A Framework for an Ontological Querying-based Cognitive Perspective for Activity Recognition.

Nadia Agti[*], Lyazid Sabri[†]
Faculty of Mathematics and Information Technology, Mohamed El Bachir EL Ibrahimi University of Bordj Bou Arriridj, Algeria

Okba Kazar[‡]
University of Kalba, Sharjah, United Arab Emirates

Abstract

Activity recognition often requires exploring what activities individuals engage in and why these activities occur in specific sequences, locations, and time intervals. Understanding individual behaviours and mental states allows for recognising complex, goal-oriented activities, predicting potential health issues, and offering personalised recommendations involving intentional actions. Our approach, which combines SPARQL-based ontological querying with the cognitive perspective, is a robust method that enhances accuracy and leads to intuitive activity recognition. Our cohesive framework not only effectively extracts relevant insights two complex datasets: Orange4Home and CASAS Aruba, but also enables a deeper exploration of human behaviour. This is achieved through the integration of sensor data with a semantic model, facilitated by our proposed structured Human Behavior Ontology (HBOnt). The HBOnt converts unstructured sensor data into a structured semantic model and incorporates important contextual information, such as the activity's time, location, contributing to a complete understanding of human behaviour in smart homes.

1 Introduction

The seamless integration of technology into daily life has transformed our homes into intelligent spaces capable of recognizing and interpreting a wide range of actions through various sensors. This evolution has enabled the development of Human Activity Recognition (HAR) systems, which play a crucial role in applications such as personalized health monitoring, behavioral analysis, home automation [1], elder care [2], and more. By leveraging data collected from smart devices, HAR systems aim to understand and predict human behavior, providing valuable insights into user actions and improving quality of life.

Deep Conventional HAR systems primarily focus on recognizing activities using raw sensor data [3]. While these systems are effective at identifying behaviors, they often struggle to understand the context and motivations behind these actions [4]. This lack of contextual comprehension can limit the performance of HAR systems, particularly in complex environments like smart homes, where activities are shaped by various factors such as time, personal preferences, and environmental conditions [5, 7].

Semantic approaches [4, 6] offer a promising solution to this challenge by incorporating knowledge representation and reasoning techniques into HAR systems. By leveraging ontologies, a formal representation of domain knowledge semantic HAR systems can transform raw sensor data into a structured model that captures the relationships and contexts of various actions [4]. Through the use of ontologies, sensor data can be annotated and interpreted with higher level concepts and connections, enabling a more comprehensive understanding of the activities being performed.

The development and implementation of HAR systems encounter numerous challenges across various contexts. In smart home environments, the diverse range of activities and variable human behaviors can lead to errors in activity recognition. Individuals often perform similar tasks in different ways due to environmental influences, personal preferences, and habits. This unpredictability complicates the accurate recognition of actions and increases the likelihood of misunderstandings, ultimately reducing the overall reliability of HAR systems.In the context of elder care, the ability to detect subtle changes in daily routines is crucial for timely assistance to elderly individuals. Traditional HAR systems may struggle to recognize these nuances, potentially leading to missed opportunities for intervention in critical situations. For example, changes in an elderly person's eating or sleeping patterns may indicate underlying health issues; however, without adequate detection tools, these changes may go unnoticed, jeopardizing the individual's well-being. Furthermore, accurately tracking health-related behaviors, such as medication adherence and physical activity levels, is essential for personalized health monitoring. Achieving this requires a comprehensive understanding of context, as the relevance of activities is significantly influenced by various factors, including the user's emotional state, the time of

[*]LMSE Laboratory, Computer Science Department. Email: nadia.agti@univ-bba.dz
[†]Intelligent Systems and Cognitive Computing Laboratory. Email: lyazid.sabri@univ-bba.dz
[‡]Department of Computer Science, College of Arts, Sciences and Information Technology. Email: kazar.okba@gmail.com

day, and the environment. These contextual characteristics are crucial for generating personalized health insights and recommendations but are often overlooked by current HAR systems. Ultimately, comprehending the reasons behind human actions is intrinsically intricate and usually necessitates extensive contextual details. Because they only use raw sensor data, traditional HAR systems could miss crucial contextual linkages that affect activity patterns. Without this knowledge, computers' capacity to interpret user behavior meaningfully is constrained, eventually reducing their usefulness in context-aware computing and behavioral analytic applications.

To overcome these challenges, we present a unique semantic approach to human activity identification and analysis in smart homes using the CASAS Aruba dataset [8], and Orange4Home dataset [37]. Our approach employs ontology-based knowledge representation techniques to map unstructured sensor data to a structured semantic model. This transformation converts unstructured readings into RDF triples that encapsulate the semantic meaning of the data. By leveraging SPARQL, a query language tailored for RDF data, we can derive comprehensive insights into activity sequences, contextual elements, and behavioral patterns.

Human behavior analysis requires understanding the cognitive processes and contextual factors influencing various activities. We propose a systematic approach to examine human activities using ontology-driven data extraction. By leveraging the HBOnt ontology, we aim to uncover the complexities and interrelations of human activities, providing insights into the cognitive motivations behind them.

The HBOnt ontology helps represent and organize knowledge of human activities, capturing relationships among concepts within this domain. This formal structure enables effective data integration and reasoning, offering a framework for understanding diverse activities and the factors that influence them.

Our goal is to develop a comprehensive understanding of the motivations and contexts surrounding various activities. By analyzing the relationships between activities, their durations, and contextual factors, we aim to generate insights that inform interventions and support systems to improve well-being.

The contribution of our work lies in establishing a novel framework for ontology-based human activity analysis using SPARQL queries. This approach enhances data analysis granularity and fosters a deeper understanding of cognitive processes. By enabling nuanced queries, we offer a richer exploration of human behavior beyond traditional activity recognition.

Understanding behavior also requires exploring why activities occur in specific sequences, locations, and times. Our ontology-based queries delve into these cognitive motivations, enabling insights into decision-making and routine formation. Through SPARQL, we can analyze activity data with greater precision, such as examining how environmental factors impact sleep duration and quality. This method opens new opportunities for studying various activities, including work, exercise, social interactions, and leisure.

The rest of this paper is organized as follows: Section 2 provides a survey of relevant work in the field. In Section 3, we describe our proposed framework for human activity analysis, including the data used and the method details. Section 4 discusses the experiments conducted and presents the outcomes. Finally, Section 6 concludes the paper and suggests potential avenues for further investigation.

2 Related work

Recent research in human activity recognition for smart homes has leveraged sensor data to analyze user behavior. Traditional machine learning approaches have demonstrated effectiveness but often struggle with complex activity relationships. Advanced models, such as the Depthwise Separable Convolutional Neural Network (DS-CNN) [9], improve efficiency by separating spatial filtering and feature combination, yet may lack contextual awareness in dynamic environments. Similarly, Deep Recurrent Neural Networks (DRNNs) [10] have been employed for temporal pattern recognition using mobile sensors, achieving high precision but facing limitations in generalizing to diverse real-world settings. These studies highlight the need for models that balance efficiency, contextual reasoning, and adaptability to heterogeneous sensor data.

Explainable Artificial Intelligence (XAI) methods, such as LIME, SHAP, and Anchors, have been integrated into activity recognition frameworks to generate natural language justifications [11]. However, achieving a balance between transparency and trust remains challenging, as SHAP may inadvertently reduce user confidence. A fine-tuning approach [12] enhances recognition accuracy by mapping activities into vector representations via Word2Vec, enabling efficient knowledge transfer and reducing annotation efforts. Despite its benefits, this method may not fully capture behavioral variations across different smart home environments, and reliance on open datasets limits adaptability to real-world scenarios.

In [13], ESP32 Wi-Fi devices are used to collect Channel State Information (CSI) for real-time human activity recognition in smart homes, leveraging IoT and edge computing for low-latency analysis. Lightweight machine learning and basic statistical methods are applied for effective recognition, but the simplicity of the features may limit accuracy, especially in handling complex activities or user behavior variations. Similarly, [14] proposes a probabilistic neural network for distinguishing typical and atypical behaviors using sensor data. An H2O autoencoder detects anomalies based on event attributes and durations, but its reliance on boxplots for anomaly ground truth may reduce reliability, and the lack of a comprehensive evaluation framework limits generalizability across varied real-world scenarios.

In [16], a hybrid 4-layer CNN-LSTM architecture is proposed to enhance human activity recognition (HAR) performance. Although the model offers improvements, its ability to handle diverse user behaviors and contextual variations across different environments may limit its practical applicability. In [15], a spatial distance matrix and a Sensor Data Contribution Significance Analysis (CSA) are introduced to evaluate sensor impact on behavior recognition. The HAR_WCNN algorithm utilizes a wide time-domain CNN for multi-environment sensor data, but like the previous approach, it may struggle with contextual variations and human behavior differences in real-world smart home settings.

Incorporating semantic techniques into human activity recognition (HAR) systems offers higher-level interpretation of sensor data, enabling a more structured and comprehensible understanding of activities [4]. By using ontologies and semantic analysis, HAR systems can reason and model actions effectively [26]. Several studies demonstrate how raw sensor data can be transformed into relevant activity descriptions using semantic models like RDF and SPARQL [27, 28]. These systems excel at contextualizing activities by linking objects, actors, and environments. However, traditional ontologies, which emphasize structure, often lack behavioral components. Larhrib et al. [21] propose incorporating behavior flow concepts into ontologies, improving validation and testing processes. Furthermore, ontology-based HAR systems [29] facilitate the modeling of human activities, temporal linkages, and hierarchical action dependencies, offering great potential for inferring higher-level behavior in environments like smart homes, where activities are ordered in time and space.

Ni et al. [20] propose a human activity representation model for smart homes, crucial for discreet wellness monitoring, especially for older adults. Developed using the NeON methodology, the model consists of three ontology categories: users, smart home contexts, and Activities of Daily Living (ADL). It employs the DOLCE+ DnS Ultralite (DUL) ontology as an upper ontology, ensuring high reusability and compatibility across different smart home applications.

Context-aware systems enhance HAR by utilizing real-time environmental data to infer human activities more accurately [22]. These systems reason across multiple contextual dimensions, such as time, location, and object proximity, to identify complex, multi-step tasks. They integrate inference mechanisms to dynamically update their environmental understanding and adjust predictions based on changing conditions. Moulouel et al. [23] introduce an ontology-based framework for identifying user context and detecting anomalies in ambient intelligence systems. Their approach leverages event calculus in answer set programming (ECASP), integrating machine learning, probabilistic planning, and common-sense reasoning. To manage uncertainty, the framework employs probabilistic fluents and a partially observable Markov decision process (POMDP). Additionally, the authors propose a hybrid technique [25] that combines deep learning with probabilistic commonsense reasoning for action prediction in ambient intelligence (AmI) environments. Deep learning models recognize human hands, interior locations, and environmental objects, while ECASP incorporates probabilistic fluents for reasoning. An ontology-based representation of the user's surroundings enables temporal projection and abductive reasoning, contributing to an explainable artificial intelligence (XAI) approach. HAR research, informed by cognitive psychology [24], extends beyond motion detection to infer cognitive states and goals, enhancing behavioral analysis. This multidisciplinary approach advances applications in health and well-being.

Existing HAR techniques still have limitations despite significant progress. Many systems struggle to manage complex, overlapping tasks, and scaling these systems in larger smart home contexts remains a challenge. Furthermore, ongoing issues with sensor accuracy, unbalanced datasets, and real-time processing restrict the use of HAR systems in practical applications. As research progresses, these issues must be addressed to develop reliable and effective HAR systems that can meet a range of user demands and seamlessly integrate into smart homes.

3 Method

This section details the proposed approach. It describes the datasets used, preprocessing steps, model architecture, and evaluation methodology.

3.1 Datasets description

To evaluate the proposed approach, we utilized two datasets: the CASAS Aruba dataset and the Orange4Home dataset. These datasets were selected due to their structured time-series data and their ability to capture diverse activity and behavior recognition scenarios.

The CASAS Aruba dataset, part of Washington State University's smart homes project, was compiled using thirteen motion sensors, three door sensors, five temperature sensors, and three light sensors, all installed in a single-occupant house. Each recorded sensor event is timestamped to the second, capturing data over several months. This continuous, real-time observation documents the temporal evolution of daily activities and offers a comprehensive understanding of daily patterns. Over the course of 132 days, eleven distinct actions were recorded. The structure of the Aruba dataset is detailed in Table 2. It is important to note that certain behaviors are more prevalent than others, resulting in an imbalance within the dataset.

Given the large size of the dataset (1,048,576 rows), preprocessing is necessary to handle missing data, filter out irrelevant information, and prepare the data for mapping to the ontology. Due to the very large quantity of data to process, we used only the first four days of the Aruba dataset, which equals 20,897 events. Table 1 is a sample of the data in Aruba dataset with the column specifications.

The second dataset, the Orange4Home dataset [37], was selected due to its structured time-series data and complex

Table 1: Sample data from the CASAS Aruba dataset

Date	Time	Sensor	Value	Activity	Log
2010-11-04	00:03:50.209589	M003	ON	Sleeping	begin
2010-11-04	00:03:57.399391	M003	OFF	Sleeping	begin
2010-11-04	00:15:08.984841	T002	21.5	Sleeping	begin
2010-11-04	00:30:19.185547	T003	21	Sleeping	begin
2010-11-04	00:30:19.385336	T004	21	Sleeping	begin

Table 2: CASAS Aruba Dataset Structure

Column Name	Description
Date	The date when the sensor data was recorded.
Timestamp	The exact time the data was captured.
Sensor ID	Identifier for the sensor that recorded the data.
Sensor Value	The value recorded by the sensor, varying by type: • M Type (Motion Sensor): ”On” or ”Off”. • T Type (Temperature Sensor): Temperature value. • D Type (Door Sensor): ”Open” or ”Closed”.
Activity Type	The activity being performed.
Activity Value	Indicates whether the activity is beginning (Begin) or ending (End).

multimodal nature, making it suitable for diverse activity and behavior recognition scenarios.

The Orange4Home dataset provides approximately 180 hours of multimodal data from a two-floor smart home, where a single occupant performed daily activities over four consecutive work weeks. It includes 17 annotated activities: *Entering, Living, Preparing, Cooking, Washing the dishes, Eating, Watching TV, Computing, Using the toilet, Going up, Going down, Using the sink, Showering, Dressing, Reading, and Napping*. The datasetś complexity, with wearable, object, and ambient sensors, enables the evaluation of ontology-based reasoning and the SVM classifier. To maintain consistency, the data was segmented using a sliding window of 3 seconds, which balances fine-grained activity detection with sufficient contextual information.

To ensure consistency and optimize the dataset for input into our model, we applied a series of preprocessing steps tailored to its characteristics. These steps included label encoding, linear interpolation, normalization, segmentation, and one-hot encoding.

The preprocessing of the Orange4Home dataset followed a structured approach. The 17 activities were assigned unique numerical labels using label encoding. To address missing sensor readings, forward-fill interpolation was applied. Continuous sensor values were then normalized to the range [0,1]. Additionally, sensor fusion was performed by integrating data from all available sensors into a unified feature matrix. The data was subsequently divided into 3-second overlapping windows, with the majority label assigned to each segment. Finally, one-hot encoding was used to transform the activity labels into binary vectors suitable for classification.

Table 3 summarizes the characteristics of the Orange4Home dataset used.

To ensure robust evaluation, the dataset was split into 70% training, 15% validation, and 15% testing. The training set was used for model learning, the validation set for hyperparameter tuning, and the test set for final performance assessment.

Table 3: Summary of Orange4Home dataset characteristics

Property	Details
Sensor Types	Wearable, object, and ambient sensors
Data Types	Binary, integer, real number, categorical
Number of Activities	17 annotated activities
Participants	Single occupant
Preprocessing	Normalization, segmentation into fixed-size windows
Recording Duration	180 hours over four consecutive work weeks

3.2 Mapping the dataset to an ontology

This section explains the process of mapping information from the smart home environment to an ontology that semantically describes the relationships between actions, sensors, and contextual components. This ontology provides a structured framework for representing human activities and their associated sensor data, enabling advanced querying and inferencing.

Our ontology includes classes: *Activity*, *ActivityTime*, *Location*, *Sensor*, *Object*, and *Subject*. The instances of the subclasses of *Activity* distinguish occurrences of activities based on their day and time of occurrence, allowing multiple occurrences of the same activity across different days and times of the day. Sensors are categorized into three types, each of them linked to specific locations within the smart home.

These concepts are connected by different relationships: *occursOn*, *hasStartTime*, *hasEndTime*, *hasActivityLocation*, *hasActor*, *hasTimeOfDay*, *hasSensorID*, and other properties, which capture the connections between activities, sensors, and their contextual details. This ontology facilitates structured semantic representations of the data, enabling advanced queries and inference about human activity patterns.

- *Activity* ($\mathscr{A}$): Represents the human activities described in the datasets. The class has the different activity types as subclasses, and each of these subclasses has its occurrences as instances based on the day and the time of occurrence.
- *ActivityTime* ($\mathscr{D}$): Represents the day of the activity, and the time of the day the activity is done.
- *Location* ($\mathscr{L}$): Represents the various spaces or rooms where sensors are installed in the smart home.(e.g., Bedroom, Kitchen).

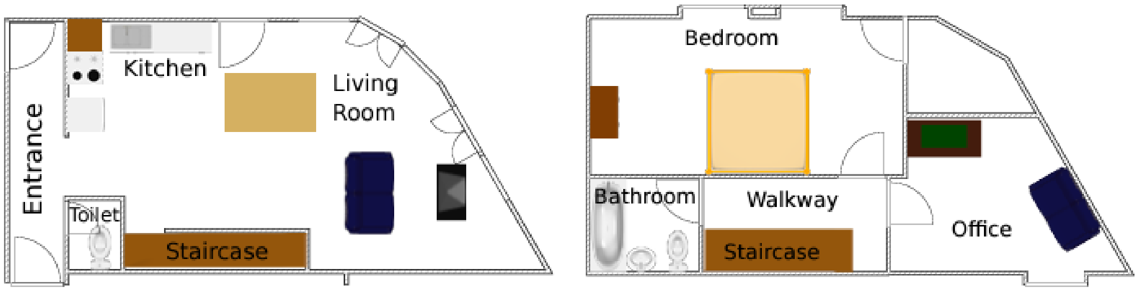

Figure 1: Smart Home Layout Used for Orange4Home Dataset Collection [37]

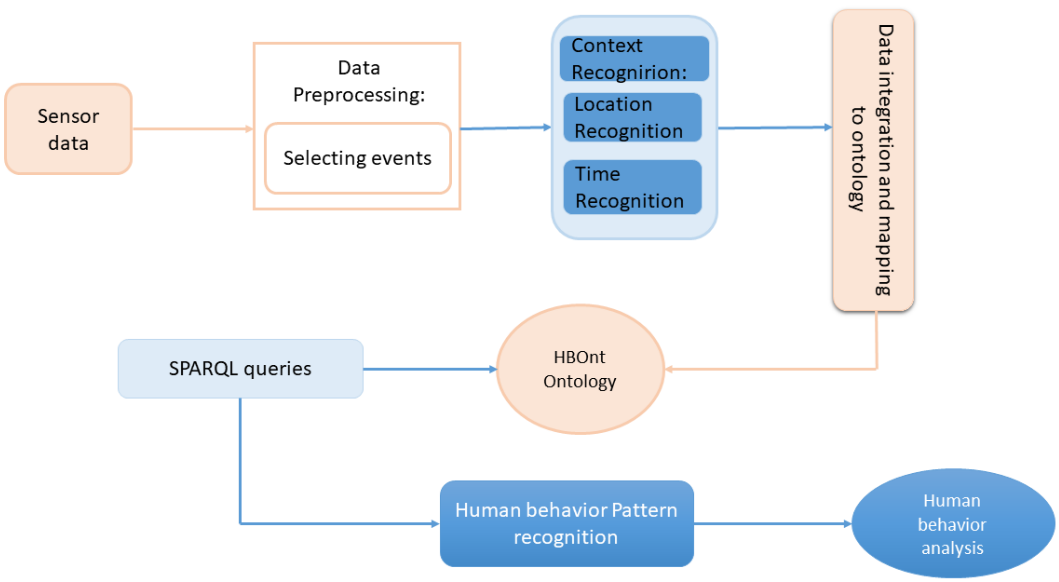

Figure 2: General architecture of the proposed method

- *Sensor* ($\mathscr{S}$): Represents the various types of sensors installed in smart homes:
  - *DoorSensor* ($\mathscr{S}_D$)
  - *MotionSensor* ($\mathscr{S}_M$)
  - *TemperatureSensor* ($\mathscr{S}_T$)

  Individuals are created to correspond to the actual sensors in the datasets for each type of sensor.
- *Object* ($\mathscr{O}$): Represents the different objects involved in the activities classified by the location the object can be found in (e.g., desktop, toothbrush).
- *Subject* ($\mathscr{S}_B$): Represents the various subjects performing the activities; in our datasets, we have a single subject.

These classes and subclasses are related using object and data properties, from which we cite:

- *hasActor* (*hasActivity* : $\mathscr{A} \to \mathscr{S}_B$): Each occurrence of the activities is linked to a specific *Subject*.
- *occursOn* (*occursOn* : $\mathscr{A} \to \mathscr{D}$): Each *Activity* is linked to a specific day and time of the day.
- *isMonitoredBy* (*isMonitoredBy* : $\mathscr{A} \to \mathscr{S}$): Each *Activity* is associated with one or more sensors in the location where it is monitored.
- *hasActivityLocation* (*hasActivityLocation* : $\mathscr{A} \to \mathscr{L}$): Each activity occurrence is associated with a specific *Location* in the smart home.

To capture the temporal aspects of activity occurrences, we define the data properties: *hasStartTime* (*hasStartTime* : $\mathscr{A} \to xsd : dateTime$) specifies the start time of each activity occurrence, and *hasEndTime* (*hasEndTime* : $\mathscr{A}_O \to xsd : dateTime$) specifies the end time of each activity occurrence. The XSD (XML Schema Definition), a World Wide Web Consortium recommendation, specifies how to describe an element formally. The xsd:dateTime is a Datatype of the XML Schema language definition. One way to conceptualize time values is as objects with integer-valued year, month, day, hour, and minute attributes.

For each row in the datasets, we create instances of the class *Activity* ($\mathscr{A}$) that capture contextual details (e.g., day, location, start time, and end time, object). Activity occurences ($\mathscr{A}_O$) are derived directly from the dataset's activity labels. Each occurrence of an activity is captured as an instance of *Activity* subclasses, with associated temporal data using the properties *hasStartTime*, *hasEndTime* and *hasActivityLocation*.

Sensors in the datasets are categorized into the subclasses *DoorSensor* ($\mathscr{S}_D$), *MotionSensor* ($\mathscr{S}_M$), and *TemperatureSensor* ($\mathscr{S}_T$). Each sensor is represented as an individual, with properties such as *SensorID*, *Location*, and *SensorType*. Locations ($\mathscr{L}$) represent different rooms in the smart home, and each sensor is linked to its respective location through the property *isInstalledIn*.

Each *Activity* type ($\mathscr{A}$) is linked to an *activityTime* ($\mathscr{D}$) and a *Location* ($\mathscr{L}$), and is associated with a *Subject* ($\mathscr{A}$) through the object properties *occursOn*, *hasActivityLocation*, and *hasActor* respectivly.

The formal relationships can be expressed as follows:

$$\forall a_0 \in \mathscr{A}, \exists d \in \mathscr{D}, \exists l \in \mathscr{L} \mid occursOn(a_0,d) \wedge hasActivityLocation(a_0,l) \quad (1)$$

$$\forall a_0 \in \mathscr{A}, \exists s \in \mathscr{S}_B \mid hasActor(a_0,s) \quad (2)$$

$$\forall a_o \in \mathscr{A} \mid hasStartTime(a_o,t_s) \wedge hasEndTime(a_o,t_e) \quad (3)$$

The data is converted into RDF triples, semantically encoding the connections between actions, their occurrences, and the contextual components in the smart home via the structured ontology mapping. This model facilitates the inference of activity patterns and behaviors, enabling sophisticated SPARQL queries. Figures 3 and 4 present an overview of the HBOnt-Ontology taxonomy. The detail box highlights part of the Stimulus-Sensor-Observation pattern in SSN [36]. To represent sensor values in observations, the *hasValue* property was added to the HBOnt ontology.

The *locatedAt* relation expresses proximity, for instance, *locatedAt* (Person, Place, Time Interval) indicates a person (Subject) being at a specific place during a given time interval. The Sensor concept includes two properties: *observes*, which describes sensor qualities (e.g., precision, resolution, response time), and *produces*, which describes the sensor's output (e.g., temperature, brightness, position). A temperature sensor (*TemperatureSensor*) has a unique identifier (Sensor ID), and the *locatedAt* property can infer a person's presence at a place during a time interval.

The Observation concept represents contextual data from sensors, with the *observed* property linking it to the Sensor concepts in the SSN ontology. Our robust taxonomy-based semantic model includes key contextual concepts such as *locatedAt*, *installedIn*, and *observed*. Physical devices like temperature and motion sensors are represented as *TemperatureSensor* and *MotionSensor*, respectively. Each sensor is uniquely identified by a Sensor ID, ensuring accurate inferences of a Subject's presence in a given space.

3.3 Human Behavior Analysis

Our SPARQL queries developed to examine human behaviors and their connections within the framework of cognitive psychology. These queries are designed to extract relevant information from the ontology to help understand why individuals engage in specific activities and the interactions between various activities, contexts, and motivations. Each query contributes to the broader analysis of cognitive processes associated with activity sequences while addressing a distinct aspect of human behavior.

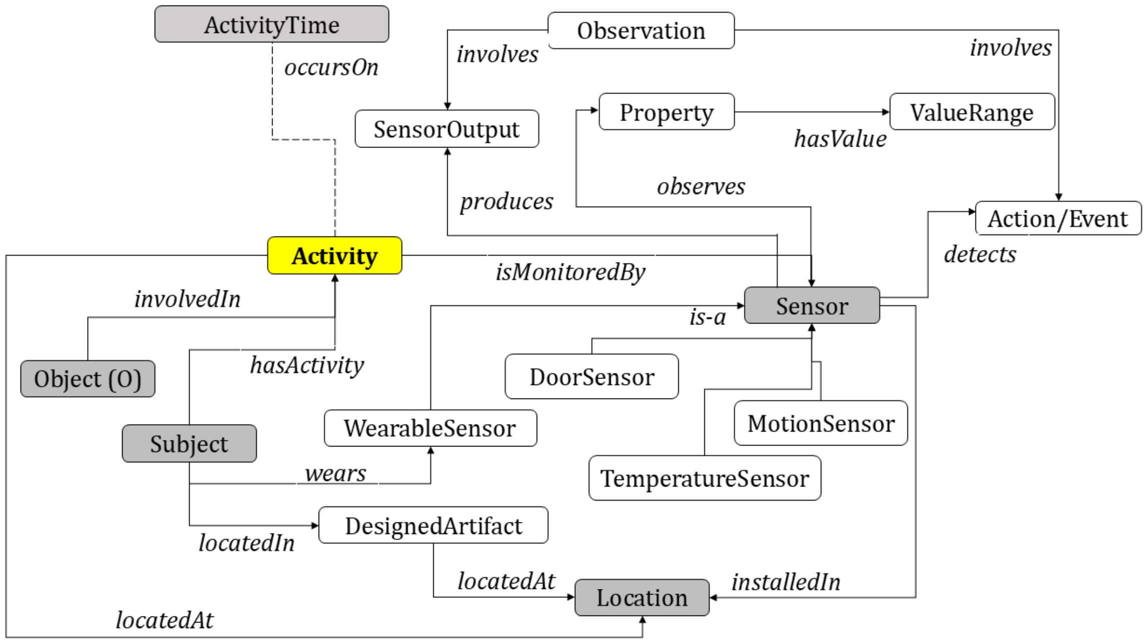

Figure 3: Main components of the HBOnt ontology to represent and organize knowledge about human activities.

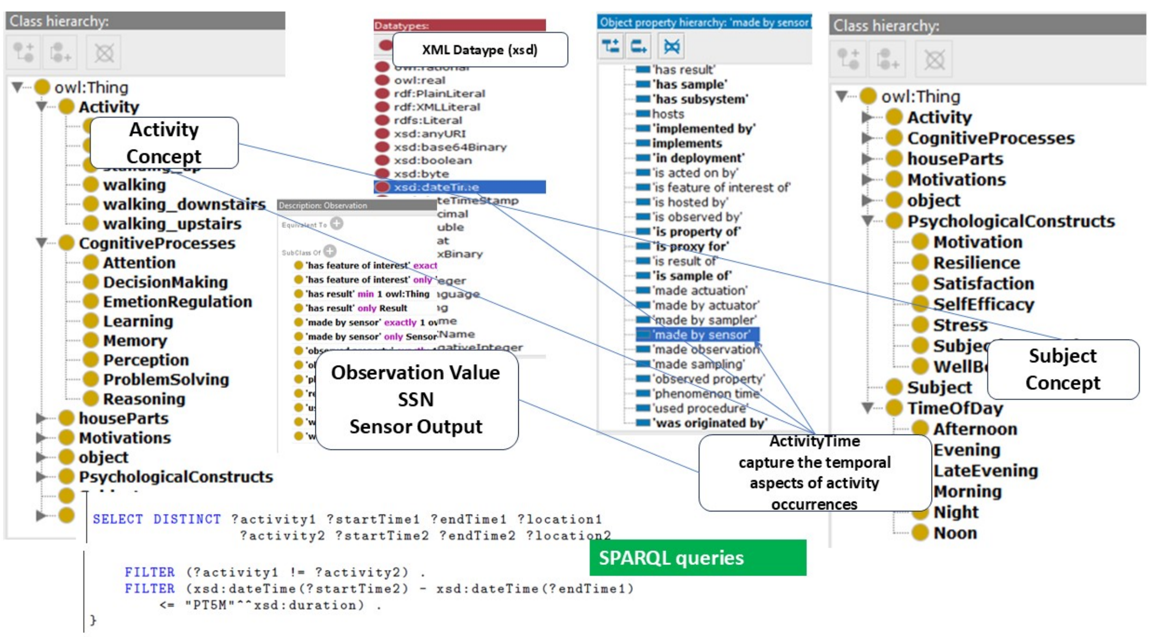

Figure 4: Structure of the ontology, adding semantic contextual information for each recorded activity occurrence, and modelling the relations of the concept Observation of the HBOnt ontology and the Subject and the Activity concepts.

Retrieve Activities of a Subject

```
SELECT DISTINCT ?activity ?startTime ?endTime
WHERE {
    <http://www.co-ode.org/ontologies/ont.owl#Mary> ex:hasActivity ?activity .
    ?activity ex:hasStartTime ?startTime ;
              ex:hasEndTime ?endTime .
}
```

This query returns specific tasks along with their start and end times for the subject. By identifying these behaviors, we can gain insights into the precise steps the individual took during a predetermined period. Understanding the sequence and duration of these activities is essential for analyzing cognitive patterns and behavioral motivations.

Filter Activities by Duration

```
SELECT DISTINCT
    (STRAFTER(STR(?activity), "http://www.co-ode.org/ontologies/ont.owl#") AS ?activityName)
    ?startTime ?endTime
WHERE {
    {
        SELECT ?activity ?startTime ?endTime
        WHERE {
            <http://www.co-ode.org/ontologies/ont.owl#Mary> ex:hasActivity ?activity .
            ?activity ex:hasStartTime ?startTime ;
                      ex:hasEndTime ?endTime .
        }
    }
    FILTER ((xsd:dateTime(?endTime) - xsd:dateTime(?startTime)) > "PT6M"^^xsd:duration) .
}
```

This query builds upon the previous one by restricting the activities to those lasting more than a specified period of time. By focusing on longer tasks, we can examine patterns that may indicate deeper cognitive engagement or preference.

Identify Activity Sequences with Contextual Locations

```

SELECT DISTINCT ?activity1 ?startTime1 ?endTime1 ?location1
                ?activity2 ?startTime2 ?endTime2 ?location2
WHERE {
    <http://www.co-ode.org/ontologies/ont.owl#Mary> ex:hasActivity ?activity1 .
    ?activity1 ex:hasStartTime ?startTime1 ;
               ex:hasEndTime ?endTime1 ;
               ont:hasActivityLocation ?location1 .

    <http://www.co-ode.org/ontologies/ont.owl#Mary> ex:hasActivity ?activity2 .
    ?activity2 ex:hasStartTime ?startTime2 ;
               ex:hasEndTime ?endTime2 ;
               ont:hasActivityLocation ?location2 .

    FILTER (?activity1 != ?activity2) .
    FILTER (xsd:dateTime(?startTime2) - xsd:dateTime(?endTime1) <= "PT5M"^^xsd:duration) .
}
```

This query retrieves the start and end times, as well as the locations of the activity pairs completed by the subject 'Mary.' By examining the temporal proximity of different activities and their surrounding contexts, we can infer potential linkages and reasons for the transitions between activities.

4 Experiments and Results

In this section, we evaluate the performance of our proposed framework, utilizing Protégé for ontology development and the GENA API in Java for implementation. The Human Behavior Ontology (HBOnt) was constructed from the dataset and queried using Apache Jena. The analysis, conducted on a machine with an Intel i5 CPU and 8 GB RAM, provides insights into human behaviors, particularly focusing on the sleep activity. By examining pre- and post-sleep activities, we uncover how daily routines and environmental conditions influence cognitive states, such as emotional health and stress management.

The study finds that regular sleep patterns are associated with cognitive strategies for stress management, aligning with existing research on the importance of sleep regularity. Additionally, the quality of sleep is linked to the nature of preceding activities, such as calming versus stimulating tasks, and the external environment, such as noise levels, reinforcing the cognitive psychology perspective that behavior and cognition are shaped by routines and surroundings.

SPARQL queries allow for detailed analysis of individual activity patterns, such as those of 'Mary' who shows a structured daily routine involving meal preparation, relaxation, and sleep. Query results reveal that activities like meal-preparation reflect personal values, such as creativity or care, while a preference for relaxation before bed suggests the importance of unwinding. The analysis of activity transitions further indicates a structured routine that balances rest and relaxation, highlighting the role of behavioral consistency in promoting well-being.

According to cognitive theory, the duration and timing of activities reveal underlying routines, physiological and mental needs, and responses to external stimuli. Unlike short impulsive acts, Query 1 screened for instances of the *Relax* activity, highlighting cases that show sustained focus or intentional rest, which can indicate deeper cognitive engagement.

- **Results for Query 1:**
  Activity: *Relax_2024-07-04_1*
  Start Time: *2024-07-04T09:29:23*
  End Time: *2024-07-04T09:34:05*
  Activity: *Relax_2024-07-06_1*
  Start Time: *2024-07-06T11:11:08*
  End Time: *2024-07-06T11:25:23*

By demonstrating cognitive recovery strategies, extended periods of relaxation align with the ideas of resource management and cognitive balance. As shown in these cases, longer or repeated rest intervals may indicate that the subject is maximizing its recovery after exertion.

The brief pauses between activities shown in Query 3 may indicate goal-driven behavior, where each activity aligns with a particular need or objective. This aligns with cognitive psychology's view of motivation as a structured action in response to external or internal stimuli.

- **Results for Query 3:**
  Start Time: *2024-07-06T11:11:08*
  End Time: *2024-07-06T11:25:23*
  Activity Name: *Relax_2024-07-06_1*
  Start Time: *2024-07-06T22:27:35*
  End Time: *2024-07-06T22:36:08*
  Activity Name: *Relax_2024-07-06_6*

The pattern of swiftly switching from *Relax* to other tasks, such as *Meal Preparation*, might indicate adherence to set schedules or routines linked to physiological requirements (like hunger), implying that some tasks are prioritized due to urgent, time-sensitive motives. This behavior aligns with motivation theories, which suggest that people balance leisure and obligations by performing specific tasks out of need or habit.

As shown with Query 3, shifts in position and activity provide information about behavior that adjusts to environmental stimuli.

- **Results for Query 3:**
  Start Time: *2024-07-06T18:29:36*
  End Time: *2024-07-06T18:41:18*
  Activity Name: *Relax_2024-07-06_2*
  Location:*Living*
  Start Time: *2024-07-04T16:36:10*
  End Time: *2024-07-04T17:06:00*
  Activity Name: *Meal_Preparation_2024-07-04_8*
  Location:*Kitchen*

In this instance, switching between tasks—for example, from *Relax* in one area to *Meal Preparation* in another—demonstrates cognitive flexibility. The ability to modify behavior in response to contextual signals or environmental resources is illustrated by this shift in tasks across locations, which shows awareness of and reactivity to the current environment. This flexibility is a key component of cognitive flexibility, where behavior is both goal-oriented and responsive to circumstances.

These examples illustrate a sample of our findings, demonstrating how ontology-based querying allows us to infer motivational states, evaluate behavior patterns, and detect abnormalities. Our ability to identify effective patterns, spot deviations that may indicate cognitive exhaustion, and recognize behaviors consistent with motivational theories is enhanced by the ontology framework.

Our ontology-based approach's flexibility in handling novel situations is one of its main benefits. Because ontologies are inherently adaptable, new concepts and relationships can be added with ease. This is essential for changing datasets and behavioral contexts. Our method can be expanded by adding additional classes or attributes in the ontology, providing scalability and adaptability, in contrast to traditional deep learning models that require costly retraining when fitted to new activities.

In HAR, interpretability is crucial, especially when behavior analysis is utilized to infer human intents. Because each conclusion is backed up by specific rules and connections, our ontology-based method provides great transparency and makes the reasoning process traceable and explicable. On the other hand, deep learning models are often referred to as 'black boxes,' having little interpretability concerning the underlying decision-making process. The openness of our approach facilitates the understanding of human behavior patterns, making it especially useful for situations where explainability is crucial.

The structure of our ontology models action sequences and their relationships, allowing for a more thorough explanation of human behavior. Our method can infer the motives underlying sequences of actions, unlike methods that only label individual activities (e.g., inferring "preparing to sleep" based on prior behaviors like "brushing teeth" and "changing clothes"). Because standard machine learning models typically lack the potential for such high-level thinking, this hierarchical and relational knowledge provides insights that are difficult to obtain.

A comparative overview of the main characteristics covered above is provided in Table 5, which also highlights the benefits of our ontology-based approach in HAR over deep learning-based models that are frequently employed in the literature.

The table 4 compares the query efficiency between the **CASAS Aruba** and **Orange4Home** datasets, focusing on how efficiently the ontology-based system can handle large amounts of data. For the **CASAS Aruba** dataset, which contains 11 activities, a total of **150 SPARQL queries** were executed. The system achieved an **average query time of 0.25 seconds**, with a **maximum query time of 0.35 seconds**. The query complexity for this dataset is classified as **medium**, indicating that the queries are moderately complex but that the system can handle them efficiently.

Table 4: Comparative Analysis of Query Efficiency (CASAS Aruba and Orange4Home)

Dataset	Number of Activities	Number of SPARQL Queries Run	Average Query Time (s)	Max Query Time (s)	Query Complexity
CASAS Aruba	11	150	0.25	0.35	Medium
Orange4Home	17	200	0.20	0.30	Medium

Table 5: Comparison of the proposed ontology-based approach with different types of deep learning models in HAR

Metric	Our Proposed Approach	Deep Learning Models
Accuracy of Inference	High correctness in composite activities	High in predefined labels [30]
Context Awareness	Detailed spatiotemporal context	Limited to training data context [31]
Flexibility and Adaptability	Easily extensible with new concepts	Requires retraining for new activities [32]
Interpretability	High, with transparent rules	Low, often a ”black box” [33]
Query Execution Efficiency	Rapid, supports real-time inference	Slower, may require preprocessing [34]
Behavioral Understanding	Hierarchical and sequence-based	Limited to labeled data [35]

On the other hand, the **Orange4Home** dataset, which involves 17 annonated activities, had **200 SPARQL queries** executed. The average query time was slightly shorter, at **0.20 seconds**, with a **maximum query time of 0.30 seconds**. Similarly to CASAS Aruba, the complexity of the query for Orange4Home is also classified as **medium**. Despite the higher number of activities, the query performance remains efficient.

Although the suggested method yields good results in general, a few practical considerations should be noted. The quality of the sensor data and the effectiveness of its adaptation to various real-world environments can influence its success. To align with the evolution of activity patterns, the ontology may require periodic updates. In environments that change quickly or are characterized by high dynamics, additional optimization could assist in preserving real-time performance. However, our findings are promising, both datasets have consistently exhibited efficient query times, with averages remaining low and peak times falling within an acceptable range. The system can handle moderately complex queries, suggesting that it is appropriate for real-time applications in smart environments, particularly those requiring rapid and reliable processing of large amounts of data.

5 Conclusion

The proposed structured human behavioural ontology has practical applications that allow a cohesive transformation of raw sensor data into a structured model that captures various actions' time, location, and events relationships. The ontological querying process based on SPARQL queries examines distinct aspects of humans and contributes to the broader analysis of cognitive processes and behaviours. Moreover, queries extract relevant information from the ontology to help understand why individuals engage in specific activities and the interactions between various activities, contexts, and motivations.

Relying on the CASAS Aruba and Orange4Home datasets, we demonstrated the efficiency of the proposed semantic framework through a series of experiments, showing a significant improvement over conventional methods in capturing the complexities of human behaviour in smart homes. In future work, we will enhance this framework by incorporating deep learning techniques to refine the accuracy of behavioural analysis. Additionally, exploring the development of personalized recommendation systems could improve quality of life by offering tailored insights based on individual activity patterns.

Acknowledgments

Not applicable

References

[1] R. Raghavendra, V. Singh, S. Arora, and M. V. Gupta, „Sensor-based human activity detection using a novel machine learning algorithm in home automation”, *Multidisciplinary Science Journal*, vol. 6, 2024.

[2] P. Kulurkar, C. K. Dixit, V. C. Bharathi, A. Monikavishnuvarthini, A. Dhakne, and P. Preethi, „AI based elderly fall prediction system using wearable sensors: A smart home-care technology with IOT”, *Measurement: Sensors*, vol. 25, p. 100614, 2023.

[3] N. Agti, L. Sabri, O. Kazar, and A. Chibani, „A Novel Deep Learning Model for Smartphone-Based Human Activity Recognition”, in *Proc. Int. Conf. Mobile Ubiquitous Syst.: Comput., Netw., Serv.*, pp. 231–243, 2023.

[4] R. Mojarad, A. Chibani, F. Attal, G. Khodabandelou, and Y. Amirat, „A hybrid and context-aware framework for normal and abnormal human behavior recognition", *Soft Comput.*, vol. 28, no. 6, pp. 4821–4845, 2024.

[5] G. Diraco, G. Rescio, P. Siciliano, and A. Leone, „Review on human action recognition in smart living: Sensing technology, multimodality, real-time processing, interoperability, and resource-constrained processing", *Sensors*, vol. 23, no. 11, p. 5281, 2023.

[6] K. Moulouel, M. Arbane, A. Chibani, G. Khodabandelou, and Y. Amirat, „Stream reasoning approach for anticipating human activities in ambient intelligence environments", in *Proc. IEEE Int. Conf. Tools Artif. Intell. (ICTAI)*, pp. 666–671, 2022.

[7] L. Arrotta, G. Civitarese, and C. Bettini, „Dexar: Deep explainable sensor-based activity recognition in smart-home environments", *Proc. ACM Interact. Mobile Wearable Ubiquitous Technol.*, vol. 6, no. 1, pp. 1–30, 2022.

[8] Washington State University, „CASAS Datasets", available at: `https://casas.wsu.edu/datasets/`, accessed Sep. 25, 2024.

[9] D. Alghazzawi, O. Rabie, O. Bamasaq, A. Albeshri, and M. Z. Asghar, „Sensor-based human activity recognition in smart homes using depthwise separable convolutions", *Hum.-Cent. Comput. Inf. Sci.*, vol. 12, no. 50, 2022.

[10] A. R. Javed, R. Faheem, M. Asim, T. Baker, and M. O. Beg, „A smartphone sensors-based personalized human activity recognition system for sustainable smart cities", *Sustainable Cities Soc.*, vol. 71, p. 102970, 2021.

[11] D. Das, Y. Nishimura, R. P. Vivek, N. Takeda, S. T. Fish, T. Ploetz, and S. Chernova, „Explainable activity recognition for smart home systems", *ACM Transactions on Interactive Intelligent Systems*, vol. 13, no. 2, pp. 1–39, 2023.

[12] Y. Yu, K. Tang, and Y. Liu, „A fine-tuning based approach for daily activity recognition between smart homes", *Applied Sciences*, vol. 13, no. 9, p. 5706, 2023.

[13] A. K. Sahoo, V. Kompally, and S. K. Udgata, „Wi-fi sensing based real-time activity detection in smart home environment", in *Proc. IEEE Applied Sensing Conf. (APSCON)*, pp. 1–3, 2023.

[14] L. G. Fahad and S. F. Tahir, „Activity recognition and anomaly detection in smart homes", *Neurocomputing*, vol. 423, pp. 362–372, 2021.

[15] Y. Li, G. Yang, Z. Su, S. Li, and Y. Wang, „Human activity recognition based on multienvironment sensor data", *Information Fusion*, vol. 91, pp. 47–63, 2023.

[16] S. Mekruksavanich and A. Jitpattanakul, „LSTM networks using smartphone data for sensor-based human activity recognition in smart homes", *Sensors*, vol. 21, no. 5, p. 1636, 2021.

[17] L. Chen, C. Nugent, and G. Okeyo, „An ontology-based hybrid approach to activity modeling for smart homes", *IEEE Transactions on Human-Machine Systems*, vol. 44, no. 1, pp. 92–105, 2013.

[18] D. Riboni and C. Bettini, „OWL 2 modeling and reasoning with complex human activities", *Pervasive and Mobile Computing*, vol. 7, no. 3, pp. 379–395, 2011.

[19] F. Palumbo, C. Gallicchio, R. Pucci, and A. Micheli, „Human activity recognition using multisensor data fusion based on reservoir computing", *Journal of Ambient Intelligence and Smart Environments*, vol. 8, no. 2, pp. 87–107, 2016.

[20] Q. Ni, I. P. de la Cruz, and A. B. Garcia Hernando, „A foundational ontology-based model for human activity representation in smart homes", *Journal of Ambient Intelligence and Smart Environments*, vol. 8, no. 1, pp. 47–61, 2016.

[21] M. Larhrib, M. Escribano, C. Cerrada, and J. J. Escribano, „An Ontological Behavioral Modeling Approach with SHACL, SPARQL, and RDF Applied to Smart Grids", *IEEE Access*, 2024.

[22] R. Mojarad, F. Attal, A. Chibani, and Y. Amirat, „A context-aware approach to detect abnormal human behaviors", in *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 89–104, 2020.

[23] K. Moulouel, A. Chibani, and Y. Amirat, „Ontology-based hybrid commonsense reasoning framework for handling context abnormalities in uncertain and partially observable environments", *Information Sciences*, vol. 631, pp. 468–486, 2023.

[24] L. W. Barsalou, „Cognitive psychology: An overview for cognitive scientists", *Psychology Press*, 2014.

[25] K. Moulouel, A. Chibani, H. Abdelkawy, and Y. Amirat, „Hybrid approach for anticipating human activities in Ambient Intelligence environments", in *2022 IEEE 18th International Conference on Automation Science and Engineering (CASE)*, pp. 2006–2011, 2022.

[26] L. Chen and C. Nugent, „Ontology-based activity recognition in intelligent pervasive environments", *International Journal of Web Information Systems*, vol. 5, no. 4, pp. 410–430, 2009.

[27] G. Meditskos, S. Dasiopoulou, and I. Kompatsiaris, „MetaQ: A knowledge-driven framework for context-aware activity recognition combining SPARQL and OWL 2 activity patterns", *Pervasive and Mobile Computing*, vol. 25, pp. 104–124, 2016.

[28] G. Meditskos, S. Dasiopoulou, V. Efstathiou, and I. Kompatsiaris, „Sp-act: A hybrid framework for complex activity recognition combining OWL and SPARQL rules", in *2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*, pp. 25–30, 2013.

[29] D. Hooda and R. Rani, „Ontology driven human activity recognition in heterogeneous sensor measurements", *Journal of Ambient Intelligence and Humanized*

Computing, vol. 11, no. 12, pp. 5947–5960, 2020.

[30] S. Zhang, Y. Li, S. Zhang, F. Shahabi, S. Xia, Y. Deng, and N. Alshurafa, „Deep learning in human activity recognition with wearable sensors: A review on advances”, *Sensors*, vol. 22, no. 4, p. 1476, 2022.

[31] L. Miranda, J. Viterbo, and F. Bernardini, „A survey on the use of machine learning methods in context-aware middlewares for human activity recognition”, *Artificial Intelligence Review*, vol. 55, no. 4, pp. 3369–3400, 2022.

[32] R. Kanjilal, M. F. Kucuk, and I. Uysal, „Sub-transfer Learning in Human Activity Recognition: Boosting the Outlier User Accuracy”, *IEEE Sensors Journal*, 2023.

[33] E. Kim, „Interpretable and accurate convolutional neural networks for human activity recognition”, *IEEE Transactions on Industrial Informatics*, vol. 16, no. 11, pp. 7190–7198, 2020.

[34] X. Cheng, L. Zhang, Y. Tang, Y. Liu, H. Wu, and J. He, „Real-time human activity recognition using conditionally parametrized convolutions on mobile and wearable devices”, *IEEE Sensors Journal*, vol. 22, no. 6, pp. 5889–5901, 2022.

[35] I. E. Jaramillo, C. Chola, J.-G. Jeong, J.-H. Oh, H. Jung, J.-H. Lee, W. H. Lee, and T.-S. Kim, „Human activity prediction based on forecasted IMU activity signals by sequence-to-sequence deep neural networks”, *Sensors*, vol. 23, no. 14, p. 6491, 2023.

[36] P. Compton et al., „The SSN Ontology of the W3C Semantic Sensor Network Incubator Group”, *Web Semantics: Science, Services and Agents on the World Wide Web*, vol. 17, pp. 25–32, 2012.

[37] J. Cumin, G. Lefebvre, F. Ramparany, and J. L. Crowley, „A dataset of routine daily activities in an instrumented home”, in *Ubiquitous Computing and Ambient Intelligence: 11th International Conference, UCAmI 2017*, pp. 413–425, 2017.

Agti Nadia is a Ph.D. student at the University of Bordj Bou Arréridj, Algeria, specializing in Decision Support Systems Engineering. She obtained her Master’s degree in Decisional Informatics and Multimedia from the University of Biskra. Her current research interests include artificial intelligence and human activity recognition.

Sabri Lyazid is an Assistant Professor at the Bachir Ibrahimi University. He holds a Ph.D. in Computer Science, Images, Signals and Intelligent Systems from University Paris-Est Créteil (UPEC). He is a senior consultant on artificial intelligence, information systems architectures, and cybersecurity. While at UPEC, he worked on several collaborative research projects (e.g., SembySem, Web of Objects, Predykot, A2nets) dealing with IoT and ambient assisted living, robotics, artificial intelligence, and access management. His research interests are in ontology, knowledge representation and reasoning, robotics, artificial intelligence, deep learning, cognitive psychology, the Internet of Things paradigm, and blockchain technology.

Kazar Okba holds degrees in Computer Science and Artificial Intelligence from the University of Constantine, including a PhD. He has been a Full Professor at the University of Biskra since 2011, where he also helped establish the Computer Science Department and founded the Smart Computer Science Laboratory (LINFI). Dr. Kazar has published over 415 papers, authored three books, and contributed to 17 book chapters. His research interests cover a wide range of topics, including artificial intelligence, multi-agent systems, health management, big data, IoT, cloud computing, and digital twins. He has served as a reviewer and session chair at international conferences and has been a visiting professor in several European countries and the UAE. He is currently a professor at Kalba University.