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A Hybrid and Context-Aware Framework for Normal and Abnormal Human Behavior Recognition

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Abstract

Human behavior recognition is one of the significant components of Ambient Assisted Living (AAL) systems and personal assistive robots allowing to improve the quality of their lives in terms of safety, autonomy, and well-being. A critical aspect of preventing dangerous situations for users, especially elderlies, is to recognize abnormal human behavior. In spite of the extensive exploration of abnormality recognition in various fields, there remain some challenges in developing effective approaches for recognizing abnormal human behaviors in AAL systems due to the limitations of data-driven and knowledge-driven approaches. In this paper, a context-aware framework combining data-driven and knowledge-driven approaches is proposed to better characterize human behaviors and recognize abnormal behaviors using commonsense reasoning while considering human behavior context. The proposed framework comprises five main modules, which leverage Long Short-Term Memory (LSTM) models and Probabilistic Answer Set Programming (PASP)-based commonsense reasoning to recognize human activities and represent abnormal human behaviors, as well as reason about those behaviors. The proposed framework is evaluated using two datasets, namely *Orange4Home* and *UCI HAR*. The obtained results indicate the capability of the proposed framework to characterize human behaviors and recognize abnormal human behaviors with high performance.

Keywords: Human activity and behavior recognition, Context-aware framework, Machine-learning models, Ontology, PASP

1 INTRODUCTION

Ambient Assisted Living (AAL) systems are designed to enhance people's lives by improving their safety, well-being, and autonomy [1], [2], [3]. Designing AAL systems that can automatically recognize human activities, human behaviors, and abnormal human behaviors with considering the user's context results in many challenges. The concept of context is defined by A. K. Dey as any information that describes the situation of an entity. It can include a person, place, or object associated with the interaction between a user and an application, including the user and the application itself [4].

Researchers have paid considerable attention to abnormal human behavior recognition approaches in a variety of applications, such as healthcare [5] and AAL systems [6]. These approaches aim to detect unexpected behaviors of a user as they are different from his/her usual behaviors [5]. Since people usually follow daily routines [7], changes in their routines can be an indication of a health issue or a dangerous situation [8]. It is critical to recognize abnormal human behavior in order to prevent users, especially the elderly, from becoming in danger. The existing approaches for abnormal human behavior recognition can be classified into two groups: (1) non-vision-based approaches [9] and (2) vision-based approaches [10], [11], [12]. In this paper, we focus on the first group due to several limitations associated with vision-based abnormal human behavior recognition approaches [13], [14], such as visual occlusions and privacy concerns.

Unexpected or unusual behavior in humans is classified as abnormal, and can indicate underlying health issues or hazardous incidents [8, 15]. For example, a sudden loss of appetite, excessive sleeping, or a significant decrease in physical activity levels could indicate an underlying health issue or potentially hazardous incident. For AAL systems to accurately detect such behavior, they require advanced reasoning and data analytics capabilities to consider the context of human activity and behavior. The primary necessity to recognize abnormal human behaviors is human behavior recognition. The latter enables AAL systems to learn about the behavior of users and provide suitable assistance services. For instance, human behavior recognition is necessary to help users maintain a healthy lifestyle, and consequently, help them prevent and manage chronic diseases [16]. Despite the fact that human behavior and human activity are often used interchangeably in the literature [17], [18], [19], there are few existing studies that distinguish these two terms; in general, human behavior refers to a person's frequent activities in many different situations [20] or activity routines [21], [20], [6]. This definition is general and doesn't consider different attributes of human behavior context. Therefore, proposing comprehensive and machine-understandable definitions of normal human behavior and abnormal human behavior that consider different attributes of human behavior context [22] is the main challenge in recognizing normal and abnormal human behaviors. Our proposed definition of abnormal human behavior includes six different types : (i) unexpected recurrent activities in specific locations, (ii) unexpected recurrent activities involving specific objects, (iii) unexpected recurrent activities at specific times of day, (iv) unexpected recurrent activities of specific durations, (v) unexpected recurrent activities with specific frequencies per day, and (vi) unexpected recurrent sequences of activities. In the human behavior and abnormal human behavior recognition domains, handling the uncertainty of captured context attributes and recognized human activities is significant. Moreover, handling the uncertainty of sensor data is considered as a primary requirement, since human activities and behaviors are generally recognized by exploiting data collected from sensors worn by the user or disseminated in the environment. Sensor data are usually subjected to some level of imperfection due to the hardware restrictions of sensors. In addition, the quality of sensor data is often reduced by sensor failures or malfunctions. Therefore, handling imperfect sensor data is a requirement to reduce information misunderstandings [23]. While existing approaches to human activity and behavior recognition have made significant progress, they are still limited in their ability to accurately identify and classify abnormal behaviors in complex, real-world environments. This is due in part to challenges such as variability in human behavior and the difficulty of detecting subtle or context-dependent cues. Additionally, current approaches often do not consider the various contextual attributes of human activity, such as location, involved objects, duration, frequency, time of day, and sequence of human activities. Although some studies have considered some of these contextual factors [24], [6], most of these existing approaches do not allow for handling uncertainty in activity predictions, making it difficult to apply them in real-world scenarios. By addressing these limitations, our proposed framework has the potential to improve the accuracy and usefulness of abnormal human behavior recognition systems. In this paper, to deal with these limitations, a hybrid and context-aware framework exploiting the advantages of data-driven and knowledge-driven approaches is proposed to recognize human behaviors and abnormal human behaviors. In this approach, machine-learning models are exploited to recognize human activities, and ontology and commonsense reasoning are used to capture context and recognize normal and abnormal human behavior. The proposed framework is evaluated using two datasets, namely *Orange4Home* [25] and *UCI HAR* [26] datasets in terms of precision, recall, F-measure, and accuracy.

The contributions of this paper are as follows:

- Development of a hybrid and context-aware approach for recognizing human behavior, which incorporates context attributes using machine-learning models, HAT ontology, and PASP.

- Development of a hybrid and context-aware approach for detecting abnormal human behavior, which considers human behavior context and handles uncertainty in activity predictions and abnormal human behavior rules using probabilistic reasoning.
- Evaluation of the proposed framework for recognizing human activities, human behaviors, and abnormal human behaviors using two datasets, namely *Orange4Home* [25] and *UCI HAR* [26] datasets, based on precision, recall, F-measure, and accuracy.

The remainder of the paper is structured as follows: In section II, we review related works in the field of Human Activity Recognition (HAR), human behavior, and abnormal human behavior recognition. Section III provides an overview of the datasets used in this study. In section IV, we detail the proposed framework. Section V presents the results of the experiments conducted to evaluate the framework's performance. Lastly, in section VI, we discuss the conclusions and future perspectives of our research.

2 Related Works

This section presents and analyzes the state-of-the-art human activity, human behavior, and abnormal human behavior recognition domains.

2.1 Human Activity Recognition (HAR)

The human activity recognition approaches can be classified into three main categories [27]: (1) data-driven approaches [28], (2) knowledge-driven approaches [29], and (3) hybrid approaches [30], [31]. Data-driven approaches strongly depend on data, which is usually subject to different imperfections: imprecision [32], uncertainty, ambiguity [32], incompleteness, conflict, etc. Many machine learning models are used in HAR domain to cope with mentioned problems such as Support Vector Machine (SVM) [33], Naive Bayes (NB) and K-Nearest Neighbour (K-NN), [34], Decision Tree (DT), K-mean [35], Random Forest (RF) [28], Hidden Markov Models (HMMs) [36]. Several deep learning models are also used in HAR domain such as a Convolutional Neural Network (CNN) model in [37] or CNN-LSTM models in [38] and [39]. In [40], an intelligent attendance monitoring system is proposed which uses spatio-temporal human action recognition, combining skeleton gait, multi-action body silhouette, and face recognition. It utilizes temporal weighted KNN and multiple KNN algorithms. In [41], an overview of the latest research and developments in the field of human activity recognition and behavior analysis is provided. A novel context-aware mutual learning method is proposed in [42] to address three important issues: overfitting, distribution deviation, and lack of contextual information, which are the main problems of data-driven approaches. The proposed method uses a semi-supervised mutual learning framework to reduce overfitting by training the main and auxiliary networks together with supervised information from each other. It also introduces a distribution-preserving loss to prevent deviation of the distribution by minimizing the distance between predicted and labeled class distributions. Lastly, a context-aware aggregation module is adopted to extract richer information from a broader range of sequences. In [43], different data-driven HAR approaches are reviewed for processing data from supervised, unsupervised, ensembled, deep, reinforcement, transfer learning, and metaheuristics approaches.

Knowledge-driven approaches do not depend on data, but they rely on the experts' knowledge. In these approaches, activities are recognized using knowledge representation and automated reasoning models [44]. These approaches have evolved from earlier attempts in First-Order Logic (FOL) [45] towards more formal logic models [46]. The main advantage of these approaches is their ability in knowledge representation and in verifying the correctness of properties in their axiomatizations [47]. In [48], an Event Calculus (EC)-based framework is proposed for modeling high-level activities, consisting of more than one event performed consecutively or simultaneously. In this framework, sensor data are analyzed to recognize the occurrence of events; the recognized events are then exploited by a reasoning engine for identifying high-level activities, such as having breakfast. In [49] and [50], EC is exploited to recognize long-term activities. Ontologies have been broadly exploited to infer human activities due to their powerful semantic representation of real-world and reasoning capabilities [51]. In [52], an ontology is used to model sensors and activities as classes considering object-based and location-based concepts of activities; these concepts are exploited by reasoning approaches to recognize human activities. Different ontologies are proposed in the literature to represent different human activity concepts in [53], [54].

In [55], the advantage of ontology-based approaches in comparison to data-driven ones [55] are presented. This study also shows that the use of ontologies in case-based reasoning approaches allows dealing with the overfitting problem in machine-learning-based approaches in the case of a small set of labeled training data [56]. In [57], Web Ontology Language (OWL)-Description Logics (DL) is used to recognize high-level activities by exploiting context features that allow modeling certain aspects of the physical environment. This study indicates how expressive, sound, and decisive algorithms can be exploited to detect inconsistencies among context features and recognize human activities. Ontological representations provide the means to reuse a commonly agreed definition of activity concepts. The expressiveness limitations of OWL 1 have been recognized in various fields; therefore, this language was extended while keeping the decidability of its OWL 1 DL fragment. The result of this extension is the language OWL 2. OWL 2 introduces new functionality in comparison to OWL 1; some of the additional features are syntactic sugar that makes things easier to read or to express, e.g., disjoint union of classes, while others offer new expressivity, including keys, property chains, richer data types, richer data ranges, qualified cardinality restrictions, asymmetric property, reflexive property, and disjoint property, and enhanced annotation capabilities [58]. In [54], the use of OWL 2 is investigated for recognizing high-level activities. In [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], and [29], human activities are recognized using ontology-based approaches. In [69], the proposed approach utilizes domain knowledge, ontologies, and semantic reasoning for both coarse-grained and fine-grained activity recognition. The authors analyze the characteristics of smart homes and human activities, present a generic system architecture, and describe the underlying ontology-based recognition process. The paper [70] provides a comprehensive survey of the progress made in sensor-based activity recognition, which is gaining increasing attention in various disciplines and applications. They highlight the strengths and weaknesses of these approaches, categorizing them into data-driven and knowledge-driven approaches, and providing insights into promising directions for future research.

Hybrid approaches combine data-driven and knowledge-based approaches to address their limitations and exploit their advantages. In [71], a hybrid approach that exploits a Markov Logic Network (MLN) is proposed for HAR. This study is improved in [30] via the consideration of probabilistic ontology-based activity recognition. MLN is also used in [72] where low-level activities are modeled using MLN soft rules learned from contextual characteristics of activities, such as objects, time, and location of activities while high-level activities are modeled using MLN hard rules. In [73], a hybrid approach exploiting ontological modeling and production rules is proposed for activity recognition and uncertainty handling. In [74], a probabilistic EC-based approach is proposed to recognize human activities. This approach allows handling the data uncertainty using a linear-time algorithm, where data uncertainty refers to incomplete or missing events due to a malfunction of sensors. In [75], a hybrid HAR approach using ontology-based reasoning combined with machine-learning models, called Combined Ontological/Statistical Activity Recognition (COSAR), is proposed. In [76], a hybrid approach exploiting ontology and an iterative process is proposed for activity recognition and assistance in ambient assisted living. In [77], a hybrid approach using machine-learning models and ontological reasoning is proposed for HAR. In this study, machine-learning models, such as Extreme Learning Machines (ELM), are initially used to recognize low-level activities. Ontological reasoning is exploited to recognize high-level activities. In [78], a hybrid HAR approach using a Gaussian Mixture Models (GMM) model, multi-class SVM model, and ontology-based reasoning is proposed. The authors of [79] propose a fine-grained HAR method that fuses multimodal data from single objects and handles the imprecise nature of non-binary sensor measurements. The approach leverages fuzzy ontology to model fine-grained actions and a fuzzyDL reasoning tool to classify action completion. In [80], a hybrid HAR approach using HMM and symbolic reasoning is proposed. In [80], a framework for HAR is proposed, which represents composite activities using a hierarchical structure of lower-level actions and gestures, transformed into formal logical formulas and rules that are resolved using automated reasoning.

Hybrid approaches provide promising benefits by exploiting the advantages of both data-driven and knowledge-driven approaches. These approaches can be used in a manner considering the human context and consequently provide better HAR performance.

2.2 Human Behavior Recognition

It is common to interchange the terms human behavior and human activity in the literature [17], [18], [19]. GMM and Gaussian mixture regression models are used in [17] to recognize human behaviors. In [18], a CNN model is used to automatically capture the spatial data features. In order to recognize human behaviors, a Multi-Layer-Perceptron (MLP) model is used. In [81], a framework exploiting Dynamic Bayesian Network (DBN) is proposed to recognize human behaviors. In [19], human behaviors are recognized using a fuzzy inference-based approach. In [82], different ontologies and a Restricted Boltzmann Machine are exploited to recognize human behaviors. In [83], a hybrid model combines the Planning Domain Definition Language (PDDL), a predicate-based language, with the DBN model to recognize human behaviors. The PDDL language models human behaviors, while the DBN model estimates the probability distribution over the activities for human behavior recognition. In the mentioned studies, the terms human behavior and human activity are not distinguishable; however, these terms are different. Although there are various definitions of human behavior, the latter can be generally defined as activity routines [20], [6] or frequent activities [20].

The article [20] proposes an approach for extracting human behaviors using a Markov Decision Process (MDP) framework [84] and the Maximum Causal Entropy (MaxCausalEnt) algorithm [85]. This method enables the extraction of behaviors by modeling the decision-making process of the human subject in a probabilistic manner, using the MaxCausalEnt algorithm to estimate the probability distribution of the subject's actions given the observed context. The article [6] examines human behavior in various contexts, such as specific activities (e.g., eating), days (e.g., Friday), times (e.g., 18:00), or combinations thereof. The authors propose a method for mining contextualized sequential patterns using a contextualized prefix tree. These patterns are sequences of activities that frequently occur together within a specific context. However, this approach is unable to handle uncertain information. The article [86] presents a new method for recognizing periodic human activities using a novel tree-based data structure called a Temporal Correlated-Periodic tree (TECP-tree). To construct the TECP-tree, the authors propose a TECP-growth algorithm, which is based on frequent pattern mining algorithms. To ensure that only correlated activities are discovered, the authors use a productiveness test to model the interdependency between the discovered patterns. Additionally, the user context is adapted to the discovered patterns by modeling the variation in the user's activity context. In [87], a human behavior recognition approach based on data fusion incorporates room-level location information to trigger sub-classification models pre-trained by wearable data. is proposed. In [88], a behavior is modeled using a mapping from a state to an action; where the former is the set of conditions of the agent, and the latter is the expected activity regarding those conditions.

Previous studies on human behavior recognition have had limited consideration of different human behaviors due to difficulties in acquiring large labeled data in data-driven approaches or limitations in handling uncertainty in knowledge-driven approaches. However, handling uncertain knowledge and data is crucial in recognizing complex human behaviors. The existing hybrid approaches have also struggled to define human behaviors based on different context attributes and their uncertainty. In [24], a novel human behavior recognition approach that considers four context attributes of human activity is proposed: activity, activity duration, activity location, and human posture. The approach uses an HMM model to recognize human activities based on location information and a Boolean method to check compatibility with human posture. The Viterbi algorithm is then used to find the most probable activity using input sequences. However, this study does not consider other important human behavior contexts such as time of day, involved objects, and frequency of activities.

2.3 Abnormal Human Behavior Recognition

In the literature, abnormal human behavior is defined as unexpected behaviors of a user as they are different from his/her usual behaviors [5]. The authors of [89] propose a probabilistic spatiotemporal model for recognizing human daily behaviors. Anomalies, which are defined as significant changes from the learned behaviors, are detected using a cross-entropy measure. In [90], the authors suggest using a DBN for identifying specific human behavior patterns and then employing the Likelihood Ratio Test (LRT) to detect abnormal behaviors by measuring cumulative abnormality. The data-driven approaches intended to detect abnormal human behaviors often use machine-learning models, such as Support Vector Data Description (SVDD) [91], SVM [5], and Recurrent Neural Network (RNN) [92] models. In [93], an algorithm is proposed to detect abnormal patterns based on past events. A rule is fired for the current day if certain events occur, and the number of matching cases from the past 5-8 weeks is considered to define normal behavior. In [94], a rule-based approach is proposed to detect abnormalities in sleeping behavior by considering location, time, and activity duration. In [95], an approach based on Intertransaction Association Rule (IAR) [96] mining is proposed to detect abnormal behaviors. This procedure allows for finding abnormal human behaviors based on remarkable differences in the number of recognized patterns, such as a significant drop in the number of recognized patterns indicating abnormal behavior. In [97], a hybrid approach using machine-learning models and temporal reasoning is proposed to recognize abnormal human behavior. Temporal relations among daily activities are defined using 13 Allen's temporal relations. Frequent sequential patterns are captured using an Apriori algorithm. Probability is then calculated based on the occurrence of events and their temporal relationships, and abnormal human behavior is recognized if the probability approaches 1. In [98] and [73], MLN is used to detect and recognize abnormal human behaviors. In [98], the starting and ending times of activities are analyzed using a knowledge-based inference engine. In [73], a causal association rule mining algorithm (CARMA) is used with MLN to identify abnormal behaviors without expert intervention. In [99], a hybrid framework using an RF model and a reasoning approach is proposed to recognize human behavior and detect abnormal behaviors. The RF model classifies events into activities, while a refined method called Smart Aggregation characterizes behaviors based on activity conditions. OWL 2 language is used in a reasoning approach to incorporate external knowledge about human behaviors and detect abnormalities. In [27], a hybrid approach is proposed to recognize abnormal human behaviors using an HMM model trained with normal and abnormal behavior samples. A statistical method detects abnormalities, while a forecasting technique predicts trends in physiological parameters. A fuzzy fusion process combines outputs for a final decision and alerts healthcare providers. In [100], a K-means model recognizes human activities, and a sequential pattern mining algorithm identifies the most frequent activity sequences for each user. To recognize abnormal behaviors, an ontology is employed to formally represent activities, and new activity sequences are compared to recognized frequent sequences using the Longest Common Subsequence (LCS) algorithm. In [101], the proposed approach exploits the multi-label MLN classification method to recognize resident types based on their activity habits and preferences in a multi-occupancy scenario. The method includes activity preference features such as time sequence, duration, period, and location, and uses reasoning to determine family roles such as mother, father, daughter, etc. The paper [102] provides an extensive review and comparison of abnormal human behavior recognition approaches.

Although some of the mentioned abnormal human behavior recognition approaches allow considering context attributes of human activity, such as sequence and duration of human activities, they do not take into account comprehensive human behavior context, such as considering the location, involved objects, frequency, time of the day, duration, and sequence of activities. Moreover, some of the above-mentioned approaches for human behavior recognition and abnormal human behavior recognition do not allow for handling the uncertainty of activity predictions. In this paper, a hybrid and context-aware framework using machine-learning models, HAT ontology, and PASP is proposed to deal with these challenges.

3 DATASETS DESCRIPTION

In this section, the datasets used in the study are described.

3.1 Orange4Home dataset [25]

This dataset was built using 236 sensors collecting data about the state of doors (open/close), use of electrical equipment, water consumption, etc.; these data are of different types: binary, integer, real number, or categorical. An instrumented home with two floors was equipped with these sensors in different locations, see Fig. 4. To build this dataset, seventeen daily living activities were performed by one occupant during four consecutive weeks during working days. Three main context attributes of human activity are considered in this dataset, namely time, location, and activity. Table 1 shows activities grouped by their locations considered in this dataset. The *Orange4Home* dataset was chosen for the evaluation of the proposed framework due to its data sequential structure and long-term

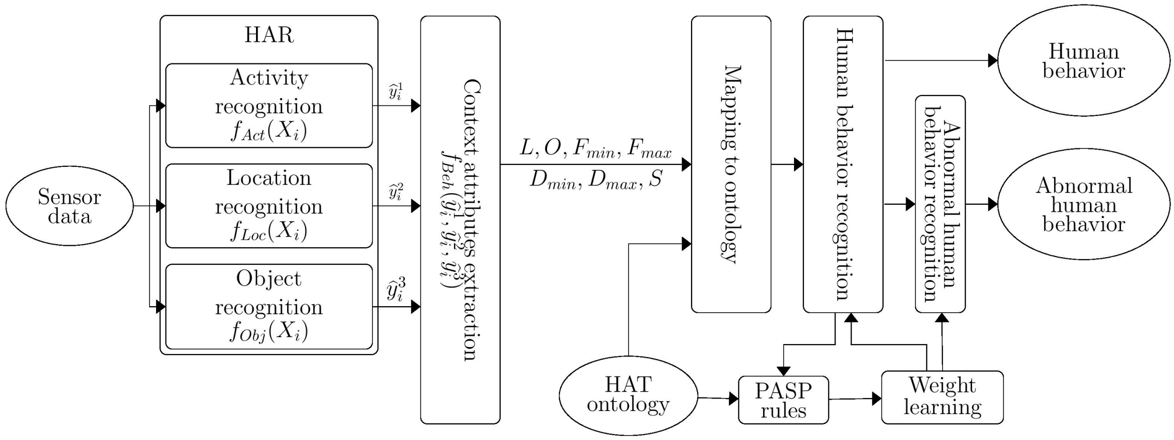


Fig. 1: Architecture of the proposed framework.

Table 1: List of activities grouped by their locations considered in the *Orange4Home* dataset.

Location	Activities
Entrance	Entering, Leaving
Kitchen	Preparing, Cooking, Washing the dishes
Living Room	Eating, Watching TV, Computing
Toilet	Using the toilet
Staircase	Going up, Going down
Bathroom	Using the sink, Using the toilet, Showering
Office	Computing, Watching TV
Bedroom	Dressing, Reading, Napping
All locations	Cleaning

recording, which are required for human behavior recognition.

3.2 UCI HAR dataset [26]

In this dataset, participants in this study were fitted with a waist-mounted smartphone (Samsung Galaxy S II) equipped with inertial sensors (accelerometers and gyroscopes) to collect data related to their movements. A sampling rate of 50Hz is used to collect triaxial linear acceleration and angular velocity signals. Thirty participants wear smartphones on their waists while performing six activities: (1) Walking, (2) Walking-upstairs, (3) Walking-downstairs, (4) Sitting, (5) Standing, and (6) Laying.

4 Proposed Framework

In this framework, probabilistic reasoning and machine-learning models are combined to better characterize abnormal human behaviors by considering different context attributes of human behavior and handling their uncertainties. The framework consists of five main modules: (1) HAR, (2) context attributes extraction, (3) mapping to the HAT ontology, (4) human behavior recognition, and (5) abnormal human behavior recognition. In the first module, a set of labels describing ongoing human activity is generated by using machine-learning models of the LSTM type. In the second module, the obtained labels are exploited to extract the six attributes characterizing human behavior: frequent activities in specific locations, frequent activities with specific objects, frequent activities in particular dayparts, frequent activities with specific duration ranges, recurrent daily activities with specific frequencies, frequent sequences of activities. The third module conceptualizes human behavior context attributes using the HAT ontology. Modules fourth and fifth focus on PASP, which is a probabilistic version of ASP. PASP is exploited to represent human behavior context attributes and infer human behaviors. Abnormal human behaviors can be detected using PASP. In the latter, besides assigning a probability value to each rule to handle the uncertainty of defined PASP rules, a probability value is assigned to each predicate or fluent used in rules to handle the uncertainty of extracted attributes of human behavior context. An overview of the proposed framework can be seen in Fig. 1.

4.1 HAR

The input data D can be represented as a set of pairs formed from the data X_i and a vector of labels Y_i [103]:

$$D = \{(X_i, Y_i) \parallel 1 \leq i \leq N\} \tag{1}$$

with $i \in \{1, 2, ..., N\}$; N represents the total number of data samples and X_i the i^{th} data sample. Each data sample is composed of d data features. A vector of labels Y_i, which is assigned to the data sample i, is composed of three labels:

$$X_i = \{x_i^1, x_i^2, ..., x_i^m, ..., x_i^d\} \tag{2}$$

$$Y_i = \{y_i^1, y_i^2, y_i^3\} \tag{3}$$

where y_i^1, y_i^2, and y_i^3 represent respectively the human activity, activity location, and involved objects labels assigned to the i^{th} data sample. Each label has a specific number of classes; for instance, the number of classes for the activity label is q while it is w for the location label. Formalizing these labels is as follows [103]:

$$\begin{aligned} y_i^1 &\in \{c_1^1, c_2^1, ..., c_q^1\} \\ y_i^2 &\in \{c_1^2, c_2^2, ..., c_w^2\} \\ y_i^3 &\in \{c_1^3, c_2^3, ..., c_z^3\} \end{aligned} \tag{4}$$

where q, w, and z represent respectively the number of classes for activity, activity location, and involved objects labels. Three models are used by the HAR module to classify input data into the mentioned labels: activity recognition, activity location recognition, and involved object recognition models. The HAR module classifies input data independently into these three labels. Functions f_A, f_L, and f_O are used to formalize these models, such as:

$$\widehat{y}_i^1 = f_A(X_i), \quad \widehat{y}_i^2 = f_L(X_i), \quad \widehat{y}_i^3 = f_O(X_i) \tag{5}$$

where $\widehat{y}_i^1$, $\widehat{y}_i^2$, and $\widehat{y}_i^3$ indicate the predicted labels for human activity, activity location, and involved object in the activity, respectively. Prediction functions of f_A, f_L, and f_O predict the activity, location, and object, respectively. LSTM models are used as these prediction functions. LSTM [104] is a specific kind of RNN with the capability of learning long-term dependencies between the input data. LSTMs generally avoid the long-term dependency problem and are ideally suited to time-series models[105]. Therefore, LSTM can be used to model human daily living activities because they are time-series data. Fig. 2 depicts the architecture of the used LSTMs. Each model consists of five layers: (1) an LSTM layer containing 100 neurons, (2) a dropout layer (fraction rate of 0.5), (3) an LSTM layer containing 50 neurons, (4) a dropout layer (fraction rate of 0.5), and (5) a dense layer containing a number of neurons same as the number of classes. *Adam* is assigned to the optimization function while *categorical-crossentropy* to the loss function. A grid search (parameter sweep) is used to estimate the hyperparameters of this model.

4.2 Context Attributes Extraction

In this paper, an algorithm is proposed to extract the five context attributes of them; the context attribute related to frequent activities in particular dayparts are captured using PASP rules exploited in the human behavior recognition module. We define a novel function g that formalizes this algorithm:

$$R^{loc}, R^{obj}, R^{dur}, R^{freq}, R^{seq} = g(\widehat{y}^A, \widehat{y}^L, \widehat{y}^O) \tag{6}$$

where the list of frequent activities in specific locations is represented by R^{loc}, with specific objects R^{obj}, within specific ranges of duration R^{dur}, with specific frequencies R^{freq}, the list of the frequent sequences of activities is represented by R^{seq}. Seven hash tables, namely locations, objects, minimum duration, maximum duration, minimum frequency, maximum frequency, and previous activity, are used in the developed algorithm to extract the mentioned five lists. $\mathcal{L}$, $\mathcal{O}$, $\mathcal{D}_{min}$, $\mathcal{D}_{max}$, $\mathcal{F}_{min}$, $\mathcal{F}_{max}$, and $\mathcal{S}$ respectively represent locations, objects, minimum duration, maximum duration, minimum frequency, maximum frequency, and previous activity. Each table is dedicated to each context attribute of human behavior. Activities are mapped to one list of context attributes of human behavior using a hash table. For instance, the extraction of minimum frequency $\mathcal{F}_{min}$ and maximum frequency of an activity $\mathcal{F}_{max}$ is described in Algorithm 1. The other context attributes used in the human behavior definition are extracted similarly.

4.3 Mapping to an ontology

In the HAT ontology, we provide a formal specification of shared conceptualizations to characterize human activities, human behaviors, and their contexts using classes, individuals, and relations [106]. Taking inspiration from *ConceptNet* semantic network [107], the HAT ontology is developed. *ConceptNet* is

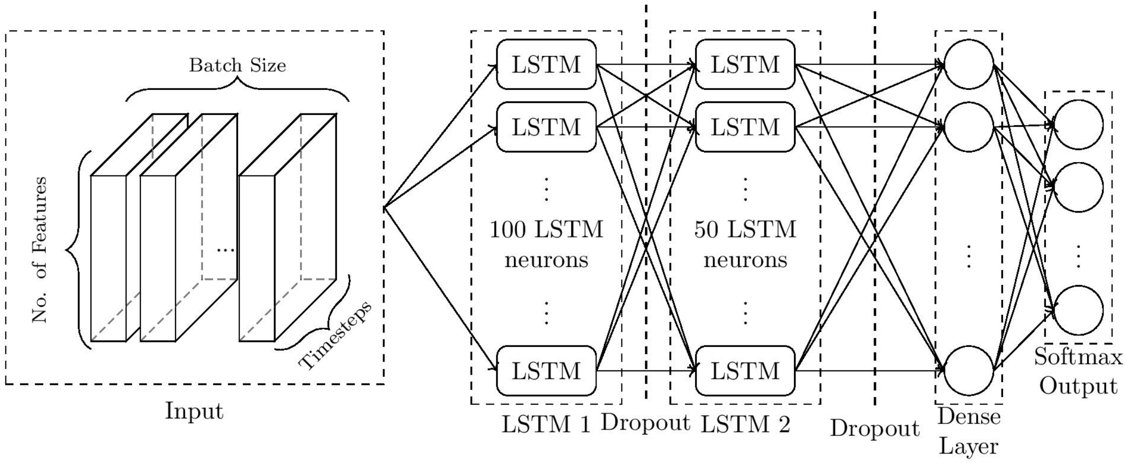


Fig. 2: Architecture of the LSTM model.

Algorithm 1 : Context attributes extraction

Input: $\mathcal{B} = \{(Time_i, Activity_i, Location_i, Object_i)\}$;
$0 \leq i \leq N$
Output:
$\mathcal{F}_{max} : frequency \leftarrow activity$
$\mathcal{F}_{min} : frequency \leftarrow activity$
Let $\mathcal{A}$: the set of all activity types
Let $TH_{\mathcal{R}}(activity)$: the minimum number of acceptable recurrence for an $activity$
Let $F_{currentDay} : frequency \leftarrow activity$ ▷*Number of repetition of each activity in a day*
Let $F_{allDays} : frequency[\,] \leftarrow activity$ ▷*Collection of* $F_{currentDay}$ *for all days*
Let $index_{date} = 0$
for $i = 1$ to N **do**
  if $Date(Time_i) = Date(Time_{index_{date}})$ **then**
    increment $F_{currentDay}(Activity_i)$
  else ▷*if the date has changed*
    for $a \in \mathcal{A}$ **do** ▷*append the current day counter to the list of frequencies and reset the counter*
      $F_{allDays}(a) \leftarrow F_{allDays}(a) \| F_{currentDay}(a)$
      $F_{currentDay}(a) = 0$
      $index_{date} = i$
    end for
  end if
end for ▷$F_{allDays}$ *is filled with the different frequency of each activity*
for $a \in \mathcal{A}$ **do**
  if $NonZeroCount(F_{allDays}(a)) \geq TH_{\mathcal{R}}(a)$ **then** ▷*filtering the recurrent activities*
    $\mathcal{F}_{max} \leftarrow Max(F_{allDays}(a))$
    $\mathcal{F}_{min} \leftarrow Min(F_{allDays}(a))$
  end if
end for
return $\mathcal{F}_{max}, \mathcal{F}_{min}$

a knowledge graph that allows linking terms, such as words and phrases of natural language with labeled edges [107], e.g., the terms *oven* and *cooking* are linked using the labeled edge *is used for*. Fig. 3 illustrates the overview of the HAT ontology modeled using the Semantic OWL [108]. We define this

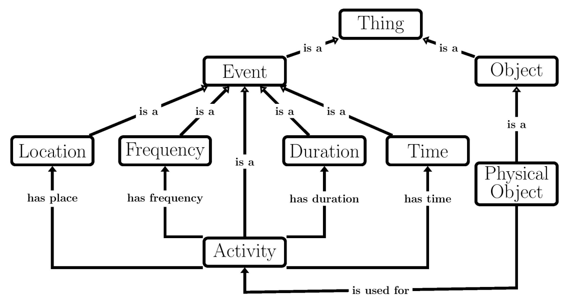


Fig. 3: Overview of the HAT ontology [103].

ontology in two upper-level concepts, namely *Event* and *Object*. From these two concepts originate six additional concepts: *Activity*, *Location*, *Time*, *Physical Object*, *Duration*, and *Frequency*. These concepts are connected using six different relationships, namely *has place*, *has frequency*, *has duration*, *has time*, *is used for*, and *is a*. Table 2 shows the formal relationships between these concepts. Human behavior and abnormal human behavior recognition modules use the concepts and relationships defined in the HAT ontology to determine rules and predicates.

4.4 Human Behavior Recognition

In the human behavior recognition module, the outputs of the mapping to the HAT ontology module are exploited to characterize human context from a human behavior point of view. In this module, PASP, a probabilistic version of Answer Set Programming (ASP),

Table 2: Formalized relationships between the main concepts in the HAT ontology [103].

$\mathsf{Object}(x) \vee \mathsf{Event}(x) \rightarrow \mathsf{Thing}(x)$.
$\mathsf{Location}(x) \vee \mathsf{Activity}(x) \rightarrow \mathsf{Event}(x)$.
$\mathsf{Activity}(a) \rightarrow \exists o\, \mathsf{Object}(o) \wedge \mathsf{isusedfor}(o, a)$.
$\mathsf{Activity}(a) \rightarrow \exists l\, \mathsf{Location}(l) \wedge \mathsf{hasplace}(a, l)$.
$\mathsf{Activity}(a) \rightarrow \exists t\, \mathsf{Time}(t) \wedge \mathsf{hastime}(a, t)$.
$\mathsf{Activity}(a) \rightarrow \exists d\, \mathsf{Duration}(d) \wedge \mathsf{hasduration}(a, d)$.
$\mathsf{Activity}(a) \rightarrow \exists f\, \mathsf{Frequency}(f) \wedge \mathsf{hasfrequency}(a, f)$.

is used to infer human behaviors. ASP is a declarative programming paradigm intended to solve Nondeterministic Polynomial (NP) and NP-complete search problems [109]. ASP is used for knowledge representation and reasoning [110]. Knowledge is represented using answer-set programs while reasoning is performed using answer-set solvers. In ASP, the syntax is derived from Prolog, and the semantics are defined based on Gelfond et al.'s stable model semantics. [111]. In formal terms, ASP rules are as follows:

$$l \;:-\; b_1, ..., b_m, not\, b_{m+1}, ..., not\, b_{m+n} \quad (m, n \geq 0).$$

l, the left-hand side of the rule, is called a head, and $b_1, ..., b_m, not\, b_{m+1}, ..., not\, b_{m+n}$, the right-hand side, is called its body. not is a negation symbol, which is used for representing the non-monotonic default negation, or the epistemic negation [112]. Facts are rules with an empty body and a single disjunct in the head, while constraints are rules with an empty head.

A collection of ASP rules makes up an ASP program. An ASP program uses S as a set of ground atoms; when $\{b_1, ..., b_m\} \subseteq S$ and $S \cap \{b_{m+1}, ..., b_{m+n}\} = \varnothing$, the body of a rule is satisfied. Whether S satisfies a constraint depends on whether S satisfies the body, whereas whether S satisfies a rule depends on whether it satisfies $h \in S$. In the formal term, an answer set is defined as follows:

Grounding is used to replace variables used in ASP programs with ground atoms, resulting in a set of ground atoms called S. A Reduct I^S does not contain negated atoms. The Reduct is achieved by using two steps: (1) drop rules with $not\ l$ in their body, where l is atom $l \in$ S, (2) from all other rules, drop literals that are $not\ l$. Then, the answer set S is the minimal model of (I^S).

In general, ASP is described by the following characteristics: [109], [113]:

- Non-monotonic reasoning: ASP allows invaliding some inferences by adding more knowledge, i.e., the inferences are changed by adding more knowledge [109]. For instance, the knowledge domain contains: (i) the object *book* is located in the location *bedroom*. (ii) the object *pan* is located in the location *kitchen*. (iii) the user *Adam* uses the object *book*. (iv) the activity *reading* is recognized when the object *book* is used. (v) the activity *cooking* is recognized when the object *pan* is used.
  From the above sentences, ASP allows inferring that *Adam* performs the activity *reading*. However, if one another fact is added to the knowledge base, such as "the user *Adam* uses the object *pan*", the above conclusion is then invalidated.
- Postdictive reasoning: ASP allows exploiting knowledge about the present to retrospectively obtain additional knowledge about the past [113]. For instance, the knowledge domain contains: (i) the location *bedroom* is recognized in time $t1$, (ii) the location *toilet* is recognized in time $t3$, (iii) the location *bedroom* is connected to *toilet* via the location *kitchen*.
  ASP allows inferring that the user was in the location *kitchen* between the time $t1$ and the time $t3$.
- Handling the frame problem: ASP allows representing the effects of each action in logic without having to represent a variety of intuitively apparent non-effects [114].

In this study, the additional condition is considered to infer a new fact, $p_{rule} \times P_{act} \times P_{loc}$ should be greater than its complement, $1-(p_{rule} \times P_{act} \times P_{loc})$. It means that the inferred fact will be considered in the answer set of PASP programs if and only if the probability of the inferred fact is more than the probability of its complement.

Several axioms are proposed to recognize human behaviors based on activities, locations, involved objects, activity duration, activity frequencies, and activity sequences.

Axiom 1. $behActLocObj(Act, Loc, Obj, P_{act} \times P_{loc} \times P_{obj}) : -act(Act, T, P_{act}), loc(Loc, T, P_{loc}), obj(Obj, T, P_{obj})$

Axiom 1 describes human behaviors when a specific activity is executed by the user in a particular location using a specific object, e.g., sitting on a chair in the bedroom. The human behavior without location or object can be inferred from the other Axioms derived by the Axiom 1. The temporal relationships among human activities are necessary to better characterize human behaviors. Therefore, Allen's interval algebra [115] is used to model these relationships among human activities using PASP.

Axiom 2. *start(Act_1, Act_2, $P_1 \times P_2$):- act(Act_1, T_{1s}, D_1, P_1), act(Act_2, T_{2s}, D_2, P_2), $T_{1s} = T_{2s}$.*

Axiom 3. *overlap(Act_1, Act_2, $P_1 \times P_2$):- act(Act_1, T_{1s}, D_1, P_1), act(Act_2, T_{2s}, D_2, P_2), $T_{2s} < T_{1s} + D_1$, $T_{1s} < T_{2s}$, $T_{1s} + D_1 < T_{2s} + D_2$*

Axiom 4. *during(Act_1, Act_2, $P_1 \times P_2$):-act(Act_1, T_{1s}, D_1, P_1), act(Act_2, T_{2s}, D_2, P_2), $T_{1s} > T_{2s}$, $T_{2s} + D_2 > T_{1s} + D_1$.*

Axioms 2, Axiom 3, and Axiom 4 are some of the used axioms to represent temporal information $start$, $overlap$, and $during$, respectively. Act_m represents the m^{th} activity. T_{ms} and D_m represent the starting time and duration of the activity Act_m.

Axiom 5.
SequentialActivity$(Act_1, Act_2, ..., Act_n, T_{ns}, P_1 \times P_2, ..., \times P_n)$:- *act*$(Act_1, T_{1s}, D_1, P_1)$, *act*$(Act_2, T_{2s}, D_2, P_2)$, ..., *act*$(Act_n, T_{ns}, D_n, P_n)$, $meet(Act_1, Act_2)$, ..., $meet(Act_{n-1}, Act_n)$.

Axiom 5 is used to represent the sequences of activities. This axiom defines the fact that there is an activity sequence when each activity in the sequence has a temporal relationship *meet* with its next activity in the activity sequence. This temporal relationship is inferred when the ending point of an activity Act_1 is equal to the starting point of another activity Act_2. In this study, n, used in this axiom, sets to 4. It is noticeable that the activity sequence inferred using PASP is more comprehensive in comparison with those captured using the module of context attributes extraction since the latter is the most straightforward case of the former one, i.e., n is equal to two.

Axiom 6. *daypart(Act, T, P_1) : $-$act(Act,T_s, D_1, P_1), $T_s < TH_e$, $T_s + D_1 \geq TH_s$.*
daypart(Act, T, P_1) : $-$act(Act, T_s, D_1, P_1), $T_s > T_s + D_1$, $T_s + D_1 \geq TH_s$.

The daypart of activities is an important context to recognize human behaviors, e.g., eating breakfast in the early morning. In this study, ten different dayparts are considered; therefore, ten axioms are defined to represent these dayparts. The main structure of these axioms is shown in Axiom 6, where *daypart* represents the temporal parts of a day. TH_s, and TH_e illustrate respectively starting time and ending time of the *daypart*. These thresholds are defined in the HAT ontology. Table 3 shows the threshold boundaries of each specific daypart, e.g., when an activity happens from 10:00 to 10:30, the morning is assigned to the daypart of this activity. When an activity period exceeds midnight, the value of the ending point of that activity might be less than the value of its starting point due to the time changes from 23:59 to 00:00 at midnight. The second rule of the Axiom 6 is defined to handle this challenge.

Table 3: Definition of ten different dayparts to analyze human behaviors.

Temporal parts of a day (daypart)	Threshold of starting time (TH_s)	Threshold of ending time (TH_e)
NightAfterMidnight	0	5
EarlyMorning	5	8
Morning	8	11
LateMorning	11	12
Noon	12	13
EarlyAfternoon	13	14
Afternoon	14	16
LateAfternoon	16	18
Evening	18	21
NightBeforeMidnight	21	24

Axiom 7.
$loc(Loc2, T_s, D_1, P_1 \times (1 - P_2) \times (1 - P_3) ... \times P_6)$:-
$activity(Act, T_s, D_1, P_1), object(Obj1, T_s, D_1, P_2)$,
$not\, location(Loc1, T_s, D_1, P_3)$,
$\neg relatedLocObj(Loc1, Obj1, P_4)$,
$not\, relatedLocObj(Loc2, Obj1, P_5)$,
$relatedActLoc(Act1, Loc2, P_6)$, $Loc1 \,!= Loc2$.

Axiom 7 is used when the location information is not complete; PASP allows inferring the activity location from the facts related to the current activity and involved object. Where $relatedLocObj(Loc2, Obj1, P_5)$ represents that there is a relationship between location $Loc2$ and object $Obj1$ with the probability P_5. $relatedActLoc(Act1, Loc2, P_6)$ depicts that activity $Act1$ and location $Loc2$ are related with the probability P_6. To make it simple, the temporal information of activity, object, and location are presumably identical in Axiom 7, e.g., T_s is the same starting point for activity, object and location. There are two negations in this Axiom: strong negation (i.e., classical negation)($\neg$) and non-monotonic negation (i.e., epistemic negation) (not). For example, $\neg F$ means that F is false, while $not\ F$ means that F is not known or F cannot be shown.

Axiom 8.
$location(Loc3, T_{3s}, D_3, P_1 \times P_2 \times (1 - P_3) \times P_4)$:- $location(Loc1, T_{1s}, D_1, P_1), location(Loc2, T_{2s}, D_2, P_2), \neg link(Loc1, Loc2, P_3), access(Loc1, Loc2, Loc3, P_4), T_{1s} < T_{2s}, T_{1e} < T_{3s} < T_{2s}, Loc1\,! = Loc2, Loc1\,! = Loc3, Loc2\,! = Loc3.$

Axiom 8 exploits the ability of PASP in postdictive reasoning; this axiom is used to infer facts related to the user's previous location based on his/her current location. The predicate $link(Loc1, Loc2, P_3)$ represents that two locations $Loc1$ and $Loc2$ are linked with the probability P_3. The predicate $access(Loc1, Loc2, Loc3, P_4)$ illustrates that two locations $Loc1$ and $Loc2$ are only accessible through the location $Loc3$ with the probability P_4.

4.5 Abnormal Human Behavior Recognition

We divide abnormal human behavior into six types: (1) Unexpected activities that occur repeatedly in specific locations, (2) Unexpected activities that occur repeatedly with specific objects, (3) Unexpected activities that occur repeatedly in particular dayparts, (4)Unexpected activities that occur repeatedly within particular ranges of duration, (5) Unexpected activities that occur repeatedly with particular frequencies per day, and (6) activities that occur repeatedly in unexpected sequences. In the abnormal human behavior recognition module, PASP is exploited to recognize abnormal human behaviors while handling the uncertainty of human contexts, e.g., human activity, location, object, etc; i.e., using PASP, probabilistic inferences can be made about abnormal human behaviors. The concepts defined in the HAT ontology are used to define these rules. In consequence, PASP rules are weighted by their truth degree, which is achieved by optimizing a pseudo-likelihood measure [116].

Several axioms are defined to recognize abnormal human behaviors based on activities, locations, involved objects, activity duration, activity frequencies, and activity sequences.

Axiom 9. $abnormalActLoc(act, loc, T, p_{rule} \times P_{act} \times P_{loc}) :- act(act, T, P_{act}), loc(loc, T, P_{loc})$

Axiom 9 is exploited to describe the first type of abnormal human behaviors, e.g., sleeping at the entrance. It is noticeable that 116 PASP rules are generated using different pairs of activities and their unexpected location based on this axiom.

Axiom 10. $abnormalActObj(act, obj, T, p_{rule} \times P_{act} \times P_{obj}) :- act(act, T, P_{act}), obj(obj, T, P_{obj})$

Axiom 10 is used to represent the second type of abnormal human behaviors, e.g., sleeping with a coffee machine.

Axiom 11. $abnormalActDaypart(act, daypart, T, p_{rule} \times P_{act} \times P_{daypart})$:-$act(act, T, P_{act}), daypart(act, T, P_{daypart})$

The third type of abnormal human behaviors is represented using Axiom 11, e.g., walking after midnight.

Axiom 12. $abnormalActDuration(act, dur, T, p_{rule} \times P_{act} \times P_{dur}) : -act(act, T, P_{act}), dur(dur, T, P_{dur}), dur > D_{TH_{max}}$

$abnormalActDuration(act, dur, T, p_{rule} \times P_{act} \times P_{dur}) : -act(act, T, P_{act}), dur(dur, T, P_{dur}), dur < D_{TH_{min}}$

The fourth type of abnormal human behaviors is represented using Axiom 12, e.g., eating with a duration of three hours. To recognize this type of abnormal behavior, two thresholds are defined for each activity, namely the threshold of minimum duration and the threshold of maximum duration.

Axiom 13. $abnormalActFreq(act, freq, T, p_{rule} \times P_{act} \times P_{freq}) : -act(act, T, P_{act}), freq(freq, T, P_{freq}), freq > F_{TH_{max}}$

$abnormalActFreq(act, freq, T, p_{rule} \times P_{act} \times P_{freq}) : -act(act, T, P_{act}), freq(freq, T, P_{freq}), freq < F_{TH_{min}}$

Axiom 13 is used to represent the fifth type of abnormal human behavior. To recognize this type of abnormal behavior, two thresholds, namely the threshold of minimum frequency and threshold of maximum frequency, are defined for each activity.

Table 4: List of abnormal human behaviors with their fluents in PASP.

Description	Fluents
unexpected behavior in particular locations	*AbnormalActLoc(act, loc, time)*
unexpected behavior with particular objects	*AbnormalActObj(act, obj, time)*
unexpected behavior in particular dayparts	*AbnormalActTime(act, timeday, time)*
unexpected behavior with particular duration	*AbnormalActDur(act, dur, time)*
unexpected behavior with particular frequencies	*AbnormalActFreq(act, freq, time)*
unexpected behavior with particular activity sequences	*AbnormalSeqAct(act1, act2, time)*

Axiom 14. $abnormalActSeq(act1, act2, T, p_{rule} \times P_{seq}) : -sequentialActivity(act1, act2, T, P_{seq})$

Axiom 14 is exploited to describe the sixth of abnormal human behaviors. 227 PASP rules are generated using a different sequence of activities based on this axiom.

PASP is more suitable than standard rule-based approaches, such as Semantic Rule Markup Language (SRML) for human behavior and abnormal human behavior recognition due to the elimination of unused rules during weight learning. SRML provides a framework for representing rules in a way that is easily understandable by both humans and machines, and it can be used to define complex rule sets for behavior recognition. It can also incorporate context-specific knowledge and reasoning, which can be useful for recognizing abnormal behavior in specific situations. However, SRML may not be as effective for probabilistic reasoning and dealing with uncertain or incomplete data. On the other hand, PASP provides a probabilistic framework for reasoning about uncertain and incomplete data. This can be useful for recognizing abnormal behavior when there is a high degree of uncertainty, or when there is incomplete information about the situation. PASP allows handling the uncertainty of predictions of human activity, activity location, and involved objects through the weight learning process and probabilistic reasoning; the erroneous predictions of machine-learning models are handled using PASP by assigning a probability value to each predicate and fluent used in the rules besides assigning a probability value to each rule. Therefore, PASP allows for dealing with the misclassification in predictions of activities, activity locations, and involved objects in activities.

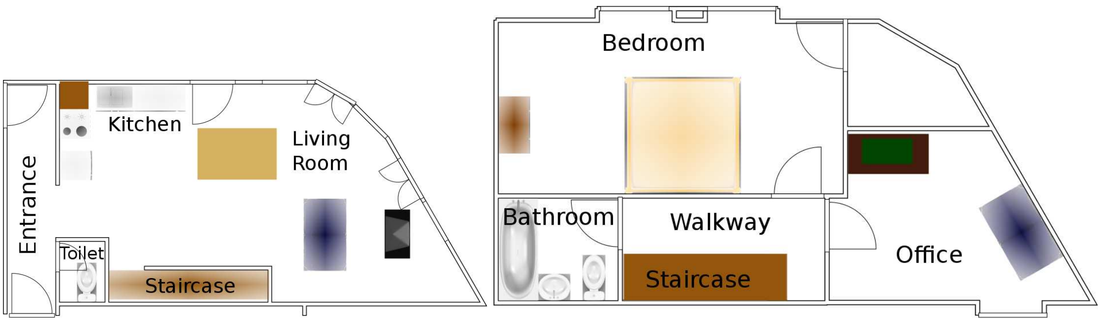
5 EXPERIMENTS, RESULTS, AND DISCUSSION

An evaluation of the proposed framework is presented in this section in terms of F-measure, accuracy, precision, and recall on the *Orange4Home* [25] and the *UCI HAR*, [26] datasets. Since the objective of the proposed framework is human behavior and abnormal human behavior recognition, the evaluations are performed using different experiments to show the effectiveness of the proposed framework to infer new facts about human behavior context and to recognize abnormal human behaviors. The framework is implemented and evaluated on a computer equipped with an Intel i7-8650U 2.11GHz CPU and 32GB RAM. The modules HAR and capturing human behavior contexts are implemented in *Python 3.8* using the *Keras* deep learning library. The mapping to ontology module is implemented in *Protégé 5.5* and *Python 3.8* using the *Owlready2* library. The modules of human behavior and abnormal human behavior recognition are implemented using *CLINGO 5.4.0*.

5.1 HAR performance

Precision, recall, F-measure, and accuracy are the metrics used to evaluate LSTM models in HAR. With the *Orange4Home* dataset, two independent LSTM models are trained independently for activity and activity location recognition since this dataset contains activity and location labels. The obtained results given in Table 5 show that the LSTM models allow recognition activities and activity locations with high accuracy. The LSTM model dedicated to activity recognition achieves more than 95% in terms of all performance metrics while the LSTM model dedicated to location recognition gives more than 97%. The reason for this is that there is more differentiation between the classes of location in comparison to the activity classes due to the environmental sensors used in *Orange4Home* dataset.

The normalized confusion matrices for activity and location recognition are respectively shown in Fig.



(a) Ground floor (b) First floor

Fig. 4: Layout of the instrumented home used for the construction of the *Orange4Home* dataset [25].

Table 5: Performance obtained with the LSTM models using the *Orange4Home* dataset [117].

Performance metrics	Activity recognition	Location recognition
Precision	96.00	97.98
Recall	95.71	97.89
F-measure	95.63	97.83
Accuracy	95.71	97.90

5 and Fig. 6 to analyze recognition based on each class. Fig. 5 shows that the rate of activity recognition of most classes is higher than 90%. Two activities *Going-up* and *Going-down* are recognized with high accuracy using the LSTM model. Moreover, Fig. 6 shows that the location *Staircase*, which is the location of these two activities, is correctly classified.

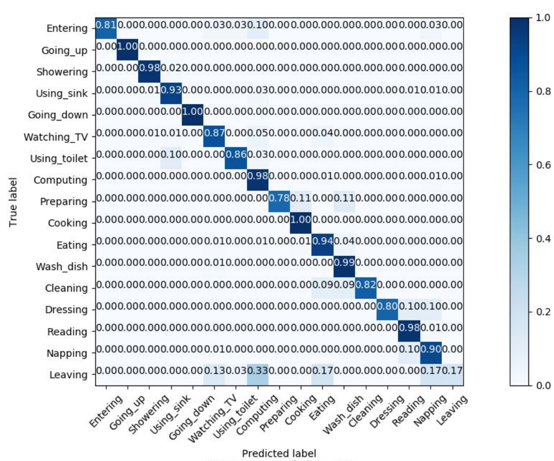


Fig. 5: Normalized confusion matrix for activity recognition based on the LSTM model on the *Orange4Home* dataset.

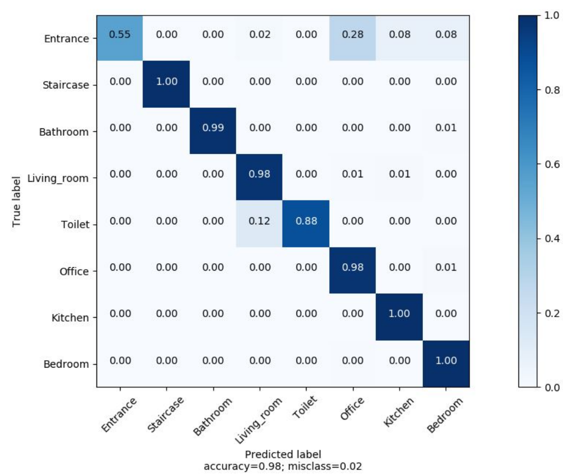


Fig. 6: Normalized confusion matrix for location recognition based on the LSTM model on the *Orange4Home* dataset.

The LSTM model dedicated to HAR is compared with MultiLayer Perceptron (MLP) and SVM models used in [118] using the *Orange4Home* dataset. In [118], these models are exploited in two configurations, *Home* and *Place-based*. In the first configuration, a single classifier is used for activity classification, while for the second configuration, eight classifiers assigned to eight places of the instrumented home are used for activity classification, i.e., in the *Place-based* configuration, each classifier is assigned to a place of the home. Table 6 shows the results obtained using the LSTM, MLP, and SVM models in both configurations. The LSTM model shows superiority in comparison to other models due to the fact that MLP and SVM models do not take into account

Table 6: Comparing LSTM model performance with other approaches used in [118] on the *Orange4Home* dataset [117].

Models	F-measure
Approaches used in [118]	
Home SVM	89.61
Home MLP	77.85
Place-based MLP	93.05
Place-based SVM	92.08
Proposed Approach	
Proposed LSTM model	95.63%

Table 7: Performances achieved utilizing the LSTM models on the *UCI HAR* dataset [117].

Evaluation Metrics	Activity Recognition
Precision	94.08
Recall	94.03
F-measure	94.05
Accuracy	97.98

temporal relationships between activities, while the LSTM model is more suitable for time series.

In the case of the *UCI HAR* dataset, there is only one label, the activity label; therefore, an LSTM model is used for activity recognition. The obtained results, reported in Table 7, show that this model achieves a performance greater than 94% in terms of F-measure, accuracy, precision, and recall.

Fig. 7 shows the normalized confusion matrix for activity recognition based on the LSTM model on the *UCI HAR* dataset. One can observe that the model obtained the best performance results in recognizing the *Laying* activity. This is explained by the fact that this activity consists of the different orientations of the accelerometer compared with other activities, which makes the *Laying* activity the most distinguishable activity. Hence, this activity is well-classified. Fig. 7 also shows high confusion between the activities *Sitting* and *Standing*. This can be explained by the fact that the positioning of the sensors cannot clearly differentiate these two activities [119].

In the case of the *UCI HAR* dataset, the LSTM model is compared with approaches used in [33], namely KNN and the SVM model. Table 8 demonstrates the superiority of the LSTM model due to the fact that LSTM models can model activity sequences and temporal relationships while other models cannot.

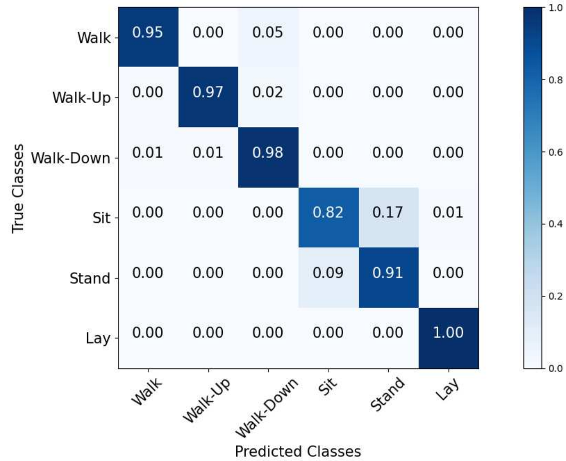


Fig. 7: Normalized confusion matrix obtained using the LSTM model on the *UCI HAR* dataset.

Table 8: Comparing the performance of the LSTM model with the approaches used in [33] on the *UCI HAR* dataset [117].

Models	F-measure
Proposed Approaches in [33]	
KNN	90.16
SVM	93.79
Proposed Approach	
Proposed LSTM model	94.05%

5.2 Baseline models

To show the ability of the LSTM model to recognize human activity, different baseline models, namely DT, RF, SVM, KNN, and CNN, commonly used in HAR, are applied to both datasets, the *Orange4Home* dataset and the *UCI HAR* dataset. The parameters of baseline models are estimated using a grid search technique, see Table 9 and Table 10. The results obtained in the case of the *Orange4Home* dataset and the *UCI HAR* dataset are respectively shown in Table 11 and Table 12. According to these results, the LSTM model outperforms the baseline models on every performance metric. In the case of the *Orange4Home* dataset, the LSTM model achieves 95.63% in terms of F-measure; however, RF model yields 67.78%. The performance obtained with the DT model and KNN model is similar in terms of all performance metrics. The RF model provides better results than the DT, KNN, and SVM models in terms of F-measure, accuracy, precision, and recall. However, the CNN model outperforms the RF model in terms of all performance metrics. As can be seen, the LSTM model yields the best results in comparison to the other ones. In the case of the *UCI HAR* dataset, the LSTM model achieves 95.63% in terms of F-measure while 90.93%, 87.87%, 83.90%, 74.50%, and 72.50% are respectively obtained with CNN, SVM, RF, KNN, DT models. The LSTM model yields the best results, followed by CNN, SVM, RF, KNN, and DT models, in terms of F-measure, accuracy, and recall.

5.3 Human behavior recognition performance

PASP has been implemented using CLINGO [121], an ASP system for grounding and solving logic programs; CLINGO takes such a logic program and computes answer sets representing solutions to the given problem. Human behavior recognition is evaluated using two different metrics. The first one is the number of inferred facts related to the context attributes of human behavior from facts related to other attributes, while the second one is the number of inferred facts related to the location context attribute when the facts related to this context attribute are incomplete. Moreover, the accuracy of inferred facts related to the location context attribute is evaluated to show the effectiveness of the proposed framework in dealing with incomplete information.

5.3.1 Inferred facts related to the human behavior context

Table 13 shows the obtained performance in terms of inferred facts related to the human behavior context and its computation time. It can be observed that the initial facts are related to the activity and location context attributes, while the inferred facts are related to the temporal relations, daypart, and sequences of activities context attributes. In this evaluation, the number of initial facts varies from 50 to 700. The obtained results show that the human behavior recognition module generates a significant number of facts related to human behavior context, up to 2103 facts. Most inferred facts are related to the temporal context attribute, i.e., the temporal relationships between activities, such as *before*, *after*, and *equals*. One can also observe that when the number of initial facts is between 50 and 100, the number of inferred facts related to the temporal relations between activities is relatively high (926 facts); however, this number increases slightly when the number of initial facts becomes greater than 100. This can be explained by the fact that the user's activities are similarly repeated; therefore, the number of inferred facts related to the temporal relations between activities is limited. The number of inferred facts related to the daypart context attribute depends on the number of initial facts related to the activity context attribute. When the number of initial facts varies from 50 to 100, the number of inferred facts related to the daypart context attribute varies from 15 to 26; when the number of initial facts varies from 100 to 600, the number of inferred facts increases slightly, up to 34 facts. This is due to the repeated activities in the specific dayparts. In the *Orange4Home* dataset, there are 17 activities and ten different dayparts; some of the activities cannot take place in specific dayparts; therefore, the possible inferred facts related to the daypart context attribute are few; consequently, when the number of initial facts related to the activity context attribute is greater than 100, the number of the inferred facts related to the daypart context attribute is few. The increasing number of inferred activity sequence context attribute is explained by the fact that when there is more than 100 initial facts related to the activity context attribute, there are few inferred facts related to the temporal context attribute, which results in the saturation of inferred facts related to the activity sequence context attribute. The computation time needed for reasoning increases with the number of initial facts related to the activity context attribute.

5.3.2 Handling incomplete information

To show the ability of the human behavior recognition module to deal with incomplete information, another evaluation is performed. In this evaluation, the facts related to the location context attribute are removed from the initial facts, and then the facts related to the location context attribute are inferred using PASP. The latter allows inferring them accurately due to the fact that the activities and their related locations are represented with commonsense knowledge. An accuracy rate of 83.43% is obtained in the case of 350 initial facts related to the activity context attribute. Table 14 shows the performance in terms of accuracy obtained with the human behavior recognition module for inferring facts related to the location context attribute. Since each activity is performed in one location, the number of inferred facts related to the location context attribute is the same as that of initial facts related to the activity context attribute. The obtained results show that the accuracy of the inferred location context

Table 9: Baseline models parameters in the case of the *Orange4Home* dataset.

Model	Parameters	Testing values	Optimal values
KNN	Algorithms	[auto, ball_tree, kd_tree, brute]	brute
	N_neighbors	[1,2,3,4,5,6,7,8,9,10]	10
SVM	C	[0.1, 1,10]	10
	γ	[0.001, 0.01, 0.1]	0.001
	Kernel	[rbf, poly]	rbf
CNN	Optimizer	[sgd, adam]	adam
	Activation function	[relu, tahnh]	relu
DT	max_depth	[1,10,20,30,40,50,60,70,80,90,100]	30
RF	n_estimators	[1,20,40,60,80,100,120]	120
	max_depth	[1,20,40,60,80,100]	100
	min_samples_split	[2,3,5,7]	7
	min_sample_leaf	[1,2,4]	1
	bootstrap	[True, False]	True
	max_features	[auto, sqrt]	auto

Table 10: Baseline models parameters in the case of the *UCI HAR dataset*.

Model	Parameters	Testing values	Optimal values
KNN	Algorithms	[auto, ball_tree, kd_tree, brute]	auto
	N_neighbors	[1,2,3,4,5,6,7,8,9,10]	1
SVM	C	[0.1, 1,10]	1
	γ	[0.001, 0.01, 0.1]	0.01
	Kernel	[rbf, poly]	rbf
CNN	Optimizer	[sgd, adam]	adam
	Activation function	[relu, tahnh]	relu
DT	max_depth	[1,10,20,30,40,50,60,70,80,90,100]	70
RF	n_estimators	[1,20,40,60,80,100,120]	120
	max_depth	[1,20,40,60,80,100]	20
	min_samples_split	[2,3,5,7]	3
	min_sample_leaf	[1,2,4]	1
	bootstrap	[True, False]	False
	max_features	[auto, sqrt]	auto

Table 11: Comparing the performance of the LSTM model with baseline models for activity recognition on *Orange4Home* dataset.

Models	F-measure	Accuracy	Precision	Recall
DT	66.34	73.56	70.54	73.56
KNN	67.08	73.64	69.60	73.64
RF	67.78	74.36	74.36	72.39
SVM	65.28	69.45	72.85	72.85
CNN	76.75	77.64	75.35	84.70
LSTM	95.63	95.71	96.00	95.71

Table 12: Performance obtained using the LSTM model and baseline models in the case of activity recognition using the *HAR* dataset.

Models	F-measure	Accuracy	Precision	Recall
DT	72.50	72.58	72.49	72.58
KNN	74.50	73.87	82.75	73.87
RF	83.90	78.18	91.65	78.18
SVM	87.87	87.89	87.97	87.87
CNN	90.93	90.94	91.27	90.94
LSTM	95.63	95.71	96.00	95.71

attribute remains similar after the first 100 facts related to the activity context attribute. This is due to the fact that the dataset contains repetitive activities and locations; it can be argued that the first 100 facts associated with the activity context attribute are almost sufficient to represent the entire dataset.

5.4 Abnormal human behavior recognition performance

Since the *Orange4Home* and *UCI HAR* datasets do not include the involved objects label in each sample data, abnormalities related to the "*recurrent unexpected activities with specific objects*" abnormal human behavior is not taken into account in the evaluation. In the case of the *Orange4Home* dataset, five abnormal human behaviors, namely *AbnormalActLoc*, *AbnormalActTime*, *AbnormalActDur*, *AbnormalActFreq*, and *AbnormalSeqAct*, are considered, see Table 4. In the case of the *UCI HAR dataset*, two abnormal human behaviors, namely *AbnormalActDur* and *AbnormalSeqAct* are considered. This can be explained by the fact the *UCI HAR dataset* does not include activity location label and time information. Due to the fact that neither of the datasets used in this study includes abnormal behaviors, these latter are randomly injected into the datasets to simulate their presence, allowing the framework to be evaluated

Table 13: Performance of the human behavior recognition module in terms of inferred context attributes of human behavior [120].

Number of initial facts	50	100	200	300	400	500	600	700
Activity context attribute	25	50	100	150	200	250	300	350
Location context attribute	25	50	100	150	200	250	300	350
Number of inferred facts	661	1145	1304	1474	1628	1785	1945	2103
Temporal context attribute	545	926	932	935	936	937	938	939
Daypart context attribute	15	26	30	32	33	34	34	35
Activity sequence context attribute	46	69	72	89	92	98	107	114
Time consumption (ms)	13	22	43	53	80	128	182	236

Table 14: Performance of the human behavior recognition module when the facts related to the location context is incomplete [120].

# Initial facts related to the activity context attribute	25	50	100	150	200	250	300	350
# Inferred facts related to the location context attribute	25	50	100	150	200	250	300	350
Accuracy of inferred ones	72.00	80.00	83.00	84.00	83.5	84.0	84.66	83.43

based on its ability to detect and classify abnormal behaviors under random selections of time of injection and type of human abnormal behaviors.

The results obtained in the case of the *Orange4Home* dataset and the *UCI HAR* dataset are respectively shown in Table 15 and Table 16. The results show that PASP achieves greater than 93% on average in terms of F-measure, accuracy, precision, and recall for both datasets. One can observe that 100% precision is yielded using PASP, which means that abnormal human behaviors are correctly recognized. In other words, there is no false positive in the PASP-based abnormal human behavior recognition. The latter yields better results in the case of the *AbnormalActTime* abnormal human behavior due to its dependency on one activity prediction while it depends on multiple activity predictions in the case of the *AbnormalActDur*, and the *AbnormalActFreq* abnormal human behaviors. Table 16 shows that a better performance is obtained using PASP in the case of the *AbnormalSeqAct* abnormal human behavior in comparison to the case of the *AbnormalActDur* abnormal human behavior. In terms of precision, the performance obtained with PASP is also 100% in the cases of the *AbnormalSeqAct* and *AbnormalActDur* abnormal human behaviors. These results show clearly the effectiveness of the PASP-based framework to recognize accurately abnormal human behaviors.

Since SVM and MLN are two of the most common models used for abnormality recognition [5], [122], [73], these models are selected as baselines for the evaluation of the abnormal human behavior recognition module. In the SVM model, the kernel function is Radial Basis Function (RBF). This kernel is defined

Table 15: Performance obtained utilizing PASP for abnormal human behavior recognition on the *Orange4Home* dataset [117].

Abnormality types	Precision	Recall	F-measure	Accuracy
AbnormalSeqAct	100	88.45	93.87	95.93
AbnormalActFreq	100	94.11	96.96	99.00
AbnormalActDur	100	91.89	95.77	98.97
AbnormalActTime	100	98.10	99.04	99.82
AbnormalActLoc	100	94.21	97.02	98.26
Average	100	93.35	96.53	98.39

Table 16: Performance obtained utilizing PASP for abnormal human behavior recognition on the *UCI HAR dataset* [117].

Abnormality types	Precision	Recall	F-measure	Accuracy
AbnormalSeqAct	100	100	100	100
AbnormalActDur	100	96.15	98.04	99.87
Average	100	98.07	99.02	99.93

on two samples v and v' as follows:

$$K(v, v') = exp(-\frac{\|v - v'\|^2}{2\sigma}) \tag{7}$$

The two samples v and v' represent the feature vectors in input spaces. $\|v - v'\|^2$ is seen as Euclidean distance between the two feature vectors [123]. Two main parameters of the SVM model, γ and C, set respectively one and ten, which are obtained using a greed search technique. The fundamental of MLN is weighted FOL rules that allow for probabilistic reasoning. Since there is a need to exploit both hard constraints and soft ones to recognize abnormal human behaviors, MLN is suitable to contextualize the notion of hard and soft constraints for abnormal human behavior recognition. Hard constraints are rules with

Table 17: Performance obtained using SVM and MLN on the *Orange4Home* dataset.

	SVM					MLN				
Abnormality types	ActLoc	ActTime	ActDur	ActFreq	SeqAct	ActLoc	ActTime	ActDur	ActFreq	SeqAct
precision	95.22	98.66	81.47	66.45	76.61	89.40	94.98	72.00	81.25	87.76
recall	95.11	98.66	79.59	81.52	72.85	94.63	99.53	97.29	76.47	70.37
F-measure	95.14	98.66	74.53	73.22	72.71	91.94	97.20	82.75	78.78	78.11
accuracy	95.11	98.66	79.59	81.52	72.85	95.03	98.28	94.86	93.06	86.12

Table 18: Performances obtained using SVM and MLN on the *UCI HAR* dataset.

	SVM		MLN	
Abnormality types	ActDur	SeqAct	ActDur	SeqAct
precision	80.98	62.04	96.15	90.44
recall	84.89	77.31	96.15	94.53
F-measure	84.17	70.24	96.15	92.44
accuracy	84.17	70.24	99.15	94.69

certainty, whereas soft constraints are rules without certainty. The learning task of MLN consists of two subtasks: (1) structure learning and (2) weight learning. The structure of MLN can be learned using rules written by experts while weight learning is an optimization problem. In the MLN, an expert defines the FOL rules about abnormal human behaviors based on the context attributes characterizing these behaviors, whereas weights are learned by optimizing iteratively a pseudo-likelihood measure. In this experiment, the total number of defined FOL rules to recognize abnormal human behaviors is 433.

Table 17 and Table 18 show the results obtained using MLN and SVM in the case of *Orange4Home* and *UCI HAR* datasets. In the case of the *Orange4Home* dataset, the SVM model achieves 83.68% in terms of precision while the MLN and PASP yield 85.08 and 100%, respectively, see Table 17 and Table 15. In the case of the *UCI HAR* dataset, the SVM model gives 71.51% in terms of average precision while MLN achieves 93.29%. These results show the superiority of the MLN-based framework in comparison to the SVM-based one due to the fact that the latter is limited in considering the context attributes of human behavior, whereas MLN allows handling the uncertainty of rules by exploiting probabilistic rules. The superiority of PASP in comparison to MLN can be explained by the fact that MLN allows handling the uncertainty of rules while the uncertainty of both rules and predictions is handled using PASP. In other words, MLN does not allow considering the uncertainty of activity and activity location predictions whereas PASP allows handling them by assigning a probability value to each rule and a probability value to each predicate and fluent used in the rules.

6 Conclusion and Future Works

In this paper, a hybrid and context-aware framework is proposed for human behavior and abnormal human behavior recognition in AAL systems. LSTM models are firstly used to classify input data, i.e., sensor data, into activity, activity location, and involved object labels. Different context attributes of human behavior are extracted from the recognized labels. These attributes are conceptualized using the HAT ontology. PASP, exploiting a set of probabilistic rules, is then used to recognize human behaviors by inferring new facts about human context while handling uncertain rules and captured context attributes. PASP is also exploited to recognize abnormal human behaviors using probabilistic rules. The proposed framework is first evaluated in terms of activity recognition. The obtained results show that the LSTM model yields higher performance in comparison to the DT, KNN, RF, SVM, and CNN models in terms of all evaluation metrics. This can be explained by the fact that the LSTM model is well-suited to model time series. This framework is then evaluated in terms of inferred facts related to the human behavior context and in the case of handling incomplete information. The proposed framework is finally evaluated and compared with the MLN and SVM models in terms of abnormal human behavior recognition. In comparison with MLN and SVM models, the proposed framework achieves superior results due to the fact that handling the uncertainty of activity and location predictions impacts abnormal human behavior recognition performance.

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Appendix A Statements and Declarations

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A.2 Data Availability

The datasets used during the current study are available in [https://amiqual4home.inria.fr/orange4home/] and [shorturl.at/loNTV].