follows: Section II highlights related works on the present research objectives. In Section III, the methodology of the proposed method is presented. Human activity is formulated as a multivariate Gaussian problem. In Section IV, a detailed description of the proposed SmartWall, features for activity classification and the results of the experiment are presented and discussed. Next, we present the proposed algorithm. Section V presents the performance evaluation of the proposed solution using different performance metrics. The observation and areas for further improvement are summarized in section VI.

## II. RELATED WORKS

Reliable HAR systems are implemented using various techniques to better understand user's AAL demand and solve the complex issues arising from recognizing sequential and concurrent human activities. HAR is achieved via two key approaches: data-driven and knowledge-driven technique [20]. Data-driven techniques involve the application of machine learning techniques and probabilistic approaches including Naï ve Bayes (NB) classifiers [21], Decision Trees [22], Hidden Markov Models [23], Bayesian Networks [24], and Support Vector Machine (SVM) classifiers [25]. In the data-driven technique, the algorithms rely on inductive reasoning to detect human activities. Existing works using data-driven techniques apply the supervised approach, which requires manual labelling of data for training. However, this approach is often complex and unpractical with additional computational cost [26]. The unsupervised approach often suffers from low performance in comparison with the supervised approach, especially in complex indoor applications. Moreover, in the knowledge-based HAR, activities along with their contextual relationship are modeled in ontologies as new activity instance is detected via deductive reasoning [27]. One key challenge of knowledge-driven HAR is the construction of ontology to describe the set of concepts along with their relationships in a machine-understandable manner. To overcome this challenge, different authors have proposed different comprehensive ontologies to describe different human activities for pervasive computing and home automation, giving the edge over supervised data-driven as knowledge-based HAR does not require training. Furthermore, to detect complex indoor activities such as target bathing, where acquiring sufficient training data to achieve higher detection accuracy is almost impossible, knowledge-based approaches show higher performance than data-driven approaches. Nonetheless, data-driven approaches are effective for detecting simple and basic activities, whilst unsupervised data-driven approaches are a better choice, as creating probabilistic models with acceptable detection accuracy is possible and convenient than modeling the sampled activities using ontology.

To this end, various work on HAR solutions via data-driven or knowledge-based techniques have been proposed in the literature. Kunze *et al.* [28] propose an on-body approach that detects if the target is walking and then apply specific sensor reading pattern to estimate the actual target's position. However, this approach requires the attachment of sensors onto the target and is limited to a small set of selected positions. In addition, changes in position are not recognized if the target is not walking. Sztyler *et al.* [29] present an on-body, device localization approach that predicts the target on-body position with an F-measure and cross-subject activity recognition using common physical characteristic. Chen *et al.* [30], a knowledge-based approach using the inter-frame algorithm convolutional neural network is applied to learn distinguishing features collected through cameras, whilst filtering non-target objects and estimate skeleton sequence from RGB images. Moreover, Wang *et al.* [31] applied the Wifi technology using commercially off-the-shelf Wifi devices to perform HAR. The authors explore deep learning to learn sensitive feature distortion from the Wifi devices and explore the timescale correlations from the extracted spectrogram. More interestingly, Sigg *et al.* [32] present a device-free radio-based activity recognition using ambient FM radio of dedicated transmitter.

## III. METHODOLOGY

In this section, we formulate the human activity as a multivariate problem. A detailed description of the methodology using multivariate Gaussian is presented. With the nonlinearity of signal propagation within indoor environments, Gaussian processes provide an efficient way to perform inference on activities within such an environment. The multivariate Gaussian distribution offers a rich approach to produce distribution for variables conditioned on any other observed variables. To apply the multivariate Gaussian, we break the proposed algorithm into two components: *Learning* or *training* and *Prediction* stage. For the learning stage, we take the given training data and learn some key parameters that can be used to describe the distribution of the data. However, in the prediction stage, we then take in some new data and compare to predict the class that each dataset belongs.

### A. TRAINING STAGE

Our aim is to learn the features that describe the class of each training set. Since the multivariate Gaussian is a parameterized representation of data, we define the mean and covariance function to describe the distribution of the sampled data. In the present subsection, the classification model is developed based on the mean and covariance matrix of the sampled data which would be used to describe the various training datasets. Therefore, considering the multi-dimensional Gaussian probability distribution function expressed in the form:

$$P\left(\overline{x};\overline{\mu},\overline{\overline{\in}}\right)=\frac{1}{(2\pi)^{D/2}\left|\overline{\overline{\in}}\right|^{1/2}}e^{\left(-\frac{1}{2}(\overline{x}-\overline{\mu})^{T}\overline{\overline{\in^{-1}}}(\overline{x}-\overline{\mu})\right)}\tag{1}$$

$\overline{\mu},\overline{\overline{\in}}$ is unknown which is determined from the training dataset. To obtain the unknowns, maximum likelihood estimation is formulated as:

Assume $\overline{x}_i^c,\overline{\mu}^c,\overline{\overline{\in}}^c$ represents the input features of the $i^{th}$ training dataset of the class, $c$, which corresponds to the twelve sampled human activities, i.e. $c = 1, 2, \ldots\ldots, 12$. The mean and covariance matrix of $c$ gives the class of activity of the target. Therefore, the objective is to find $\overline{\mu}^c$ and $\overline{\overline{\in}}^c$ that maximizes the likelihood $P\left(\left(\overline{x}_i^c\right)|\overline{\mu}^c,\overline{\overline{\in}}^c\right)$.

Mathematically, this could be expressed in the form:

$$\mu^{c*},\quad \in^{c*}=\underset{\bar{\mu}^c,\overline{\overline{\in}}^c}{\arg\max}\,P\left(\left(\overline{x}_i^c\right)|\overline{\mu}^c,\ \overline{\overline{\in}}^c\right)\tag{2}$$

We assume data independence, i.e. data input from each RFID tag at a timestamp is independent of the same tag at different time stamps. Therefore, data input from different RFID tags is independent of each other. Taking into consideration the assumption, we rewrite Eq. (2) as:

$$\overline{\mu}^{c*},\quad \overline{\overline{\in}}^{c*}=\underset{\bar{\mu}^c,\overline{\overline{\in}}^c}{\arg\max}\prod_{i=1}^{N}P\left(\overline{x}_i^c|\overline{\mu}^c,\ \overline{\overline{\in}}^c\right)\tag{3}$$

Equation (3) maximizes the joint probability across the dataset input $I$ from 1 to $N$ conditioned on the given $\overline{\mu}^c,\overline{\overline{\in}}^c$. Simplifying Eq. (3) by taking log (to base $e$) likelihood gives:

$$\begin{aligned}\overline{\mu}^{c*},\overline{\overline{\in}}^{c*}&=\underset{\bar{\mu}^c,\overline{\overline{\in}}^c}{\arg\max}\prod_{i=1}^{N}P\left(\overline{x}_i^c|\overline{\mu}^c,\overline{\overline{\in}}^c\right)\\&=\underset{\bar{\mu}^c,\overline{\overline{\in}}^c}{\arg\max}\left(\prod_{i=1}^{N}P\left(\overline{x}_i^c|\overline{\mu}^c,\overline{\overline{\in}}^c\right)\right)\\&=\underset{\bar{\mu}^c,\overline{\overline{\in}}^c}{\arg\max}\sum_{i=1}^{N}\log\left(P\left(\overline{x}_i^c|\overline{\mu}^c,\overline{\overline{\in}}^c\right)\right)\end{aligned}\tag{4}$$

From Eq. (4), we show that the Argmax, i.e. likelihood is the same as Argmax (log (likelihood)). Generally, Argmax $(f(x))$ is equal to Argmax (log (f(x)) without effect on accuracy since logarithm is a monotonically increasing function.

Therefore, by substituting Equation (1) in (4), we obtain

$$
\begin{aligned}
\bar{\mu}^c, \bar{\epsilon}^{c*} &= \underset{\bar{\mu}^c, \overline{\overline{\in}}^c}{\arg\max} \log\left(\prod_{i=1}^{N} P\left(x_i^c | \bar{\mu}^c, \overline{\overline{\in}}^c\right)\right) \\
&= \underset{\bar{\mu}^c, \overline{\overline{\in}}^c}{\arg\max} \sum_{i=1}^{N} \log\left(\frac{1}{(2\pi)^{D/2} \left|\overline{\overline{\in}}^c\right|^{1/2}} e^{\left(-\frac{1}{2}\left(x_i^c - \bar{\mu}\right)^T \overline{\overline{\in}}^{c-1} \left(x_i^c - \bar{\mu}^c\right)\right)}\right) \\
&= \underset{\bar{\mu}^c, \overline{\overline{\in}}^c}{\arg\max} \sum_{i=1}^{N} \left[\log\left(\frac{1}{(2\pi)^{D/2} \left|\in^c\right|^{1/2}}\right) \right. \\
&\quad \left. + \log\left(e^{\left(-\frac{1}{2}\left(\bar{x}_i^c - \bar{\mu}\right)^T \overline{\overline{\in}}^{c-1} \left(\bar{x}_i^c - \bar{\mu}^c\right)\right)}\right)\right] \\
&= \underset{\bar{\mu}^c, \overline{\overline{\in}}^c}{\arg\max} \sum_{i=1}^{N} \left[-\frac{1}{2} \log\left(\left|\overline{\overline{\in}}^c\right|\right) - \frac{D}{2}(2\pi) \right. \\
&\quad \left. - \frac{1}{2}\left(\bar{x}_i^c - \bar{\mu}\right)^T \overline{\overline{\in}}^{c-1} \left(\bar{x}_i^c - \bar{\mu}^c\right)\right]
\end{aligned} \tag{5}
$$

The second term is eliminated since it is a constant and have no unknown parameter. However, we factor out the negative sign to obtain the minimization problem as:

$$\bar{\mu}^{c*}, \bar{\epsilon}^{c*} = \underset{\bar{\mu}^c, \overline{\overline{\in}}^c}{\arg\max} J\left(\bar{\mu}^c, \overline{\overline{\in}}^c\right) \tag{6}$$

where

$$
\begin{aligned}
&J\left(\bar{\mu}^c, \overline{\overline{\in}}^c\right) \\
&= \sum_{i=1}^{N} \left[\frac{1}{2} \log\left(\left|\overline{\overline{\in}}^c\right|\right) + \frac{1}{2}\left(\bar{x}_i^c - \bar{\mu}\right)^T \overline{\overline{\in}}^{c-1} \left(\bar{x}_i^c - \bar{\mu}^c\right)\right]
\end{aligned} \tag{7}
$$

To obtain $\mu^{c*}$, we solve Eq. (8)

$$\frac{\partial}{\partial \mu^c}\left(J\left(\bar{\mu}^c, \overline{\overline{\in}}^c\right)\right) = 0 \tag{8}$$

$$\mu^{c*} = \frac{1}{N} \sum_{i=1}^{N} \bar{x}_i^c \tag{9}$$

In addition, solving Eq. (7) for $\overline{\overline{\in}}^{c*}$, i.e.

$$\frac{\partial}{\partial \in^c}\left(J\left(\bar{\mu}^c, \overline{\overline{\in}}^c\right)\right) = 0 \tag{10}$$

we obtain

$$\in^{c*} = \frac{1}{N} \sum_{i=1}^{N} \left(\bar{x}_i^c - \bar{\mu}^{c*}\right)\left(\bar{x}_i^c - \bar{\mu}^{c*}\right)^T \tag{11}$$

Equation (9) and (11) gives the mean and covariance matrix for the $c^{th}$ dataset. However, on further simplification Eq. (9) and (11) become

$$
\begin{aligned}
\mu^{c*} &= \frac{1}{N} \sum_{i=1}^{N} \bar{x}_i^c \\
\overline{\overline{\in}}^{c*} &= \frac{1}{N} \sum_{i=1}^{N} \left(\bar{x}_i^c - \mu^{c*}\right)\left(\bar{x}_i^c - \mu^{c*}\right)^T
\end{aligned} \tag{12}
$$

Equation (12) is applied to the training dataset to obtain the classification of the various sampled activities.

### B. NUMERICAL CONSIDERATIONS

Before applying Eq. (12) to the dataset, we normalize to scale the input vectors in Eq. (13) in the range; $x$ (0 − 1220 mm) and $z$(0 − 2440 mm) to exist within the limit 0 and 1. However, the received power ( − 31dBm to − 29dBm) is subtracted by the average power value.

$$\bar{x}_i^c = (rssi, x, z) \tag{13}$$

Therefore, by normalizing Equation (14), we obtain:

$$\bar{x}_{normalise}^c = \left(-30, x/1220, z/2440\right) \tag{14}$$

The normalization is carried out to prevent any single vector from dominating others during numerical computation involved in training the algorithm. Moreover, the data normalization helps to reduce the dominance of any value that is quantitatively large in its domain over other values that are quantitatively small.

## IV. EXPERIMENT AND RESULTS

Following most existing works, a supervised approach for the subject's localization and activity recognition is performed. A novel feature extraction approach using RFID technology is introduced using the SmartWall; a wall attached with passive RFID tags. In the following, we describe the features generated from the RFID sensor data and learning strategy used in the present study.

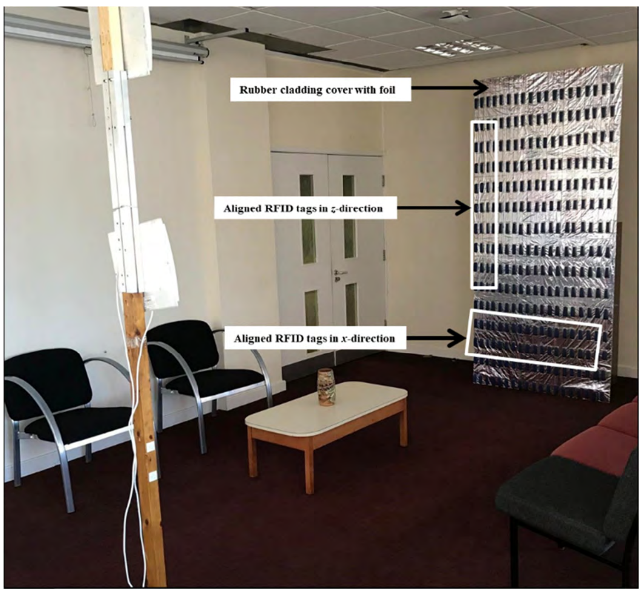



**FIGURE 1. Mock room of the experiment using smartWall for activity sampling.**

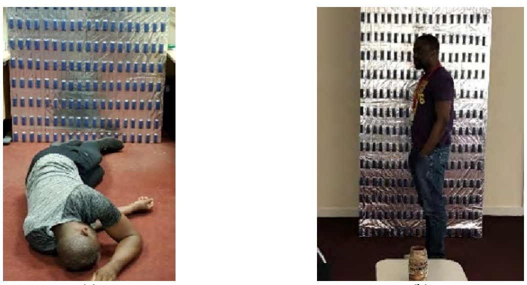
### A. EXPERIMENTATION: SMARTWALL

To achieve the proposed unobtrusive, unwearable data sensing approach for various simple and complex real-life activities, we conceptualise the SmartWall. Figure 1 shows the setup of the mock room for the experiment using the SmartWall. From Figure 1, it is shown that the SmartWall is made of thick rubber cladding of dimension 1220 × 2440 mm $^2$.

The rubber cladding is covered with the fabricated passive RFID tags arranged in a grid of dimension 19 $\times$ 12 for the mock experiment. An Impinj RAIN RFID multi-reader version 6.6.13.240 with octane firmware is used for the read the HID passive RFID tags. Two RFID reader antennas are vertically placed with the height of the upper antenna at 1.7m, whilst the lower antenna is mounted 1m to the ground. The transmitted power of the reader antenna is set to 31.5dBm. Each RFID tag consists of meander antenna of dimension 88 $\times$ 37 $\times$ 15 $mm^3$ integrated with Alien HITAG S chip of impedance 14 + j135$\Omega$. The tags are spaced 3cm in both $x$ and $z$ position and are mounted onto the surface of rubber cladding. The distance between the RFID reader and the SmartWall within the mock room is set to 4m for accurate readings.

### B. DATASET

Human ADL, regardless of age are dynamic in nature and varied ranging from simple activities of lying, sitting, standing to the more complex activities of bathing, running and swimming. Most aged in need of AAL often engage in simple activities of ADL. Bear this notion in mind we build a mock room for the experiment using the SmartWall to collect sensor information.



(a) (b)

**FIGURE 2. Example of human activities performed. (a) Class_8 activity i.e. target stands 1m away from Wall (b) Class_4 activity i.e. target falls to the ground.**

Figure 1 shows the mock room with the SmartWall employed for activity sampling. Twelve real-life activities are performed by four volunteers at the Smart Lab B3.26 and B3.03 of Faculty of Engineering and Informatics, University of Bradford. Each subject performs all twelve activities in ten iterative samplings. Figure 2a and 2b illustrate one of the sampled activities in each of the mock rooms by different volunteers. It is worth noting that all activity sampling is carried out within a 5$m$ radius from the SmartWall. A database of all twelve activities is created. Therefore, the objective is to develop an algorithm to learn and classify the sampled activities in the activity trace.

### C. MEASURED RESULTS

In this section, the results of the activity measurement taken are presented. The frequency distribution of the Gaussian score for all the sampled activities is presented in Figure 3.

**TABLE 1. Sampled activities (class) with equivalent normalized mean and covariance.**

| Class id | Class Descriptor | $\overline{\mu}^{c*}$ | $\overline{\overline{\in}}^{c*}$ |
|---|---|---|---|
| A1 | Target runs out of the room to the corridor | $[-1.0259 \quad 0.4868 \quad 0.9298]$ | $\begin{bmatrix} 0.0042 & -0.0031 & -0.0024 \\ -0.0031 & 0.0838 & -0.0078 \\ -0.0024 & -0.0078 & 0.2065 \end{bmatrix}$ |
| A2 | Target sits 1m away from the wall | $[-1.0341 \quad 0.4167 \quad 1.0952]$ | $\begin{bmatrix} 0.0037 & -0.0052 & -0.0004 \\ -0.0052 & 0.01204 & -0.0005 \\ -0.0004 & -0.0005 & 0.2204 \end{bmatrix}$ |
| A3 | Target use bathroom | $[-1.0322 \quad 0.4505 \quad 1.00003]$ | $\begin{bmatrix} 0.0040 & -0.0044 & 0.0011 \\ -0.0044 & 0.1221 & 0.0004 \\ 0.0011 & 0.0004 & 0.2272 \end{bmatrix}$ |
| A4 | Target stands 1m away from the wall | $[-1.0322 \quad 0.4505 \quad 1.00003]$ | $\begin{bmatrix} 0.0044 & -0.0029 & -0.0011 \\ -0.0029 & 0.1221 & -0.0049 \\ -0.0010 & -0.0049 & 0.1885 \end{bmatrix}$ |
| A5 | Target sits randomly at different locations in the room | $[-1.0392 \quad 0.5053 \quad 1.1294]$ | $\begin{bmatrix} 0.0036 & -0.0026 & -0.0006 \\ -0.0026 & 0.1019 & -0.0212 \\ -0.0006 & -0.0212 & 0.1343 \end{bmatrix}$ |
| A6 | Target lay on the sofa | $[-1.0296 \quad 0.4634 \quad 1.0862]$ | $\begin{bmatrix} 0.0040 & -0.0047 & -0.0003 \\ -0.0047 & 0.1221 & -0.0018 \\ 0.0003 & -0.0018 & 0.1679 \end{bmatrix}$ |
| A7 | Target walks in and out of the room | $[-1.0223 \quad 0.4917 \quad 1.0811]$ | $\begin{bmatrix} 0.0036 & -0.0030 & -0.0002 \\ -0.0030 & 0.1221 & -0.0132 \\ -0.0002 & -0.0132 & 0.1463 \end{bmatrix}$ |
| A8 | Target falls | $[-1.0429 \quad 0.5208 \quad 0.9776]$ | $\begin{bmatrix} 0.0042 & -0.0017 & -0.0006 \\ -0.0017 & 0.0921 & -0.0165 \\ -0.0006 & -0.0165 & 0.2135 \end{bmatrix}$ |
| A9 | Target brushes teeth | $[-1.0322 \quad 0.4905 \quad 1.1378]$ | $\begin{bmatrix} 0.0036 & -0.0032 & 0.00021 \\ -0.0032 & 0.1221 & -0.0209 \\ 0.0021 & -0.0209 & 0.1525 \end{bmatrix}$ |
| A10 | Target sleeps on a bed | $[-1.0344 \quad 0.5113 \quad 1.1175]$ | $\begin{bmatrix} 0.0034 & -0.0036 & 0.0021 \\ -0.0036 & 0.0931 & -0.0285 \\ 0.0021 & -0.0285 & 0.1679 \end{bmatrix}$ |
| A11 | Target prepares breakfast | $[-1.0255 \quad 0.5001 \quad 1.0246]$ | $\begin{bmatrix} 0.0040 & -0.0027 & -0.0022 \\ -0.0027 & 0.1221 & -0.0223 \\ 0.0002 & -0.0223 & 0.1648 \end{bmatrix}$ |
| A12 | No target in the room | $[-1.0238 \quad 0.4727 \quad 0.9707]$ | $\begin{bmatrix} 0.0042 & -0.0036 & -0.0026 \\ -0.0036 & 0.0941 & -0.0107 \\ -0.0026 & -0.0107 & 0.2150 \end{bmatrix}$ |

The Gaussian score relates to the value that a Gaussian probability distribution function (*pdf*) calculates when it is given an observation data $\overline{x}$, using mean $\overline{\mu}$ and covariance $\overline{\overline{\in}}$. The Gaussian score shows the likelihood of a sampled activity from the same distribution/class $\overline{\mu}$ and $\overline{\overline{\in}}$ is obtained. Moreover, Figure 3 shows that the Gaussian representation of the sampled activities is good as the data clearly distinguishes each sampled class. By scoring each sampled activity of each class, we establish how the distribution of each class varies from the rest of the classes as shown in Figure 4. Figure 4 bears key significance to the present study, as the variation in rssi of the RFID tags is used for activity classification *wrt* each tag position.

Figure 4 provides valuable insight into the multivariate Gaussian approach proposed in the present work, as it shows that the Gaussian parameters learnt each class and distinguishes each distinct class from the rest. It is worth noting that if the mean and covariance matrix estimated is the same for all activities, then the Gaussian parameter is not robust for activity classification.

### D. PROPOSED PREDICT_CLASS ALGORITHM

In this section, we present the proposed algorithm based on multivariate of maximum likelihood estimation.

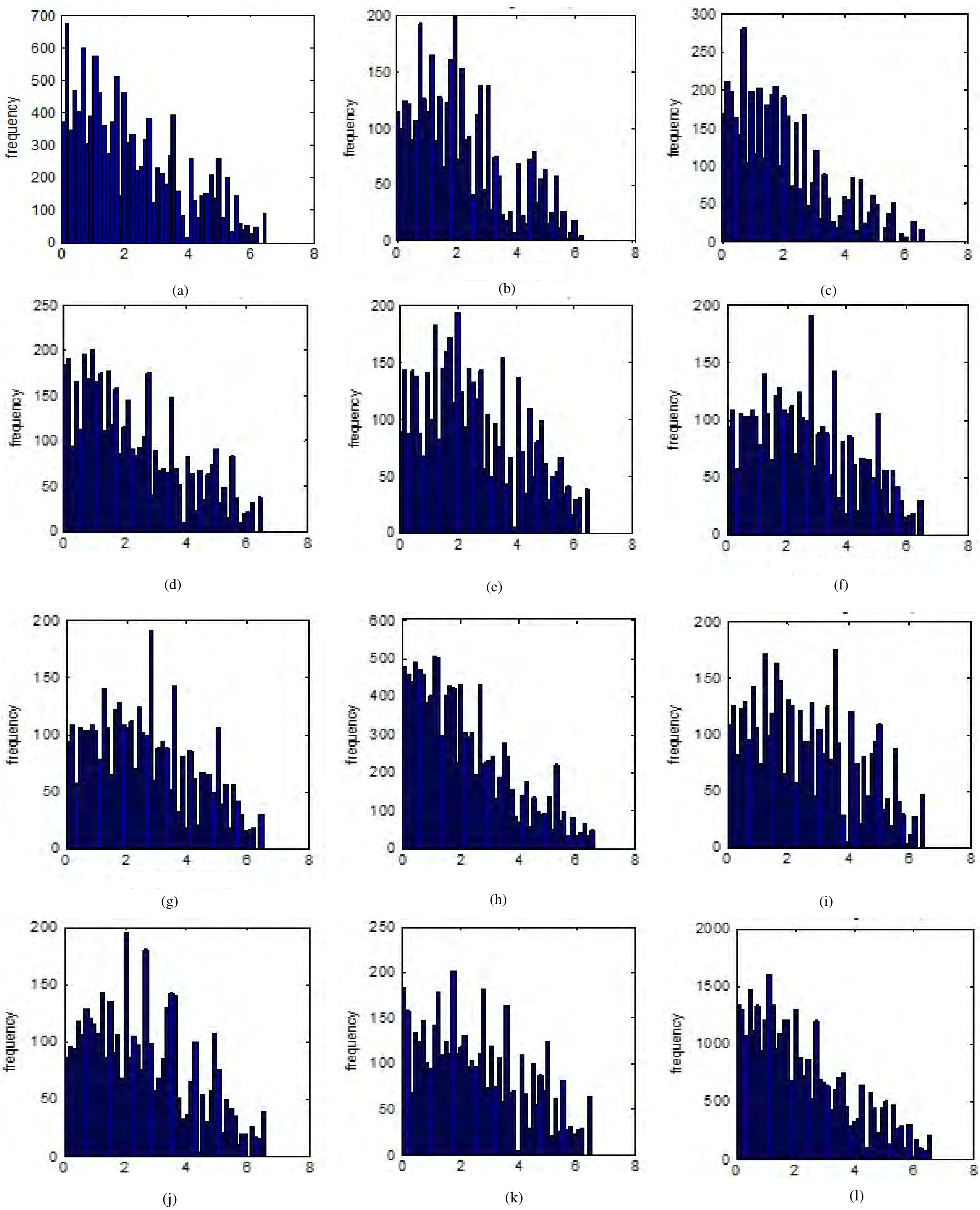



**FIGURE 3.** Frequency distribution of Gaussian score for all 12 classes. (a) Gaussian score for Class_1. (b) Gaussian score for Class_2. (c) Gaussian score for Class_3. (d) Gaussian score for Class_4. (e) Gaussian score for Class_5. (f) Gaussian score for Class_6. (g) Gaussian score for Class_7. (h) Gaussian score for Class_8. (i) Gaussian score for Class_9. (j) Gaussian score for Class_10. (k) Gaussian score for Class_11. (l) Gaussian score for Class_12.

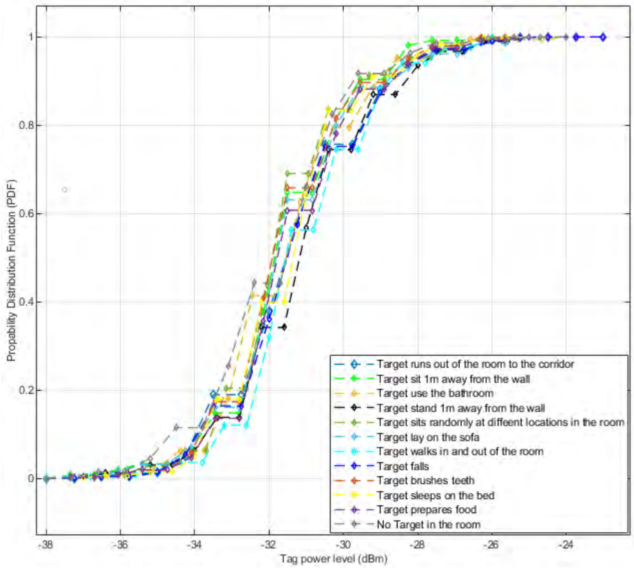



**FIGURE 4.** Frequency distribution for all 12 classes.

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**Algorithm 1** Predict_Class Algorithm: Human Activity Recognition Based on Maximum Likelihood Estimation

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Input: RFID sensor dataset

Compute mean and covariance for the sampled data $\{\bar{y}_i\}$

Sample $N$ points which refer to a number of points that correspond to an instance of ([*rssi, x, z*]) from the distribution of each class using their computed means and covariance matrices.

Sort all *rssi* values into vector $\bar{v}_{1i}$, $x$ values into vector $\bar{v}_{2i}$, and $z$ values into vector $\bar{v}_{3i}$.

Convert each vector computed above to unit vector: $\widehat{v}_{ki} = \frac{\bar{v}_{ki}}{\|\bar{v}_{ki}\|}$

Sample $N$ points from the distribution of $\bar{y}_i$ using the mean and covariance computed in (1) and sort all *rssi* values into a vector $\bar{u}_1$, all $x$ values into a vector $\bar{u}_2$, and all z values into a vector $\bar{u}_3$.

Convert each vector computed in step 4 to a unit vector: i.e.

$$\widehat{u}_k = \frac{\bar{u}_k}{\|\bar{u}_k\|}$$

The correct class to which $\bar{u}$ belongs is the class '$i$' which minimizes the total Frobenius norm i.e. Euclidean norm of the difference between $\widehat{u}_j$ and $\bar{v}_{ji}$.

$$k = ^{\arg\min}_{t \to 1\infty} \sum_{j=1}^{3} \left\| u_j - \hat{v}_{ji} \right\|$$

Return $k$
End $k$

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### E. ACTIVITY CLASSIFICATION

In Figure 3 and 4, we establish that each class has different frequency distribution over the Gaussian score. This shows that the dataset for each class has different frequency distribution over the Gaussian score which is different from other activity class. This observation is restated as:

*Lemma: Datasets of same activity exhibit uniformity but not exact Gaussian score*

From our theorem, if Class A is from newly sampled dataset and Class B is the same activity from the activity database. Class $A$ and Class $B$ is the same activity if their distribution over their Gaussian scores is symmetry though not exact, as Gaussian processes are usually affected by different indoor properties including reflection, multipath effect and object occlusion.

To validate our proposition by evaluating the prediction performance of the proposed algorithm for activity classification, new dataset of all sampled activities are fed into the algorithm. Figure 5(a)–5(l) illustrates the prediction of the new activity dataset. It can be seen from all predicted classes in Figure 5 that the true class possess the lowest Frobenius norm. This is because the Frobenius norm in the proposed algorithm determines how close a sample vector from the *pdf* of the training dataset is to the *pdf* of the newly sampled dataset. The results presented in Figure 5 shows that the total Frobenius norm serves as a reasonable distance function.

## V. PERFORMANCE EVALUATION

### A. EVALUATION METRICS

To evaluate the performance of the proposed algorithm for reliable human activity classification, five key metrics of accuracy, precision, recall, F-score and root mean square error (RMSE) are evaluated.

Accuracy is the most widely intuitive performance metric, as it gives the sum of correct classifications to the total number of instances. Accuracy is often expressed as:

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+TN+FP+TN}} \tag{15}$$

where *TP* i.e. *true positive* represents all sampled activities belonging to positive categories being classified correctly as positive categories. *TN* i.e. *true negative* are all sampled activities belonging to negative categories being classified into negative categories. *FP* i.e. *false positive* are all sampled activities belonging to negative categories being classified as positive categories, and *FN* i.e. *false negative* are all sampled activities belonging to positive categories being classified as negative categories.

To evaluate the accuracy of the proposed algorithm for activity classification, twenty instances of $N$ are fed into the proposed algorithm as shown in Figure 6.

The confusion matrix of the multivariate algorithm shows that the training accuracy is 100% for all output classes, which implies that the training dataset is accurately learned for prediction.

Figure 7 shows the confusion matrix of the testing dataset. From Figure 7, it can be seen that the algorithm performs well in predicting the sampled activities. However, there are

**TABLE 2.** Precision, recall and F-score of the proposed approach for all sampled activities.

| Activity | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 | A9 | A10 | A11 | A12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Precision (%) | 97.74 | 97.17 | 91.15 | 97.45 | 97.56 | 97.65 | 97.24 | 97.77 | 97.51 | 97.44 | 97.63 | 97.38 |
| Recall (%) | 97.50 | 96.93 | 90.91 | 97.21 | 97.32 | 97.41 | 97.00 | 97.53 | 97.27 | 97.20 | 97.39 | 97.14 |
| F-score (%) | 97.61 | 97.05 | 91.03 | 97.33 | 97.44 | 97.53 | 97.12 | 97.65 | 97.39 | 97.32 | 97.51 | 97.26 |

**TABLE 3.** Comparison of performance in the presence of object occlusion.

| | Without object occlusion | With object occlusion |
|---|---|---|
| Precision (%) | 96.97 | 79.23 |
| Recall (%) | 96.73 | 77.90 |

several misclassifications as shown from activity *A2, A4, A6* and A10. The activity misclassification is due to the similarities of those sampled classes.

Precision is a performance metric that gives the ratio of *TP* to the total predicted positive classes. Precision is usually expressed as:

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

It could be stated from Eq. (16) that the algorithm achieves high precision whenever the rate of false positive rate is low. However, it can be seen that A3 has relatively low precision and recall compared to the other activities. This is as a result of *NLOS*, as the activity is performed outside the direct *LOS* of the reader and the SmartWall. Recall or sensitivity shows the ratio of accurately predicted positive classes to all activities in the actual class.

Recall is often expressed as:

$$Recall = \frac{TP}{TP + FN} \tag{17}$$

F-score is a performance metric used to evaluate the classification correctness of an algorithm since human activities are unevenly distributed. F-score measures the weighted harmonic mean of precision and recall by taking both *FP* and *FN* into account and is usually expressed as:

$$F - Score = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall+Precision}} \tag{18}$$

Table 3 shows the F-score of all sampled activities. It can be seen that the proposed method correctly classify the sampled activities.

Root mean square error (RMSE) is another metric used to measure the performance of classification. RMSE represents the difference between the predicted activity classes from the measured class and is expressed as:

$$RMSE = \sqrt{\frac{\sum_{n=1}^{n} \left(X_{predicted,i} - X_{measured,i}\right)^2}{n}} \tag{19}$$

Figure 8 highlight the RMSE of each sampled human activities. It can be seen from Figure 8 that the RMSE of all sampled activities is low, as each RMSE value is below 0.0046. This is indicative of the high performance of the proposed algorithm for reliable HAR.

### B. EFFECT OF OBJECT OCCLUSION

Object occlusion or physical obstruction is a major performance-debilitating factor to ambient sensing. Object occlusion occurs when human and physical objects obstruct the line-of-sight (LOS) of ambient sensors resulting in non-line-of-sight (NLOS), which subsequently affects the performance of such sensors. RFID systems are not affected by NLOS. However, the presence of metallic physical obstruction affects its performance. Therefore, to investigate the effect of object occlusion, twenty instances of the sampled activities are carried out with various physical object placed in front of the SmartWall. The dataset of both with and without physical occlusion are compared. It can be seen from Table 3 that the performance of the proposed system is significantly affected by object occlusion, although the level of accuracy of the proposed algorithm is high. This investigation shows that high accuracy is achieved when there is minimal or no object occlusion between the RFID reader and SmartWall. However, the result presents a strong limitation of the proposed solution.

### C. COMPARISON WITH OTHER SOLUTIONS

We compare our proposed algorithm performance with standard algorithms including SVM, random forest and logistic regression classifiers. Our theory is that a verifiable method adjusted to the RFID user-object interaction would meet the research objective of better performance for human activity classification.

Figure 9 shows the comparison of the proposed method with standard state-of-the-art algorithms. From Figure 9, it can be seen that the proposed method outperforms the standard algorithms of random forest, logistic regression and SVM.

## VI. CONCLUSION

In this paper, we present a novel RFID-enabled data sensing approach for unobtrusive human activity recognition via the SmartWall. The experiments were performed to simulate different real-life activities that comprise of twelve human activities. The activity classification is performed via multivariate Gaussian using maximum likelihood estimation algorithm. The results obtain within the contextual framework of activity recognition using the algorithm demonstrates significant statistical performance. The proposed algorithm exhibits an improved accuracy of 97.9%. The proposed algorithm shows improved performance in comparison with standard state-of-the-art algorithms.

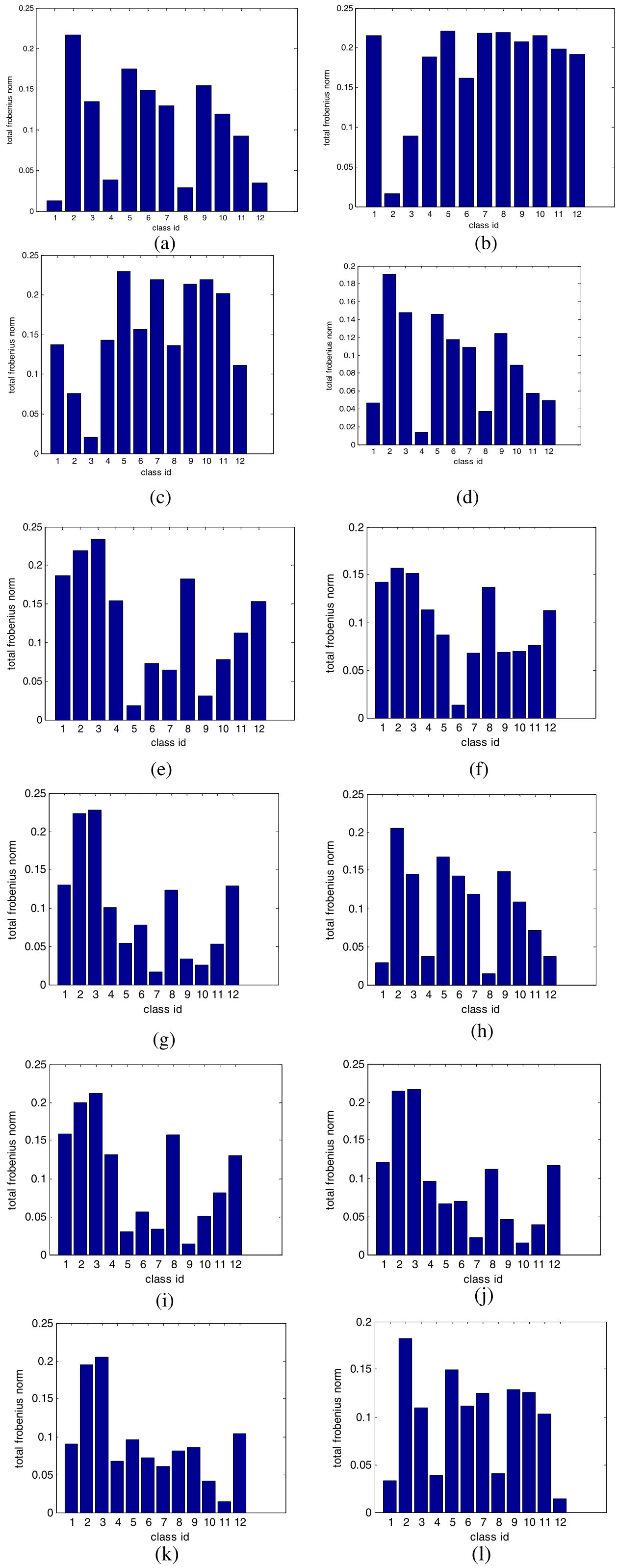


**FIGURE 5.** Frequency distribution of Gaussian score for all 12 classes. (a) Class_1. (b) Class_2. (c) Class_3. (d) Class_4. (e) Class_5. (f) Class_6. (g) Class_7. (h) Class_8. (i) Class_9. (j) Class_10. (k) Class_11. (l) Class_12.

Still, open challenge remains and presents future research queries for AAL solutions using the RFID technology. Among such queries is the development of cost-efficient algorithms and features that reduce the training effort or the amount of required knowledge to apply the RF sensors under a different home setting. A comprehensive investigation of the effect of object occlusion to achieve a more robust activity recognition system is also important. Moreover, a sampling of complex multi-human activities in large indoor areas is critical and timely. Further extension of the present investigation will focus on 3-dimensional data collection and pre-processing for improved data segmentation via deep learning. This would refine the accuracy of the developed algorithm for multiple targets which is timely for industrial HAR.

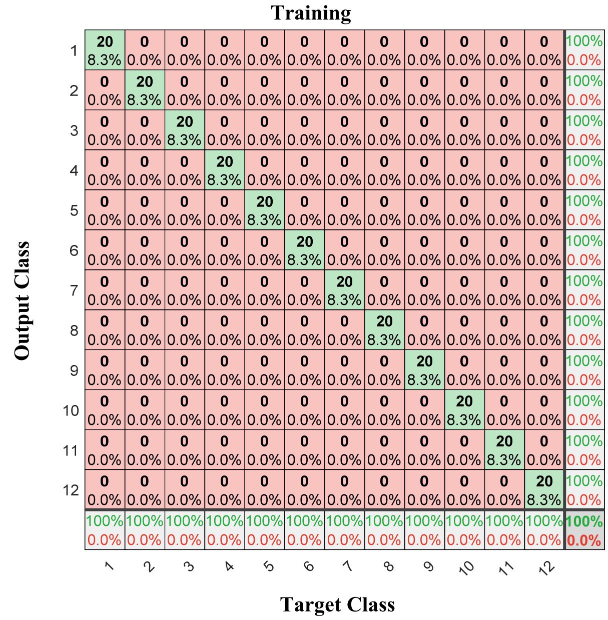


**FIGURE 6.** Confusion matrix of the training dataset.

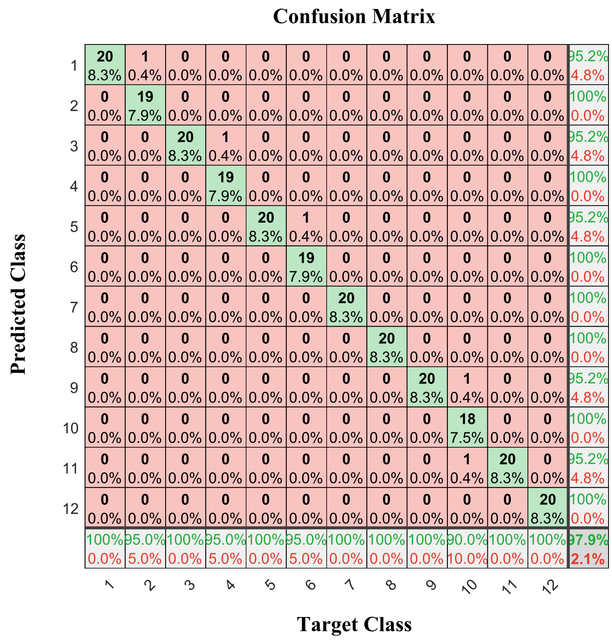


**FIGURE 7.** Confusion matrix of the testing dataset.

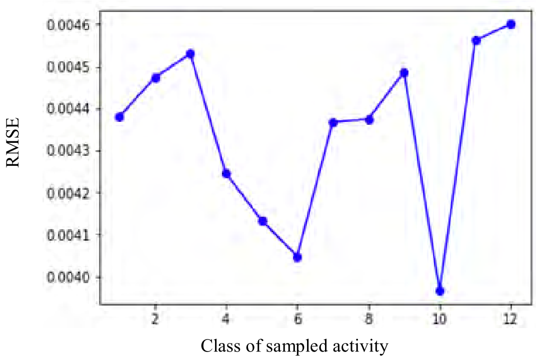


**FIGURE 8.** RMSE of sampled activities.

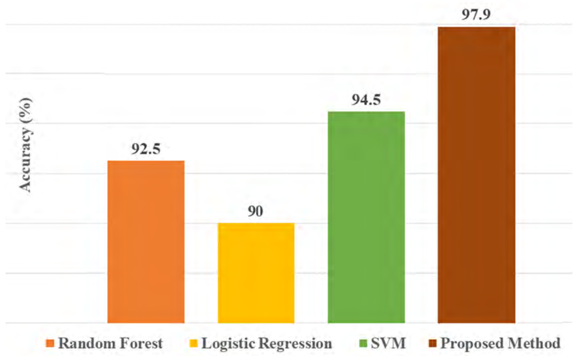


**FIGURE 9.** Comparison of accuracy of the proposed method with standard methods.

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