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Human Activity Recognition Based on Multi-Sensors in a Smart Home Using Deep Learning **

Musbah Aqel[1], and Munsif Sokiyna[2,*]

[1] *Arab University College of Technology, Amman, Jordan.*

[2] *Department of Information Systems, Statistics, and Management Science, University of Alabama, Tuscaloosa, United States.*

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ABSTRACT

Tracking or taking care of elderly people when they live alone is a much more challenging area. Because most aged people suffer from some health issues like Alzheimer's, diabetes, and hypertension, in case happening any abnormal activity or any emergency since they live alone and there is no one around them to offer any support, one of the best choices to care mature people is focusing on smart home technology. Also, one of the essential keys to expanding smart home technology is monitoring, detecting, and recognizing human activities called Ambient Assisted Living (AAL) applications. Nowadays our world highly focuses on a smart system because the smart system can learn habits, and if it finds any problem or any abnormal happenings, it can take automated decisions for residents for example, by learning cooking time, the system can prepare the oven, and by learning spare time which the resident spend for watching, the system can prepare the TV also put it to a favorite channel for the residents. To do this, a new and existing established machine learning and deep learning approaches are required to be estimated the system focusing on using real datasets. So, this study presents machine learning to analyze activities of daily living (ADL) in smart home environments. The data sets were collected from a set of binary sensors installed on two houses. This study used public data sets for detecting and recognizing human activities, the data set was tested based on machine learning classification especially Support Vector Machines (SVM) was applied as the traditional neural network also for deep learning (1-Dcnn) as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) as Recurrent Neural Network (RNN) and was used. Also, sliding window (windowing) was used in the preprocessing phase, the study concludes that all used algorithms can detect some activities perfectly, and on the other hand they can't predict all activities perfectly especially those activities that take short-time, the main key for this situation is imbalanced data.

1 Introduction

Machine learning nowadays is used generally in most of the fields in our lives such as education, business, industry, medical and health-care, so when computers, application or any systems that integrated with machine learning capable of acting without needs of programming by owners because machine learning techniques like deep learning, computational learning, natural language processing voice, vision, and activity recognition after used them to creating algorithms so they can learn from data, making predictions and making decisions based on raw data [1]. One of the main progressive approaches to machine learning is deep learning because traditional learning algorithms faced handcraft features and deep learning can handle it therefore it received much attention in the research area. Deep neural networks (DNNs) or deep learning generally consist of two main parts: a training part that uses the model for improving the accuracy, and a test part that is used for analysis as prediction or classification in the model. Currently, deep learning is used in various applications such as medical prediction, intrusion detection, natural language processing, computer vision, speech recognition, pattern recognition, and big data analytics [2].

Nowadays communities in the world focus on health care that is combined with technology because people's quality of life can be monitored by human activity recognition and more functionalities and features rise in this field gradually, depending on a wide range of software and hardware components. Human activity recognition as a research area has the arrival solutions to support people that suffering from Alzheimer's disease (AD), Motor neuron diseases (MND), Spinal muscular atrophy (SMA), Parkinson's disease (PD), Spinocerebellar ataxia (SCA) and Huntington's disease (HD) Also, quite a lot of solutions and implementation in indoor environments are used to capture the data generated by an intelligent environment when they interacted with residents. Based on the investigation of Activity Daily Life (ADL) the Human Activity Recognition (HAR) has two main objectives which are 1) the classification of the abnormal and normal behavior of individuals can be achieved by the creation of predictive models. 2) provide the required application and device for the medical staff and the caretaker to recognize the activities fulfilled by them and corrective measures and generate protective [3]. It is mandatory to recognize Activities of Daily Living (ADL) based on evaluating performance. Then making Activity Recognition Systems (ARS) be existing to end-users. Then the major problem that is being observed in deep learning there are too many techniques and algorithms that are used to identify activity so finding which one is the best choice and selecting to create a model that perfectly recognizes and predicts human activity for the elderly and disabled people especially when they live individually. In reality, applying only one sensor type in a smart home usually cannot bring enough info for detecting human activities. Therefore, several sensors are required to grant truthful information related to the observed activity. Then, in a smart home, there is a variety of sensors that are used to detect human activity such as fixed sensors, in a smart home because humans do multiple activities at home, so we need multiple sensors to be installed inside a house or building, therefore managing and controlling multiple sensors is significant because at the same time more than one sensor is activated that means simultaneously a lot of human activity is measured, so how we can arrange them based on priority and how do they detect and recognize the normal and abnormal behavior of resident. Classification algorithms are used to implement and generate an activity recognition model to satisfy the problem [4]. Therefore, this article tries to test the datasets by going throw the preprocessing and training process to recognize the characteristics of classification by using traditional machine learning like Support Vector Machine (SVM) and deep learning algorithms like Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM).

2 Background

Most of the devices in the Internet of Things (IoT) consist of sensors, and these are a significant part of perception and recognition. A smart environment without sensors is difficult to manage and encourage, and the connection among multiple sensors will carry on an important character in the future. Also, the activity of our daily lives is directly linked to a smart environment or smart home [5]. Activities of Daily Life (ADL) are defined as "the things we normally do in daily living including any daily activity we perform for self-care activities such as feeding ourselves, bathing, dressing, grooming work, homemaking, and leisure" [6]. The conception of sensors rises in the smart environments, whither a wide range of devices and sensors integrated with regular infrastructure and objects at home-based is linked to technologies by the network to gather useful knowledge about human activities. so those activities that occur in a smart environment must be collected as raw-data then take advantage of deep learning to discover valuable information or detect an emergency. The raw

* Corresponding author.
**The ICCMIT'21 program committee effort is highly acknowledged for reviewing this paper.
Email addresses: musbahaqel@auct.edu.jo, msokiyna@crimson.ua.edu
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data collected from different wearables sensors or various sensors installed in smart homes are saved in datasets. in such a way, different technique of collecting data has been used: binary sensors, audio, and visual or moveable sensors installed on the body such as gyroscopes and accelerometers, among others [7]. In intelligent buildings, two types of sensors are available to use in activity recognition which is: the binary sensor approach and the visual and audio approach. The binary sensors approach is fixed in the smart home environment based on using sensors. Environmental sensors are used to sense human activities in which they are done in specific areas or correlated to specific objects. On the other side, the visual and audio approach contains visual or audio sensor devices, such as cameras and microphones, to focus and find the environmental changes and residents' movements [8]. Activity Recognition Systems (ARS) have been developed for the improvement of sensor innovation, in general, its capability to recognize the states that ascend in circumstances in which individuals interact while fulfilling Activities of Daily Life (ADL). As shown in [9], the applications of ARS in practical are plentiful such as behavior monitoring, stress detection, energy consumption estimation, gait abnormality detection, fall detection [10], and recovery. So, estimating the reliability of Activity Recognition Systems (ARS) is a challenging task in terms of the capability to predict the different activities collected from the data file. Using machine learning in a smart system connecting the gap between domains.

2.1 Types of Sensors

2.1.1 Wearable or On-body Sensors

Most of the research used wearable sensors as the main source of collection of raw data, and mostly focused on using accelerometers [11, 12]. Less have taken benefits from a gyroscope, and magnetometer, also some researchers used and work with other types of motion sensors like barometers [13]. Overall, any module that is used in activity recognition must measure motion in the three-axis (x-axis, y-axis, and z-axis) so to cover the different directions of the device. Therefore, most activity recognition components at least must have a three-axis accelerometer to be used as an inertial measurement unit (IMU), in addition to quota motion on the three-orthogonal axes of any platform or user must have a gyroscope triad. Barometers and magnetometers because of their inaccuracy rates are insufficient on their own but they are useful as assistance to accelerometers and gyroscopes [14].

2.1.2 Environmental Sensors

Various sensors can be attached to a range of objects or installed in different areas of the home to monitor activities in a smart environment. Furthermost Activities of Daily Life (ADL) are completed with specific user and object interactions and in specific locations. For instance, opening and closing a door means individuals interacting with the door (interaction with an object), and sleeping activity usually takes place in the bed (specific space). So, the activity combined with environment observation can be diagnosed from an object and user interactions. For example, if sensors a well-known specify there is water usage in the cook's room and that the oven is on, it can be completely proposed that the activity of cooking is implemented. Then, within a smart home, data can provide notable information to observe human behaviors based on environmental sensors. Because of security and privacy in smart environments, the approval of the technology by the end-users is a serious problem [15]. That is why most of the studies pay attention to binary sensors rather than visual and audio sensors. Then below we discuss the advantages and disadvantages of some sensors and summarize well-known sensors installed in a smart environment for detecting ADLs.

2.1.3 Non-motion Environmental Sensors

A variety of other sensors that are used in smart environments sometimes called Non-motion sensors such as humidity sensors, power sensors, audio sensors, temperature sensors, and light sensors seemed to be used and installed in smart homes to detect the activities inside the house. The disadvantage of Non-motion sensors is that their signals do not represent the person's motion so their signaling represents the environment in whatever human moves [16]. In a pre-known environment, this module is easy to implement and operate, for example, residents are not allowed or expected to carry other light sources in indoors when it's fixed with light sources in immovable locations. These sensors can accomplish perceptive monitoring of objects and environments, but these sensors also offer limited information for recognizing and detecting activity in a smart home.

2.1.4 Temperature Sensor

temperature sensors are useful to measure the temperature of the object and its peripheral environment. In some cases temperature measurements provide false alarms in some motion detection and then decided to abandon them after practicing them based on the classification model, [17] smart environment can take advantage of these sensors system to control the temperature of smart home by using them in Heating ventilation and air conditioning (HVAC).

2.1.5 Humidity Sensor

The benefit of this sensor is to detect the humidity in the air in a specific location. And also used in meteorology stations to predict and report the weather, nowadays a humidity sensor is a part of, ventilating and air conditioning systems (HVAC) systems which can be controlled by a smart environment that also must take aid from other sensors. correspondingly used in museums, humidors, cars, offices, and a smart agriculture environment.

2.1.6 Biosensors

biosensors providing monitor activities to vital signals. Can be used in smart homes, especially in healthcare services, several vital signs including respiratory rate, oxygen saturation, blood glucose, blood pressure, heart rate, and Electrocardiogram (ECG) are associated with them. In down below are some biosensors that are used to measure vital signals:

- Galvanic Skin Response (GSR) for intensive care skin perspiration.
- Thermal sensors are used for monitoring the temperature of the human body.
- CO2 gas sensors for tracking respiration.
- Pressure sensors for monitoring blood pressure.
- Electromyography (EMG) sensors for monitoring muscle activity.
- Electrocardiography (ECG) sensors for tracking cardiac activity.
- Electroencephalography (EEG) sensors for tracking and detecting electrical brain activity.

During the implementation of these activities biosensor's specification can be used to monitor the user's health condition [18]. For instance, Skin temperature is a characteristic technique of observing skin perspiration and fever, it's a well-being measure of housework and sports activities. Respiration monitoring includes measuring airflow through the mouth and nose. The cardiac activity mostly focuses on monitoring heart rate, which provides measure blood pressure and rate or rhythm of your heartbeat, which illustrates sudden changes in the user's health estate like neck or throat bleeding. Also, in another body part, muscle activity may be arising. For instance, penetrating the activity of chin muscles can serve as drinking or swallowing. Also monitoring activity based on brain electrical, beta alpha, and delta waves is mostly used to identify sudden unexplained nocturnal death, panic illness, and sleep state. [16] uses an ECG sensor for the estimation of the stress state of the patient while doing daily activities fixed into a movable device to produce electrocardiographic signals. Services such as diagnosis decision-making, disease prediction, and abnormality detection and the data collected can be provided based on these biosensors. [19] modeled a movable Physiological Sensor Suite (PSS) to detect longstanding states for sick persons with neurological or cardiac cases. [20, 21] they focus on the physiological sensor to measure four bioelectric signals to gather personal health information in healthcare: EMG, EOG, EEG, and ECG. EMG sensor is used to monitor muscle activity which is mostly placed on the upper arms. EOG sensor is used to monitor eye blinking which is built into a glass, an ECG sensor is used to detect heart rate which is built into a belt to detect a signal of health-threatening values. The Biosensors have some advantages such as high accuracy, non-intrusiveness, low error levels, and low cost. Above and beyond, The Biosensors are so accurate to small modifications of physiological signals, besides accordingly they can easily be replaced for continued healthcare monitoring in smart environments. The drawbacks of vital sign sensors contain if used or attaching skin for a long-period uncomfortable feeling and reliability constraints occur.

3 Research Methodology

The data-driven methodology was used utilizing sliding windows to extract features from raw data collected by binary sensors depending on the resident activity and interactive objects with residents. Finally, these results in a time series presented as small segments are divided into train data and test data to fit our models and enhance applied learning. Data were collected in two smart homes named house (A) and house (B) each of them contains some binary sensors (Pressure, Flush, PIR, and Magnetic) to capture and collect information on human daily activity created by the resident in doing their normal activities and their interaction with objects this data previously were used for this work [22]. The raw data has to be set into the correct format, in demand to fulfill raw data to analyze and process. For example, the values are in numeric format gained straightly from a temperature sensor, which in some machine learning and deep learning algorithms is not capable to use. Some of these machine learning and deep learning algorithms demand more accepted types of features like categorical and nominal evaluates. The purpose of processing methods in the raw data is definitely to convert unprocessed data into a fitting qualifies format which fulfills the procedure necessities. For example, [23] convert the analog signals raw data gathered from ECG to digital characteristics after that for added signal analysis. As another example, [24] the raw data received by a motion sensor combined with different format such as (numeric and binomi-

Start time	End time	Activity
2011_11_28 02:27:59	2011_11_28 10:18:11	Sleeping
2011_11_28 10:21:24	2011_11_28 10:23:36	Toileting
2011_11_28 10:25:44	2011_11_28 10:33:00	Showering
2011_11_28 10:34:23	2011_11_28 10:43:00	Breakfast
2011_11_28 10:49:48	2011_11_28 10:51:13	Grooming
2011_11_28 10:51:41	2011_11_28 13:05:07	Spare_Time/TV
2011_11_28 13:06:04	2011_11_28 13:06:31	Toileting
2011_11_28 13:09:31	2011_11_28 13:29:09	Leaving

Figure 1. Sample of raw-data activity in house (A)

Start time	End time	Activity
2012_11_11 21:14:00	2012_11_12 00:22:59	Spare_Time/TV
2012_11_12 00:24:00	2012_11_12 00:43:59	Spare_Time/TV
2012_11_12 00:48:00	2012_11_12 00:49:59	Grooming
2012_11_12 00:50:00	2012_11_12 01:51:59	Spare_Time/TV
2012_11_12 01:52:00	2012_11_12 01:52:59	Grooming
2012_11_12 01:53:00	2012_11_12 01:53:59	Toileting
2012_11_12 01:54:00	2012_11_12 09:31:59	Sleeping

Figure 2. Sample of raw-data activity in house (B)

nal) so this sensor include numeric data which cannot be implemented in the association learning approach. This issue was solved by using the association rule learning method to model representative behaviors of residents for smart environment systems.

4 Analysis and Discussion

Traditional neural network (SVM) algorithm and deep learning (CNN and LSTM) algorithm was used to recognize and predict, the procedure starts by collecting data on human activity of daily life, then the data was received by two houses (A and B) which collected by binary sensor determined by two people who each of them stayed in a different house. Data was collected from two smart homes, inside these two houses binary sensors are installed so that we're able to gather information based on the movements of the human who lives inside the house, also some sensors are activated and capture the information when the resident's interactions with objects in the house like devices, and tools. So, as shown in (Figure 1), in the house (A), (9) Activities of Daily Life (ADL) were recorded in (14) days for around (20,000) minutes were labeled as (Breakfast, Grooming, Leaving, Lunch, Showering, Sleeping, Snack, Spare Time, Toileting) which those activity received by (12) binary sensors placed at (Living Room, Bathroom Room, Bedroom Room, Entrance, And Kitchen) as showed in (Figure 1 and Figure 2) and type of sensors are (Pressure, Flush, PIR and Magnetic) then installed them in specific location (Bed, Cabinet, Cooktop, Cupboard, Fridge, Main Door, Microwave, Seat, Shower, Toaster, Toilet, And Basin). Also, as presented in (Figure 3) In house (B), (10) Activities of Daily Life (ADL) were recorded in (22) days around (30,500) minutes were labeled as (Dinner, Lunch, Breakfast, Grooming, Spare Time, Showering, Toileting Sleeping, Leaving And Snack) home B has one more activity if compared with home A which is (Dinner) then those activity received by (12) binary sensors placed at (living room, bathroom room, bedroom room, entrance, and kitchen) and some types of sensors that presented in (Figure 3 and Figure 4) used are (Pressure, Flush, PIR and Magnetic) and installed them in specific location (basin, bed, cupboard, door, fridge, main-door, microwave, seat, shower, and toilet). Then after data is collected from sensors, the next phase is preprocessing, in my study, the raw data collected from the sensing stage

Start time	End time	Location	Type	Place
2011_11_28 02:27:59	2011_11_28 10:18:11	Bed	Pressure	Bedroom
2011_11_28 10:21:24	2011_11_28 10:21:31	Cabinet	Magnetic	Bathroom
2011_11_28 10:21:44	2011_11_28 10:23:31	Basin	PIR	Bathroom
2011_11_28 10:23:02	2011_11_28 10:23:36	Toilet	Flush	Bathroom
2011_11_28 10:25:44	2011_11_28 10:32:06	Shower	PIR	Bathroom
2011_11_28 10:34:23	2011_11_28 10:34:41	Fridge	Magnetic	Kitchen
2011_11_28 10:34:44	2011_11_28 10:37:17	Cupboard	Magnetic	Kitchen
2011_11_28 10:38:00	2011_11_28 10:42:41	Toaster	Electric	Kitchen

Figure 3. Data based on sensors (location, type, and place) in the house (A)

Start time	End time	Location	Type	Place
2012_11_11 21:14:21	2012_11_12 00:21:49	Seat	Pressure	Living
2012_11_12 00:22:57	2012_11_12 00:22:59	Door	PIR	Living
2012_11_12 00:23:14	2012_11_12 00:23:17	Door	PIR	Kitchen
2012_11_12 00:24:20	2012_11_12 00:24:22	Door	PIR	Kitchen
2012_11_12 00:24:42	2012_11_12 00:24:54	Door	PIR	Living
2012_11_12 00:25:35	2012_11_12 00:42:56	Seat	Pressure	Living
2012_11_12 00:43:46	2012_11_12 00:43:49	Door	PIR	Living
2012_11_12 00:46:12	2012_11_12 00:46:15	Door	PIR	Bedroom
2012_11_12 00:47:21	2012_11_12 00:47:24	Door	PIR	Bedroom
2012_11_12 00:48:38	2012_11_12 00:50:12	Basin	PIR	Bathroom

Figure 4. Data based on sensors (location, type, and place) in the house (B)

Location	Type	Place	start_time	end_time
Bed	Pressure	Bedroom	2011-11-28 02:27:59	2011-11-28 10:18:11
Cabinet	Magnetic	Bathroom	2011-11-28 10:21:24	2011-11-28 10:21:31
Basin	PIR	Bathroom	2011-11-28 10:21:44	2011-11-28 10:23:31
Toilet	Flush	Bathroom	2011-11-28 10:23:02	2011-11-28 10:23:36
Shower	PIR	Bathroom	2011-11-28 10:25:44	2011-11-28 10:32:06

Figure 5. The raw data before using dummy coding

are pre-processing to achieve a better result and easier for feature extraction and classification. As a first step of preprocessing, we used a dummy variable to transform raw data based on the model's raw data that must be set into the correct format. In demand to fulfill raw data to be ready for the next phase which is to train and test data to predict and recognize, we used dummy coding for converting a categorical variable as input into a continuous variable as the output called time-series data. For example in the house (A and B) raw data has a column called (Type) which means the type of sensor as shown in Figure 5, so by implementing dummy coding it created four columns based on the total number of type of sensors which are four after completed the entire raw data changed to two variable (0) and (1), then as shown in Figure 6 as a sample, if the type of sensor is magnetic then column type-magnetic value is (one) at the same time all other columns sensor type represented by (zero). We used and implemented sliding data windows as the timeline of the activities is segmented in time slots, for home (A) I use the window

Type_Electric	Type_Flush	Type_Magnetic	Type_PIR	Type_Pressure
0	0	0	0	1
0	0	1	0	0
0	0	0	1	0
0	1	0	0	0
0	0	0	1	0

Figure 6. the raw data after using dummy coding

```
2011-11-30 14:39:42    2011-11-30 14:55:24

[Timestamp('2011-11-30 14:39:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:40:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:41:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:42:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:43:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:44:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:45:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:46:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:47:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:48:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:49:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:50:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:51:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:52:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:53:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
[Timestamp('2011-11-30 14:54:42'), 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0]
```

Figure 7. An example of a sliding window in binary sensors

```
# # These are the 3 errors:
# # < 2011-12-01 19:28:51    2011-12-01 16:29:59 Toileting
# # > 2011-12-01 19:28:51    2011-12-01 19:29:59 Toileting

# # < 2011-12-02 12:20:41    2011-12-01 10:20:59 Grooming
# # > 2011-12-02 12:20:41    2011-12-02 12:20:59 Grooming

# # < 2011-12-02 12:27:47    2011-12-01 11:35:49 Breakfast
# # > 2011-12-02 12:27:47    2011-12-02 12:31:49 Breakfast
```

Figure 8. Capture error data activity in-house (A)

size $\Delta t = 60$s, formulated the common source [4, 13]. The same time for home (B) delta time $T = 3$s, this to different provide us two different sample data one contains more sample over other, Time slot based consists of dividing the raw data sensor into equal time duration as chunks which showed in Figure 7 This time slot length is selected by considering activity accurate labeling criteria and discrimination of raw data. After checking all my raw data for finding missing values, redundant information, or any error values, I find three errors in data raw activity in-house (A) then the others were free of errors this fault happens at the time recording of activity and the raw data was enhanced and corrected by used manual handcraft which both error and correction are shown in Figure 8. Based on my investigation in human activity recognition using machine learning I decided to use three different types of classification each model has independent feature and make them unique, as well one of the algorithms we used was Support Vector Machine (SVM) this model was selected as traditional machine learning because this SVM is one of most advanced version in the artificial neural network, one of the main key that makes me decided to select this classification was to achieve high accuracy, Also as deep learning I selected and tested two different types of deep learning, one of them is 1-Dimensional CNN selected as Convolutional Neural Networks because 1-D CNN was so suitable to be used in binary sensors if we compared with other types of Convolutional Neural Networks this model can directly handle the raw data time-series in another word, didn't require to has domain expertise as to manually input engineer features. The final classification used to predict and recognize activity was Long Short-Term Memory (LSTM) this model is used as Recurrent Neural Networks (RNN) the vital benefit of LSTM which made me to decided and choose it because this model can solve the vanishing gradient problem over the processing of information that takes a long time, in other models if the time duration of the process information is taking too long then gradually the prediction was useless. All chosen classifiers can accept and handle binary data and their results were compared with each other's to appraise the performance of all recommended approaches, as well as evaluate the performance of each class activity (like sleeping and showering) the results are well-known measured based on most known metrics which used to evaluate the model's performance. A confusion matrix: is used to evaluate the performance of a classifier the results are represented as a table this metric involves a set of data tests to find correct and incorrect predictions. It easily allows identification of confusion between classes e.g. one class is usually mislabeled as the other. By testing the classifiers based on the confusion matrix the summary of prediction result on a classification error was shown, which means I am not only evaluating the performance of the classifier correspondingly I evaluate all activity classes, It was represented by the number of true and false values with counting them and broken-down based on each activity class as showed in Figure 9. The confusion matrix was very important to every researcher because besides being through the errors continued existence of a classifier also makes predictions and more powerfully represented which kinds of errors are happening. Also, which one of your classification models was confused. As illustrated in Figure 10 the confusion matrix in-home (B) was shown as three matrices each of them related to their classifier which are SVM, 1-Dcnn, LSTM, then in Figure 11 the confusion matrix in-home (A) was represented. The diagonal lines represent the activities that are correctly identified by the classifier. Because the confusion matrix overlaps with others or to learn the model, not enough training data is available, So the matrix indicates several activities are challenging areas. While some activities were recognized accurately if compared with others, this is because certain activities, such as leaving and showering, have a clearly stable spatial-temporal signature. In matrix confusion several values and terms must be declared to better understand them: Negative (N) and Positive (P).

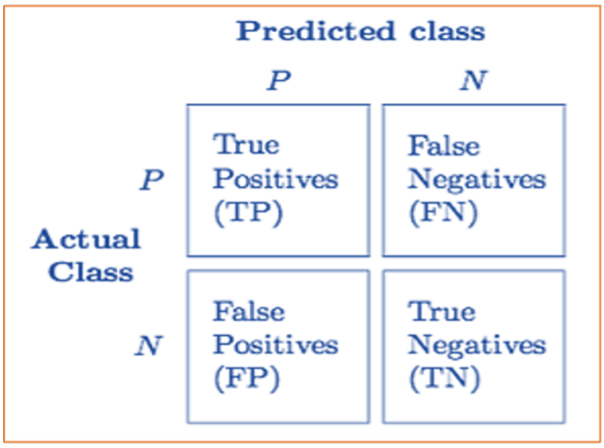

Figure 9. confusion matrix

Definition of the Terms:
Positive (P): measurement is positive (for example this activity is sleeping).
Negative (N): measurement is not positive (for example this activity is not sleeping).
False Positive (FP): measurement is negative, but is predicted positive.
True Negative (TN): measurement is negative, and is predicted to be negative.
True Positive (TP): measurement is positive, and is predicted to be positive.
False Negative (FN): measurement is positive, but is predicted negative.

- Recall (Sensitivity) = $\frac{TP}{TP+FN}$, a useful metric when you are involved in predicting the positives right. The best performance has less false negatives as possible.
- Precision= $\frac{TP}{TP+FN}$, that shows precise is positives in your prediction.
- F1- Score= $\frac{2*Precision*recall}{Precision+recall}$, a good metric, because it judges the result, got either high False Negatives and False positives.
- Accuracy= $\frac{TP+TN}{TP+FN+FP+TN}$, that its Benefits is to know what percentage of the predictions are correct.

In this study, the datasets in both houses were divided to train sets and test sets the train used 80% of the dataset, and the remaining data which was 20% used to test in all classifiers, also, LSTM is used and improved in the tests by assembling an LSTM layer followed by a fully-connected and 0.001 used as learning rate with 50% dropout rate As the same time for SVM Classification I set class weight=None, fit intercept=True, max. iteration=1000, penalty=l2, random state=None, and tolerance rate was (0.0001), this was selected as a default setting must of programmer and package set the same, likewise in 1-Dcnn classifier batch size =200 in the house (B) but in house (A) batch size =100 because the sample created in the house (B) was huge and greater so We used bigger batch size because I wanted at the end the number of cycle iteration near to equal number in both homes. In house (A) as I noticed that (LSTM) algorithm performance and f1-score was so low because some of the class activity is not recognized at all by this classifier that means the value was (0) like ("Toileting") in-home (A) also the same issues appear in ("Toileting" and "spare time/TV") class activities in-house (B) (SVM) algorithm, again the same matter happen in-house (B) of classifier (LSTM) class activity ("Toileting") which show zero as result to all of them related to the common problem, this type of error means the data was imbalanced which this is significant issue in binary data and imbalanced design mean which has an unequal number of observations per class activity as shown in Figure 12 and Figure 13, Figure 14 and Figure 15, Figure 16 and Figure 17 for instance, that means the data contain less activity in ("Toileting" and "spare time/TV") in data house (B) also ("Toileting") in data house (A) f1-score, recall and precision have zero value if we compared with others

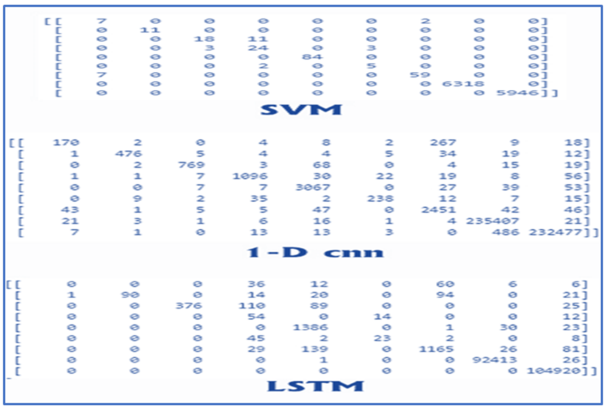

Figure 10. Confusion matrix in house (A)

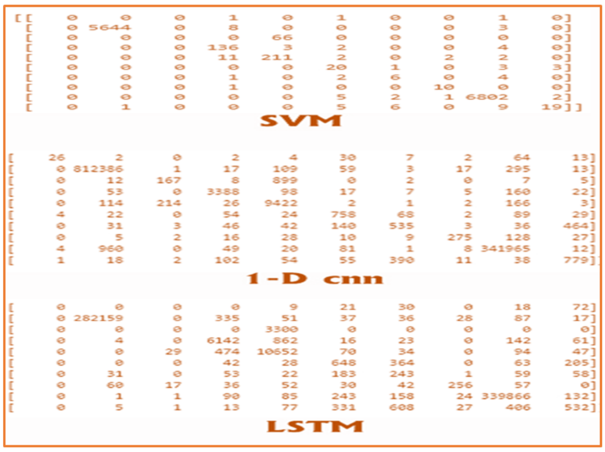

Figure 11. Confusion matrix in house (B)

activity. As can be seen, precision and recall values are lower for SVM, LSTM, 1-DCNN algorithms in the house (B). Furthermore, diving and windowing in house (B) is taken a long time during implementation, by the way (LSTM) means Long Short-Term Memory we can see this in-house (B) which Total f1-Score= 69% and SVM f1-score=65% and 1-Dcnn f1-score= 64% at the end to achieve better performance data sample when the sampling was huge the best classifier is LSTM, also the means house (B) has to be a fine-tuning in preprocessing phase and also training better phase before putting into the algorithms to execute data raw. On the other side, in-house (A) the measurement of f1-score was 61% for LSTM, 87% for 1-Dcnn, and 85% for SVM in here 1-Dcnn as deep learning has the highest value to predict the activity, the second one is SVM and the last one was LSTM this means when the sample was a little or small the best algorithm to be selected among them was 1-Dcnn. For activities ("showering") and ("leaving") in-house (B), all algorithms (SVM, LSTM, and 1-DCNN) recall= 100%, precision= 100%, and f1-score= 100% mean this activity was detected perfectly by all of the three classifiers, when Precision for activity was (1), that one shows during detection process there are no false positives. Recall, precision and f1-score for activity ("sleeping" and "spare time/TV") was (100%) in the house (A) for all classifiers. Precision for activity ("Leaving") in-house (A) based on (1-Dcnn) algorithm was a little smaller, there was false positive activity detected. Due to class activity ("Toileting"), False positives were detected and greater in the house (A) then the precision = 50%, 70%, and 0% based on algorithms (SVM, 1-Dcnn, and LSTM) at the same time in the house (B) the precision= 0%, 37% and 0% were detected based on algorithms (SVM, 1-Dcnn and LSTM), also the best activity was sleeping because perfectly detected very well by all classifiers which mean they can detect and recognize abnormal activity in sleeping for example in the sleeping take much longer than a normal day then sensor and all three classifiers can safely focus on them in case of illness which the person stay longer at one place or bed than normal days or if danger situation happens during sleeping by the resident.

5 Conclusions

Human activity recognition is a much more challenging area and prediction algorithms in smart environments with binary sensors are one of the valuable approaches to achieving better performance. Also, human activity recognition is a talented research area because it can participate in various applications including smart environments, emergencies, elderly care, health care, context-aware systems, security system, and surveillance. A higher prediction precision is the

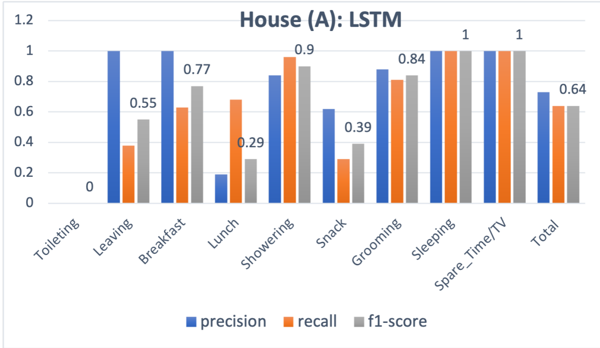

Figure 12. Recall, precision, and f1-score for LSTM in the house (A)

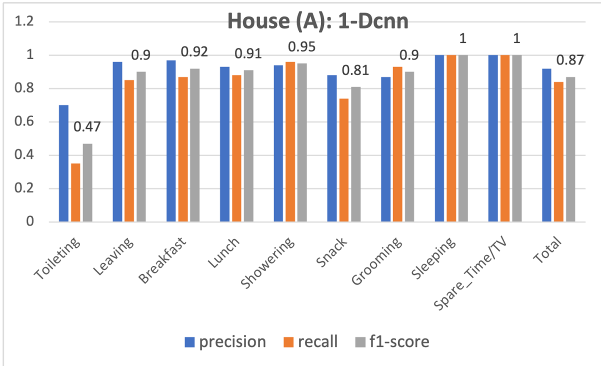

Figure 13. Recall, precision, and f1-score for 1-Dcnn in the house (A)

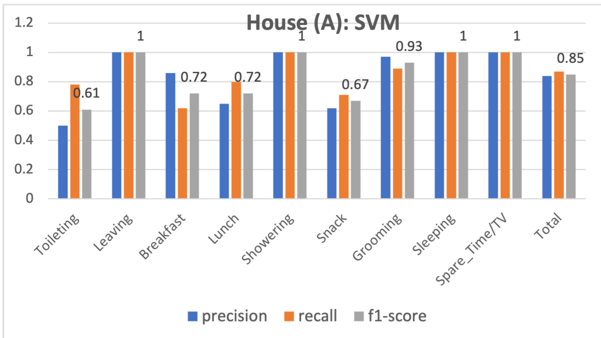

Figure 14. Recall, precision, and f1-score for SVM in house (A)

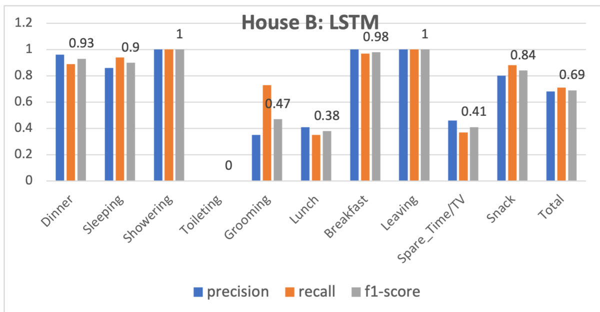

Figure 15. Recall, precision, and f1-score for LSTM in the house (B)

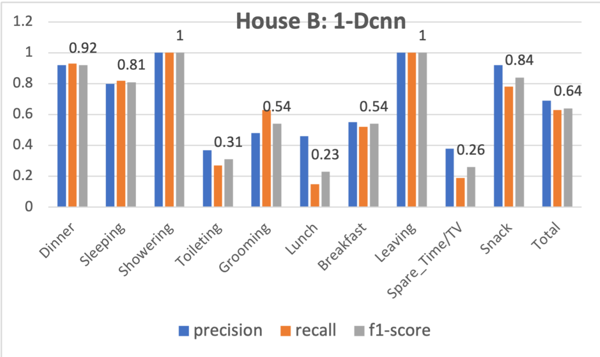

Figure 16. Recall, precision, and f1-score for 1-Dcnn in the house (B)

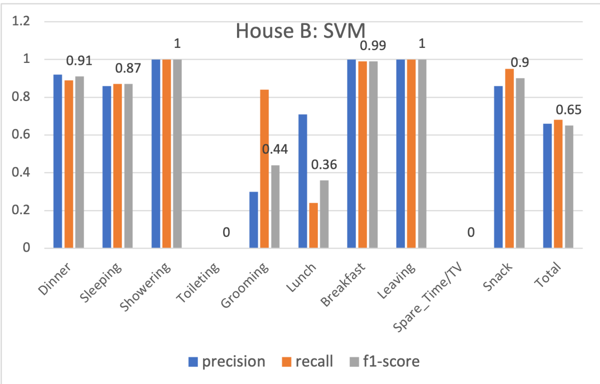

Figure 17. Recall, precision, and f1-score for SVM in the house (B)

essential part before algorithms are valid in the real house. confusion matrix used to capture significant metrics to test and evaluate my output and predict accuracy such as (f1-score, recall, and precision). All of the work informed in the study has been carried out using data collected in real-house environments. In this study, sliding window segmentation in preprocessing phase is used with delta T=60s in house A and delta T=3s in house B, also, the results are presented based on binary sensor, and prediction on data from two smart houses was collected using 24 binary sensors which installed equally in both houses, in the house (A) concluded data for twelve days and for the house (B) twenty-one days. For machine learning classification, Support vector machines (SVM) are applied as the traditional neural network also recurrent neural network (RNN), and convolutional neural network (CNN) as deep learning was used, overall the highest accuracy was achieved (99%) and the prediction was (73.33%). Then all classifier prediction, recall, and f-score accuracy were compared with each other's and investigated whether each of the classifiers can recognize some of the activities in the best way and how to recognize some of the activities. The differentiation in delta (T) provide us with different data sampling so when We used all algorithm the result showed LSTM has a great response to detecting activity when data is huge, in another side when the data isn't much bigger the best algorithm is also among deep learning classification 1-Dcnn in conclusion, a deep learning classifier has better prediction and recognition of human activity than traditional machine learning.

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Musbah J Aqel, Dean of Arab University College of Technology, Amman-Jordan. His main research interests are Expert System, Security Algorithm for Computer Networks, and E-business Software Applications. He is served Editorial Board and refereed in some international journals.

Munsif Sokiyna, Graduate research assistant at University of Alabama, Department of information systems, statistics, and management sciences, Tuscaloosa, United states. Sokiyna obtained his bachelor's degree in Management Information System (MIS) from Jordan. Then he obtained his master's degree in Electronic Business (E-business). His main research interests are Cloud computing, Big Data, and Business Analytics.