MMOU-AR: Multimodal Obtrusive and Unobtrusive Activity Recognition Through Supervised Ontology-Based Reasoning

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Abstract. The aging population, prevalence of chronic diseases, and outbreaks of infectious diseases are some of the major healthcare challenges. To address these unmet healthcare challenges, monitoring and Activity Recognition (AR) are considered as a subtask in pervasive computing and context-aware systems. Innumerable interdisciplinary applications exist, underpinning the obtrusive sensory data using the revolutionary digital technologies for the acquisition, transformation, and fusion of recognized activities. However, little importance is given by the research community to make the use of non-wearables i.e. unobtrusive sensing technologies. The physical state of human pervasively in daily living for AR can be seamlessly presented by acquiring health-related information by using unobtrusive sensing technologies to enable long-term health monitoring without violating an individual's privacy. This paper aims to propose and provide supervised recognition of Activities of Daily Livings (ADLs) by observing unobtrusive sensor events using statistical reasoning. Furthermore, it also investigates their semantic correlations by defining semantic constraints with the support of ontological reasoning. Extensive experiments were performed with real-world dataset shared by the University of Jaén Ambient Intelligence (UJAmI) Smart Lab in order to recognize the human activities in the smart environment. The evaluations show that the accuracy of the supervised method (87%) is comparable to the one, state of the art semantic approach (91%).

Keywords: Multi-sensor data fusion · Activity Recognition · Sampling · Classification · Reasoning

1 Introduction

Over the past few decades, a rapid rise in the advancement of pervasive computing in healthcare has been observed. These advancements include the gathering of Activities of Daily Livings (ADLs) in response to the prevailing challenges

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linked with global healthcare systems. The challenges most often relate to the global issues of an ageing population suffering from physical or mental health, especially related to the chronic diseases [9]. A wide variety of applications are underpinned with state of the art Machine Learning (ML) algorithms for recognizing ADLs in smart environments using obtrusive and unobtrusive sensors. The wearable devices, also called as obtrusive devices, are most commonly engaged by the users for Activity Recognition (AR), however, such devices may not be practically applicable for long-term use because of their maintenance cost, battery life, and discomfort caused by continuously wearing them. This may also lead to the noisy and imprecise state, causing an erroneous classification and recognition. This study explores how to recognize activities based on the available sheer amount of discrete and continuous multimodal data produced by obtrusive, as well as, unobtrusive devices. Above-mentioned factors affect the performance of ML-based AR from multimodal sensory data sources thus the appropriate solution is required, which can lift the performance of the ADLs in monitoring applications [7]. The selected aggregation strategy for data-level fusion determines the way in which multimodal data reach the fusion node [15]. At the fusion node, different ADLs can be best be recognized by the selecting the appropriate fusion strategy with variable window lengths [12]. Because of the promising features of unobtrusive non-wearable sensing devices to recognize human pervasive activities using smart-home applications [6], this study gives a brief overview and usage of human identification technologies categorized namely as, object-based, footstep-based, body shape-based and gait-based identification technologies. Among all, the first type of unobtrusive human identification uses a signal pattern of interaction with an object. The second type of identification strategy uses footstep's pressure, their patterns, sounds, and vibration to identify the ADLs around the home. The third category, body shape-based human identification captures individual's information based on their body shape, height, and width using an ultrasound technology.

Table 1. Unobtrusive sensing technologies applied as non-wearable sensor [5,8]

	Object-based technologies	Footstep-based identification	Body shape-based identification	Gait-based identification
Sensing technologies	• Pressure sensor • RFID • Accelerometer	• Sensor switching • Microphone • Pressure sensor • Electromechanical film • Accelerometer • Piezoelectric • Transducers • Photo-interrupter	• Ultrasonic	• Passive infrared • RF transceiver • Electric potential sensor • Wi-Fi transceiver
Features	• Object use pattern • Object use acceleration	• Walking pattern • Footstep sound • Footstep induced vibration • Centre of pressure trajectory • Geometric and holistic information	• Height • Width • Area • Perimeter • Radius	• Body heat emission • Disruption of RF & Wi-Fi signals • Body electric charge changes

Lastly, gait-based technologies use passive infrared (PIR) detector and Wi-Fi PIR to observe the human body heat emission to recognize the individual and ADLs. Some of the further details and features for the aforementioned technologies are mentioned in Table 1.

This study involves AR, ontology modeling and reasoning [2,14] based on Human Activity Recognition (HAR) dataset shared by the University of Jaén's Ambient Intelligence (UJAmI) Smart Lab [16]. The UJAmI Smart Lab measures approximately 25 square meters divided into five regions: entrance, kitchen, workplace, living room and a bedroom with an integrated bathroom. The need for considering this dataset is to tailor a framework for ADLs recognition and perform the research using sensors, as most of the technologies nowadays are underscored by the elderly people, their health and importance of their occupancy state. So for them, associated activities might affect their functionality of daily life. So ADLs recognition from multimodal sensors for each segment of a daily routine i.e. morning, afternoon and evening in a controlled environment is the primary motivation behind this study. Following are the key objectives being undertaken: (1) proposing, designing and implementing a solution for HAR from the UJAmI event-based dataset by using conventional ML-based method, by preserving temporal states; (2) designing an effective and practical algorithm to train, test and evaluate the ML-based method; (3) using the event-based dataset, such as data from binary sensors to interpret semantic rules by a domain expert, required to build the ontological model, employed further to infer sub-activities; (4) and finally a detailed discussion is performed over the results from a classical supervised ML-based method and ontological reasoning.

The rest of this paper proceeds with an introduction to the proposed model in the Sect. 2, an overview to describe the UJAmI Smart Lab dataset in terms of its structure and format. The experimental evaluations and the results prediction from test data and ontological model are presented in Sect. 3. Finally, a detailed conclusion is drawn with possible improvement, as a future work for this paper in Sect. 4.

2 Methodology

This paper deals with the analysis and recognition of a set of 24 different ADLs, performed by a single male inhabitant under several daily routines for over 10 days in the UJAmI Smart Lab. More information about the collected dataset can be found at the website [16]. The proposed layered ADLs recognition framework is described in Fig. 1. The main processing layers are listed as (a) *Data Sensing Layer*; (b) *Context Acquisition Layer*, which extracts the features, trains the model and classify ADLs; (c) *Context Fusion Layer*, which underscores the patterns and perform data aggregation; (d) the *Semantic Layer*, managed by the ontology with underlying semantic rules by facilitating reasoning using the SPARQL queries; (e) and finally *Application Layer* for disseminating the obtained context or activity.

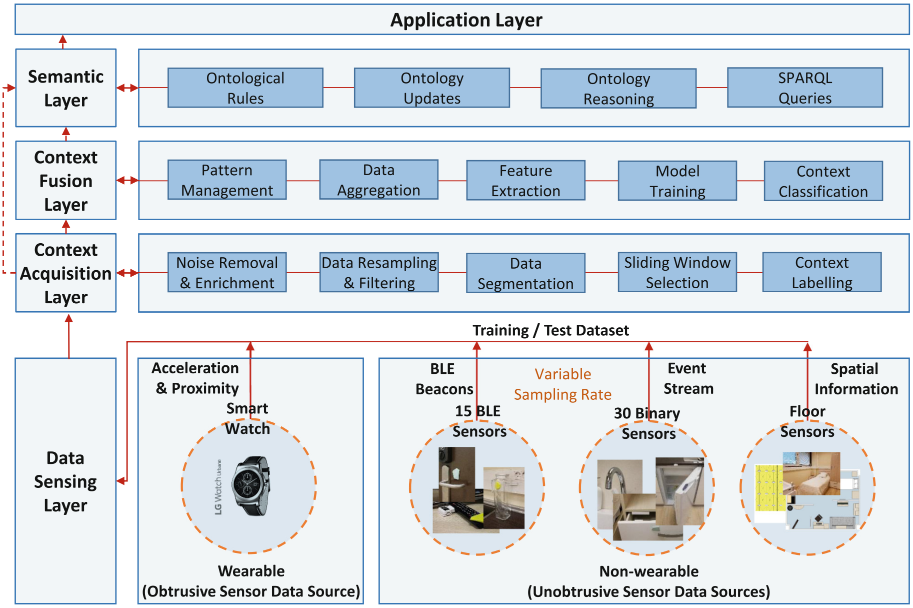

Fig. 1. Proposed framework for HAR using UJAmI Smart Lab dataset

2.1 Dataset and Data Sources Description

The multimodal dataset comprises data collected from four data sources over a period of 10 days. This dataset also preserved different sensor functionalities such as variable signal type from continuous to discrete; sampling frequency spanning from high to low; different protocols for involved magnetic, motion-based, as well as pressure sensors. However, the information related to the underlying wearable and non-wearable sensors technologies and the dataset collected is described in the following subsections:

Unobtrusive Binary Sensor Data. The dataset shared by UJAmI Smart Lab consists of an event stream from a set of 30 binary sensors (BinSens), which comprises of binary values along with the *Timestamps*. These BinSens works on the principles of Z-Wave protocol deployed in an unobtrusive wireless magnetic sensor environment. For example 'Medication box' in use means magnets are detached and such an event is considered as 'open'. When it is set to put back, sensor returns its value 'close'. The inhabitant movement within the sensor range is monitored using the wireless 'PIR sensors'. It works with the ZigBee protocol having maximum IR range of 7 m and sample rate of 5 Hz. The binary values, in this case, are represented by 'Movement' or 'No movement' for 'kitchen', 'bathroom', 'sofa', and 'bedroom' objects. Additionally, the unobtrusive motion sensor sofa, chair, and bed are also equipped with the 'textile layer sensors' to detect the inhabitant's pressure by transmitting 'Present' or 'No present' binary values using the Z-Wave protocol. The BinSens sometimes fire an event rapidly and sometimes may produce a challenging stream, which can last from few seconds to a few minutes or maybe for a few hours, such as pressure sensor stream.

Unobtrusive Spatial Data. An unobtrusive spatial data generated by the suite of capacitive sensors beneath the floor, called SensFloor dataset. It consists of 40 modules, compartmentalized in a 4×10 matrix. Each module has eight sensor fields, which are associated with an individual ID. Moreover, SensFloor collects capacitance's changed data with a variable sample rate.

Proximity Data. Another unobtrusive data source provides the proximity data as a set of 15 Bluetooth Low Energy (BLE) beacons at 0.25 Hz sample rate RSSI, which is collected through an android application installed on a smart-watch. These BLE beacons are generated for the objects like a medicine box, fridge, TV controller etc.

Obtrusive Acceleration Data. The ambulatory movements and motion intensities are reflected in an acceleration data stream, which is gathered by the Android application installed on smart-watch worn by the inhabitant. The accelerometer data is collected in tri-orthogonal (x, y, z-axis) directions at a sampling frequency of 50 Hz.

Table 2. Activities recorded in the UJAmI Smart Lab dataset.

ID	Activity name	ID	Activity name	ID	Activity name
Act01	Take medication	Act09	Watch TV	Act17	Brush teeth
Act02	Prepare breakfast	Act10	Enter the SmartLab	Act18	Use the toilet
Act03	Prepare lunch	Act11	Play a videogame	Act19	Wash dishes
Act04	Prepare dinner	Act12	Relax on the sofa	Act20	Put washing into the washing machine
Act05	Breakfast	Act13	Leave the SmarLab	Act21	Work at the table
Act06	Lunch	Act14	Visit in the SmartLab	Act22	Dressing
Act07	Dinner	Act15	Put waste in the bin	Act23	Go to the bed
Act08	Eat a snack	Act16	Wash hands	Act24	Wake up

2.2 Recognising ADLs, Ontology Modelling and Reasoning

The UJAmI Smart Lab dataset covers a maximum of 24 activities in the smart-home environment as mentioned in Table 2. It contains 43,320 training and 27,783 test samples for several routines collected over the period of 10 days. The first step in the proposed framework is to synchronize the pre-segmented dataset from different obtrusive and unobtrusive data sources. The process of synchronization was attained based on the *Timestamps* by taking care of missing values affected by different sample rates. Filling gaps is a challenging task since some data sources generate continuous streams, as well as, discrete data. In the end, generation of a single file for training dataset, over which modeling techniques can be applied to get the classification results, which needs to be applied on an unknown test data ADLs classification. So, to handle such challenges, domain expert analyzes the data tuple patterns critically in order to create SWRL rules for HAR. The Semantic Layer in the proposed framework as mentioned in Fig. 1 presents the ontological operations performed to describe the ADLs recognized from obtrusive and unobtrusive multimodal sensors. The aim behind the development of the ontology is to provide a basic model that not only allows the representation of ADLs but also supports the reasoning as and when it is queried for HAR. The outcome ensures the comprehensiveness of the ontology as shown in Fig. 2 so that it is enough to be able to represent all recorded 24 ADLs in the UJAmI dataset but should also be as concrete to facilitate the use of semantic reasoner and interpretation through SPARQL queries [11]. The ontology defines 24 major ADLs as parent classes. It is enforced with the use of SWRL rules, which provide additional constraints other than object properties and data properties. Some of the excerpt of the SWRL rules used in the modeling of ontology for 24 ADLs are described in the Table 3. The main aim of this work is to recognize activities based on the available dataset, analyze the correlation between activity type and objects involved, evaluate the classification results and address the challenges associated with the UJAmI Smart Lab dataset. Some of the key tasks as performed in [13] to automatically clean and pre-process the dataset are discussed briefly in subsequent sections.

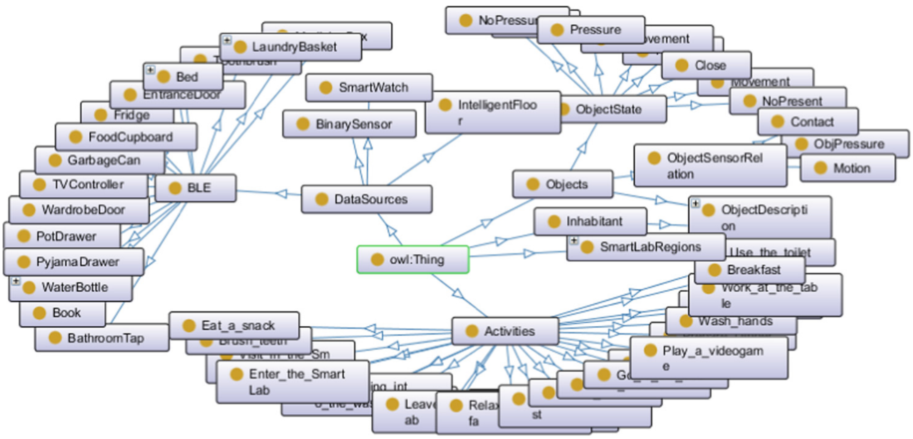

Fig. 2. Excerpt of the developed ontology for UJAmI dataset

Table 3. SWRL/SQWRL definitions: AR based on obtrusive and unobtrusive sensors.

Rule	Activity of daily livings	SWRL/SQWRL obtrusive/Unobtrusive semantic rules
1	Take Medicine	Inhabitant(?Inhab) ∧ hasLocation(?Inhab, ?Kitchen) ∧ hasObject(?Inhab, ?Waterbottle) ∧ hasState(?Waterbottle, ?Open) ∧ hasObject(?Inhab, ?MedicineBox) ∧ hasState(?MedicineBox, ?Open) ⟹ **sqwrl:select(?Inhab, ?Act)**
2	Prepare breakfast	Inhabitant(?Inhab) ∧ hasLocation(?Inhab, ?Kitchen) ∧ makes(?Inhab, ?Product1) ∧ hasType(?Product1, ?Tea) ∧ hasObject(?Inhab, ?Kettle) ∧ hasState(?Kettle, ?Open) ∧ makes(?Inhab, ?Product2) ∧ hasType(?Product2, ?MilkChocolate) ∧ hasObject(?Inhab, ?Microwave) ∧ hasState(?Microwave, ?Open) ∧ sqwrl:makeSet(?opt1, ?Product1) ∧ sqwrl:makeSet(?opt2, ?Product2) ∧ sqwrl:union(?opt3, ?opt1, ?opt2) ⟹ **sqwrl:select(?Inhab, ?opt3)**
3	Dinner	Inhabitant(?Inhab) ∧ hasLocation(?Inhab, ?DiningRoom) ∧ hasActivity(?Inhab, ?Sitting) ∧ hasActivity(?Inhab, ?Eating) ∧ hasObject(?Inhab, ?Pots) ∧ hasState(?Pots, ?Open) ∧ hasObject(?Inhab, ?Dishwasher) ∧ hasState(?Dishwasher, ?Open) ⟹ **sqwrl:select(?Inhab, ?Act)**
4	Watch TV	Inhabitant(?Inhab) ∧ hasLocation(?Inhab, LivingRoom) ∧ hasActivity(?Inhab, ?Sitting) ∧ hasObject(?Inhab, ?MotionSenorSofa) ∧ hasState(?MotionSensorSofa, ?Movement) ∧ hasObject(?Inhab, ?TVRemoteControl) ∧ hasState(?TVRemoteControl, ?Present) ∧ hasObject(?Inhab, ?TV) ∧ hasState(?TV, ?Open) ⟹ **sqwrl:select(?Inhab, ?Act)**
5	Dressing	Inhabitant(?Inhab) ∧ hasLocation(?Inhab, ?Bedroom) ∧ puts(?Inhab, ?Clothes) ∧ hasObject(?Inhab, ?LaundryBasket) ∧ hasState(?LaundryBasket, ?Present) ∧ hasObject(?Inhab, ?Closet) ∧ hasState(?Closet, ?Open) ⟹ **sqwrl:select(?Inhab, ?Act)**

2.3 Activity Recognition Methods

As shown in Fig. 1, the AR framework is a sequence of *Context Acquisition Layer*, which performs data alignment, and pre-processing; *Context Fusion Layer* responsible for applying ML techniques, and model training; and finally *Semantic layer* responsible for ontology manipulation and reasoning tasks.

Context Acquisition Layer

Data Alignment and Mapping: In this layer, the data has to be prepared from the UJAmI Smart Lab dataset corpus in such a way so that it becomes suitable for training and classification evaluation processes. For this, each of the sensor data was reordered and matched into a set of 1-s window slot based on *Timestamps*.

In order to generate uniform *Timestamps*, the data was resampled, segmented and mapped based on the basis of *DateBegin* and *DateEnd* over 1-s time window. It was applied to each instance belonging to the data sources for Spatial, Proximity and Acceleration data. The better performance [3] can be achieved using a sliding window segmentation technique [1] with the step size of 1-s to keep the maximum number of instances [18].

Data Preprocessing: Another important step for preparing data is to resample, filter, remove noise and handle missing data before performing classification and reasoning tasks. In our case, the obtrusive 50 Hz sampled accelerometer data was re-sampled by applying the commonly used time-domain statistical feature, such as a mean filter for each of x, y, and z tri-orthogonal values over a duration of 1-s. The Floor data, which was generated at a variable rate, was also re-sampled within the duration of a 1-s window by taking the mean for floor capacitances. In the case of instances having missing data fields values, which were filled by calculating the average, by taking the preceding 50 samples. All the data preprocessing tasks were accomplished using dedicated software written in Python 3.6 [10].

Context Fusion Layer

Data Modeling: To validate our approach we used 43,320 training data instances (Activity, Acceleration, Proximity, and Floor), aligned based on the *Timestamps*. The feature vector was created using the Waikato Environment for Knowledge Analysis (WEKA) library [17]. As the training dataset contains strings, as well as, numeric tokens, so we have used "StringToWordVector" filter in order to perform tokenization and indexing process. Later on, these feature vectors from the training dataset were used to train an algorithm *FilteredClassifier* to obtain the classification model.

Classification: The results obtained during the modeling phase were analyzed and we opted to choose the best classification model based on the evaluation metrics. We used 10-fold cross-validation technique on the dataset to produce a stable model [4] and predict the correct sequence of activities. We also evaluated our model by using the training dataset for 6 out of 7 days (leave one-day-cross-validation technique) to validate the evaluation metrics on the test data. To keep the vocabulary consistent both the training data and test data were processed using *FilteredClassifier* by ensuring their compatibility. Precision, Recall and F-Measure for the training model can be seen in the Fig. 3. The main observation in Fig. 3 for the activities 'Act08' and 'Act14' ('Eat a snack' and 'Visit in the SmartLab' respectively), showed lower recall leading to overall declined accuracy.

Semantic Layer

Reasoning. The final data prepared to train the classifier was understood by the ontology expert in order to interpret the semantic patterns and rules creation.

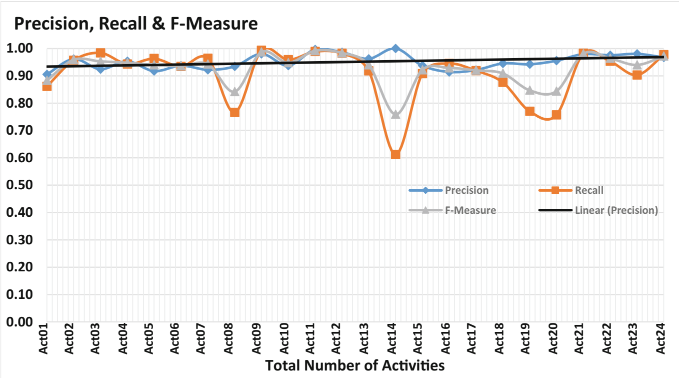

Fig. 3. Evaluation for the training dataset.

These semantic rules were designed and created manually using the training as well as test dataset patterns. We used Description Logic (DL) models to capture the semantic patterns in the dataset, which were converted to OWL2 ontology axioms and SWRL rules. The designed and developed ontology was used to perform reasoning over the unknown test dataset in addition to SPARQL queries for interpreting the axioms. The performance results are shown in Fig. 4, which proves that this method has produced accurate results in terms of predicting correct sequences of activities along with the ML method.

3 Results and Discussion

The proposed solution for this study and its development by using conventional ML method along with ontology-based reasoning is evaluated using performance metrics such as precision, accuracy, and f-measure. The performance evaluation results proved that ontology-based reasoning technique has lead to better accuracy. To improve the overall accuracy, an ontology-based reasoning can mitigate the ADLs recognition veracity. The overall accuracy of 87% was achieved using supervised ML-based classification approach with a mean absolute error of 0.0136. However, the accuracy of the same data when modeled and evaluated using ontology-based reasoning was slightly increased to 91%. The precision, recall, and f-measure for the dataset is mentioned in Fig. 4. The analysis illustrated that the activities 'Act11', 'Act12', 'Act14', 'Act19', and 'Act21' named originally as 'Play a videogame', 'Relax on the sofa', 'Visit in the SmartLab', 'Wash dishes', and 'Work at the table' respectively were mostly misclassified by ML supervised classification method but their accuracy was amplified using ontology-based reasoning.

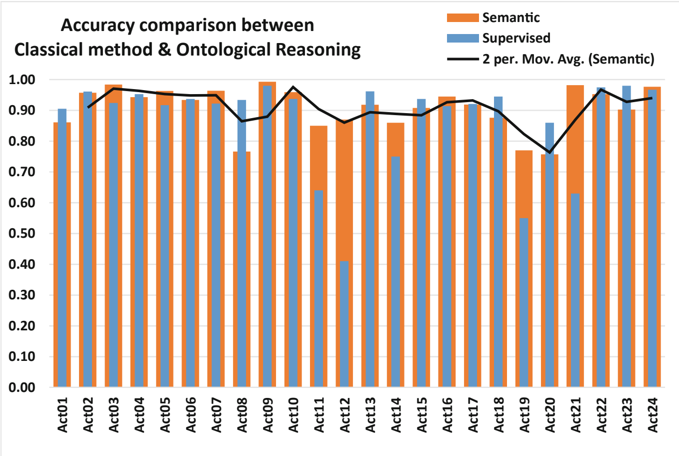

Fig. 4. Prediction vs Actual activities in the test dataset.

4 Conclusions and Future Work

In this paper, we have utilized the Human Activity Recognition (HAR) dataset for recognizing Activities of Daily Livings (ADLs). This dataset was generated by using obtrusive and unobtrusive devices in the smart environment and shared by the University of Jaén Ambient Intelligence (UJAmI) smart lab. The dataset includes data from four data sources, which include binary sensors data, proximity data, spatial data, and acceleration data. In this work, we presented a framework which preprocesses the data, trains a model using conventional Machine Learning (ML) based classifier i.e. *FilteredClassifier* and generates OWL2 axioms required to create an expert-driven ontology. In the ML-based method, during the preprocessing and training phase, several patterns were observed, required to design the basis of ontology. These axiomatic patterns were also converted to generate SWRL rules, which provided additional reasoning support to the ontology in order to infer the ADLs from the test data instances. The obtained results suggest and facilitate comparisons between actual ADLs in test data and predicted ADLs from the supervised ML-based method and ontological reasoning. The presented work discovers some meaningful insights regarding ADLs representation in the form of Ontology and SWRL rules. Further analysis also suggest that it still seems to be having some limitations on data aggregation challenges while processing ADLs using the ML-based supervised learning method. The overall obtained final accuracy of 87% for ML-based classification and 91% for ontology-based semantic reasoning also provide intuition that there seems to be the existence of some limitations while preprocessing the data for missing values and exploiting the correlations between a different set of features. These limitations may have a negative impact on classification and reasoning performance. So our future plan is to investigate these challenges by suggesting a lightweight probabilistic ML-based scheme and resolve the axiomatic conflicts while semantic rule generation.

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