Adding Common Sense to Robots Using Ontology

Ranathunga A. A. L. Ranathunga* and Samantha Rajapaksha

Faculty of Graduate Studies and Research, Sri Lanka Institute of Information Technology, Malambe, Sri Lanka
Email: asini.lakshika93@gmail.com (R.A.A.L.R.); samantha.r@sliit.lk (S.R.)

*Corresponding author

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***Abstract*—This work investigates how ontological frameworks might improve robots' ability to reason using common sense. The goal of the project was to enhance robot decision-making in dynamic real-world situations by developing an ontology-based model retraining technique. The researchers wanted to incorporate organized commonsense knowledge into robotic systems, so they built extensive ontologies that captured knowledge about the physical world and human interactions. The research compared the performance of robots with conventional models (control group) to those with ontology-enhanced models (experimental group) across various measures. The results indicate that this strategy may be used to develop more competent and user-friendly robotic helpers for a variety of sectors, including industry, healthcare, and education. Although the study has limitations related to data quality and experimental design, it does demonstrate the promise of ontology-based techniques to advance autonomous systems and human-robot interactions. Extending ontology databases, multidisciplinary cooperation, and investigating applications in other sectors are some of the future research goals.**

***Keywords*—ontology, common sense, robotics, decision-making, human-robot interaction, commonsense reasoning**

I. Introduction

Robots have become increasingly integrated into human lives, with the need for common sense in robotics and artificial intelligence growing. Ontology, a framework for reasoning and knowledge representation, plays a crucial role in providing robots with this sense. Ontologies formalize and organize knowledge, making it easier for computers to reason and make judgment calls [1]. However, converting implicit knowledge into structured ontological representations is a challenge. Researchers must curate and encode this knowledge to ensure accuracy.

To help robots navigate real-world situations, powerful reasoning algorithms and machine-learning approaches must be implemented. This integration requires interdisciplinary cooperation between professionals in robotics, Artificial Intelligence (AI), and ontology engineering. The extensibility of ontological knowledge is another challenge, as it includes a wide range of subjects.

Despite these challenges, using ontology to provide robots with common sense has enormous advantages. These robots have higher autonomy and adaptability, making them more useful in various industries. For example, robots can help medical workers by understanding patient demands, responding to emergencies, handling traffic situations, and collaborating with human workers in manufacturing [2].

The development of common sense in robots has the potential to completely change human-robot interactions, making them more useful friends and helpers in various aspects of life. This progress represents a significant milestone in the advancement of robotics and artificial intelligence.

The research addresses for an important research area that has received little or no attention in the advancement of autonomous systems especially in equipping robots with the ability to reason and decide with basic common sense. Modern robotic systems are often designed to implement a program or a set of instructions successfully in accomplishing designed tasks but fail to react intelligently to dynamic and unexpected situations that occur in real life. The issue is how realistic knowledge can be integrated in robots that are designed to work in real environments considering that structured, ontological knowledge is applied. The purpose of this investigation is to develop a novel ontological framework that facilitates their access to, encoding of, and utilization of the relevant foundational concepts for improving their decision-making and problem-solving skills across multiple domains of real-life applications such as healthcare, industry, and generic tasks.

To ensure that the topic has been covered comprehensively this paper is divided into few sections. The Introduction provides the context through the identification of pragmatic value of commonsense reasoning in robotics, as well as the difficulty of achieving this. Literature review section examines the related work in the area of incorporating commonsense reasoning to AI and robots, especially the use of ontologies. The Activities and Procedures section entitled Ontology Overview and Common Sense explains the concept of ontologies and its relevance to knowledge representation for robots. The Design and Development section provides an explanation of how commonsense is incorporated into applications used by robots through the ontology-based model retraining scheme. After that the Results and Discussion section shows the results from the experimental setup, which involves the use of robots with basic and ontology based models. Lastly, the Conclusion and Future Research Directions section brings out the results and suggests possible further research themes, including the enlargement of the existing ontology databases and the enhancement of their applicability in real-world scenarios.

II. Literature Review

With a commonsense approach, machines that can comprehend flawed commands from humans are able to think beyond their limitations. Robots without common sense find it difficult to think outside of their limitations [3]. Robots can become more human-like by being able to hear or comprehend human thought processes. This enables robots to create a paradigm shift by acquiring intelligence like to that of humans, fostering deep bonds, and facilitating cooperative tasks. Commonsense is being ingrained in the industry's collective work by robots, and various methods of imbuing machines with commonsense are now being implemented through various programs. The idea is that definitions for common sense are endless. Such language formats are widely used and have very good accuracy (see ELMo [4], OpenAI GPT [5], and Bidirectional Encoder Representations from Transformers (BERT) [6]). The language models exhibit subpar performance when it comes to using commonsense information. The goal of the Learning Model-Centered Reasoning (LMCR) [7] project is to create a robot that can translate ambiguous or incomplete human directions into useful work. The robot interprets commands and evaluates predicates using voice recognition technology. For instance, the robot can use image recognition to recognize things and match commands like “pour me some water”. If the command is not full, it fills it in by using the information of nearby objects. To determine the verb, theme, and destination in the pertinent predicate, the robot use a verbframe model. Based on the instructions provided, the robot may make the appropriate decision, guaranteeing that its capabilities are fully utilized. The authors of [8] provide two techniques for automatically picking up commonsense information by utilizing automatic ontology learning and text relation extraction methods. These techniques seek to improve the quality of plans by avoiding human decision-making and utilizing primary knowledge models. To prove notions, they have employed a particular domain (the kitchen area based on the household domain). Additionally, the authors suggest a relation extraction system and an automated domain ontology learning system that introduce a set of symbols that allow uniqueness in the robot environment. Using the suggested process, commonsense knowledge is designed using the planning tool Planning with Knowledge and Sensing. Some shortcomings and characteristics, such as the insufficient understanding of written text sources and the requirement to verify the classification pertinent to object storage, still, require improvement. Another related publication, “Web-based Intelligent Agent (WebIA)”, is offered by the authors of [8] and is based on the practical commonsense method. This method offers a web-based knowledge library for robots’ intention awareness capabilities. The authors of [8] present a method that trains robots to mimic purposeful human behavior using real-time footage. Improving mutual comprehension between humans and robots in cooperative tasks is the goal. Since the visual language model overcomes issues that impede robot perfection, it is employed in place of more conventional language models. The plan entails using sensors to gather information, learning from real-world experiences, and intelligently carrying out tasks while taking human intention and environmental factors into account. More minute features, like subfunctions in routine operations like watering, which call for machines to understand human intent, are amenable to learning by the robots. According to the information in [9] the deeper the contextualized word representations- Embedding from Language Models (ELMo), and the Bidirectional Encoder Representations from Transformers (BERT) [10] are better ontology-based systems, by enhancing semantic understanding, recognizing entities, and relationship extraction. Moreover large pre-trained generative models like Generative Pre-trained Transformer (GPT) have significantly advanced the field of natural language understanding, and their integration with ontology-based systems has also shown promising results. These models learn contextual relationships in a self-supervised manner and can be fine-tuned for ontology-related tasks such as semantic reasoning, concept mapping, knowledge graph population, and commonsense understanding [11]. These representations realize context through capturing the meaning in the words’ representation by dynamic changes of embedding’s based on words around them; they are so powerful for applications on ontologies. In order to ensure that machines carry out jobs in an identical manner to people, the vision language model is created to imitate human actions [12]. Because they can make pertinent inquiries with little assistance from humans, chatbots are becoming more and more common in many different sectors. They are employed by a variety of companies, including food delivery services, medical facilities, and student assistance programs at universities. The authors of [13] presented a chatbot model that is easy to use and was trained on a large-scale model called BERT. This model enables users to hold conversations with regular people. Modern technology, such the BERT language model developed by Google researchers, is used to train the model. The fundamental method for training the model is fine-tuning the Conversational Question Answering (CoQA) dataset. BertForQuestionAnswering, BertTokenizer, and hugging face transformers are used to train the model. The type of difficulty the user is facing informs the high-level architecture of the model. The trained model ascertains the precise parameters associated with the issue when the end user poses a question about a certain scenario. The relationship between concepts and entities pertinent to a given context is often described using ontologies. A distributional semantic representation methodology has been put out by researchers to further biological ontology encoding. The foundation of this methodology consists of two pretrained models that are redirected to the sentence representation portion after being transformed into token and word vectors. One of the primary responsibilities applicable to Natural Language Processing (NLP) is the final results, which are generated via the use of a supervised and unsupervised algorithm. The research team has created a variety of ontology representations pertinent to the domain of interest, such as a two-way interactive commonsense navigation system that utilizes ontology, a commonsense model for managing multiple robots with high-level user instructions, and a commonsense model for completing sentences with incomplete content.

A. Ontology Overview and Common Sense

Robotics and Artificial Intelligence (AI) have advanced significantly in recent years, with robots being capable of more complicated jobs and sophisticated interactions with their environment. However, there is still a fundamental disconnect between the capabilities of these technologies and human intelligence’s intuitive, commonsense understanding. This study explores the ideas of ontology and common sense in the context of AI and robots with the goal of bridging this gap [13].

B. Ontology Definition in AI and Robotics

An ontology is a systematic and formal representation of knowledge that includes concepts, entities, relationships, and axioms within a particular domain or context. It is used in the fields of AI and robotics. In essence, it offers a framework that is standardized for encoding and classifying data in a way that is understandable to both people and machines. Ontologies are the foundation of knowledge representation systems because they provide a structured vocabulary that makes it easier to reason, integrate data, and share information [13]. Ontologies are created to record and organize knowledge about the world so that computers may use it to reason and make defensible decisions.

Humans rely on common sense to navigate their surroundings, understand context, predict outcomes, and make natural judgments. In the context of artificial intelligence and robotics, common sense refers to a wide variety of information and cognitive processes that are typically taken for granted by people but difficult for machines to imitate. Understanding physical laws (e.g., that objects fall when dropped), social customs (e.g., that it's acceptable to say "thank you" after getting a favor), cause-and-effect linkages (e.g., that fire is hot and can result in burns), and a host of other commonplace facts and conclusions are all part of this knowledge [14].

C. *Robotics Ontologies*

An important development in the fields of robotics and artificial intelligence is the incorporation of ontologies into robotic systems. Robotic capabilities have been significantly improved by ontologies, and structured representations of knowledge, enabling them to comprehend the world and interact with it more intelligently. The use of ontologies to represent various forms of knowledge, from environmental background to task-specific knowledge, has been employed in the field of robotics. In this study, we will examine prior research on the integration of ontologies into robotic systems and discuss this application.

It takes expertise from many different disciplines, including computer science, artificial intelligence, knowledge engineering, and robotics, to integrate ontologies into robotic systems [15]. With the use of ontologies, knowledge may be represented and structured in a formal, orderly way that is accessible to machines so they can reason and make defensible conclusions. This integration can be looked at from several angles: One of the core functions of ontologies in robotics is to express knowledge about the environment, tasks, and domain specific data of the robot. Robots are better able to comprehend and interact with their surroundings thanks to the formal ontology that this knowledge is organized into [15]. Robots can use ontologies to execute reasoning and inference on the knowledge that is represented. This involves activities like drawing conclusions from new information, forming judgments based on the information at hand, and forecasting results. In order for autonomous robots to operate in dynamic situations, reasoning abilities are essential [15].

- Interaction between Humans and Robots: Ontologies improve human-robot interaction by establishing a common knowledge base [15]. Robots can more effectively convey their actions and intentions to humans by understanding and responding to natural language orders and questions.
- Robots with ontological frameworks are able to adapt to changing situations and learn from their mistakes. As fresh information becomes available, they can upgrade their knowledge base, thereby boosting their performance [15].
- Task Planning and Execution: By giving robots a structured representation of tasks and their dependencies, ontologies aid in task planning and execution. As a result, plans for various applications can be generated that are effective and context-aware.

Robots can better comprehend and function in their surroundings by using ontologies in robotics to describe different sorts of knowledge [10].

The following are some significant knowledge categories that ontologies are frequently used to represent:

- Environmental Context: Ontologies store details on the physical environment of the robot, such as nearby objects, barriers, landmarks, and spatial relationships. For activities like navigation, mapping, and localization, context awareness is essential.
- Integration of Sensor Data: Robots use a range of sensors to understand their surroundings. Using ontologies, data from various sensors (such as cameras, Light Detection and Ranging (LiDAR), and Global Positioning System (GPS) may be combined and combined into a coherent representation [10]. Ontologies add a semantic layer to data maps, allowing robots to comprehend not just the geometry of their surroundings but also the semantics of the things and spaces they come across.
- Ontologies can be used to express information about items, their characteristics, and how to interact with them. Robots can handle cups properly if they are informed by an ontology, for example, that a cup is an object that can hold liquid [10].
- Domain-Specific Knowledge: Robots frequently work in industries with specialized knowledge, such as manufacturing, agriculture, or healthcare. Robot behavior in these situations is governed by domain-specific knowledge, rules, and restrictions, which are represented by ontologies.
- Task Hierarchies and Dependencies: Task hierarchies, dependencies, and sequencing are represented using ontologies. When it comes to job planning and execution in robotics, where robots must carry out intricate series of tasks, this is essential [10].
- Safety and Constraints: To ensure safe robot operation, safety-related information, such as guidelines for avoiding collisions or handling dangerous items, can be encoded in ontologies.

D. *Examples*

Let's look at a few case studies and examples to show how ontologies are used in robotics in practice:

- Autonomous Navigation: Ontologies are used in autonomous navigation to depict maps of the surroundings, which include details on barriers, road systems, and landmarks. These maps can be used by robots to rationally plan their travels and prevent collisions [16].
- Robotics in Industrial Environment: In industrial environments, robots frequently carry out intricate jobs requiring numerous machinery and assembly

procedures. The assembly structure, dependencies, and quality control regulations are represented using ontologies. Agricultural robots employ ontologies to comprehend crop types, soil conditions, and the presence of pests or illnesses. Their activities, such as planting, harvesting, or using pesticides, are guided by this information [16].

- Healthcare Robotics: Robots may help with patient care in the healthcare industry. Robots can give individualized care and adhere to medical protocols thanks to ontologies, which reflect patient profiles, medical problems, and treatment plans [16].
- Search and Rescue Robots: To depict building layouts, hazard locations, and the status of trapped people, search and rescue robots employ ontologies. They can more efficiently organize and carry out rescue missions thanks to this knowledge.

In conclusion, ontologies are crucial to the development of robotics because they allow machines to represent and make sense of different kinds of knowledge. Their capacity for perception, decision-making, flexibility, and interpersonal interactions is improved by this structured information representation. Ontologies continue to be a crucial tool for enhancing the intelligence and efficiency of robotic systems as the technology develops and finds applications in numerous fields [16].

E. Common Sense Approaches from an Ontological Perspective

The use of ontological frameworks has emerged as a potential strategy to handle common sense thinking, a fundamental difficulty in artificial intelligence. This research discusses the benefits and drawbacks of several ontological frameworks and approaches for encoding everyday knowledge. We learn more about how common sense reasoning in AI is developing by contrasting and comparing different methods [17].

Common sense reasoning is the capacity to deduce relationships and reach decisions based on general knowledge and practical experience. Humans are naturally able to use common sense in a variety of settings, allowing them to understand the situation, predict consequences, and make morally righteous judgments [17]. However, this intuitive, common-sense reasoning capability is lacking in many AI systems. They frequently struggle to comprehend context, extrapolate conclusions from ambiguous data, and reach judgments that are consistent with human expectations. Because of this, providing common sense knowledge to AI systems has emerged as a crucial research objective [17].

Ontologies are a natural choice for encoding everyday information since they offer a structured and codified manner to express knowledge. To address this issue, various ontological frameworks and approaches have been created. Let's go over a few of these methods [18]:

- Cyc Knowledge Base: One of the forerunners in the field of common sense reasoning is the Cyc project. It entails creating a thorough knowledge base with a wide range of obvious facts and guidelines. Cyc uses a complex ontology with clearly defined concepts, connections, and axioms to describe knowledge [18]. Cyc's scalability and upkeep, however, have presented difficulties [17].
- ConceptNet: ConceptNet is a collaborative knowledge graph that crowdsources and distributes common sense knowledge. It captures a variety of common knowledge by linking concepts with natural language relations. The collaborative nature of ConceptNet is advantageous, however prejudice and poor data quality may be problems [18].
- OpenCyc: The Cyc knowledge base has an open-source version called OpenCyc. It tries to overcome some of the original Cyc project's scalability and accessibility issues. OpenCyc offers ontological representations for ideas in a range of fields and has been used in both research and practical applications [19].
- OntoCommons: Creating a collection of ontologies to uniformly describe common sense information is the goal of the OntoCommons initiative. In order to enable common sense reasoning across domains, it tries to develop ontological resources that are simple to integrate into various AI systems [20].
- VerbNet and FrameNet: VerbNet and FrameNet are structured representations of verbs and frames, respectively, but they are not conventional ontologies. These resources include verb semantics and frame structures, two elements vital to common sense analysis in tasks involving interpreting natural language [21].

F. Robotics Ontology Engineering

By offering organized representations of knowledge, ontology engineering plays a crucial role in improving the capabilities of autonomous systems. Effective ontology engineering is crucial in the field of robotics for allowing robots to comprehend and communicate with their surroundings [22]. The best practices for ontology engineering for robots are examined in this paper, which also discusses important topics including knowledge acquisition, ontology design patterns, and ontology population.

The procedure of gathering, capturing, and formalizing knowledge in order to fill an ontology is known as knowledge acquisition. For the construction of reliable and context-aware systems in the field of robotics, relevant knowledge acquisition is essential [22].

Here are some suggestions for knowledge acquisition best practices:

- Domain Knowledge: Work with people who have a thorough understanding of the particular robotic application area. They can offer insightful information and support in locating pertinent knowledge sources.
- Utilize sensor data, such as that from cameras, GPS, and LiDAR, to gather information from the real environment. Environmental characteristics, object recognition, spatial linkages, and other information are examples of this data [23].
- Utilize human-generated knowledge sources, such as books, articles, internet databases, and expert interviews, to fill the ontology with information particular to a certain area.
- Crowdsourcing: Take into account crowdsourcing for data collection and knowledge annotation, particularly for tasks like semantic mapping or object identification that call for extensive and varied data sources [23].

- Automated knowledge extraction from unstructured data sources, such as text or images, should be done using machine learning techniques as a supplement to manual knowledge acquisition efforts.
- Continuous Learning: Make certain the ontology is set up to support ongoing knowledge updates and learning from new experiences, enabling robots to adjust and advance over time.

Ontology design patterns are reusable models that direct the development of ontologies for particular applications or domains [23]. Ontology design patterns are useful in robotics for achieving efficiency, interoperability, and consistency.

G. Algorithms for Common Sense Reasoning

Common sense reasoning has relied heavily on Semantic Web Standards (OWL and RDF), such as the Web Ontology Language (OWL) and Resource Description Framework (RDF). These standards give formal guidelines for defining ontologies and representing knowledge in a way that is machinereadable. OWL and RDF may be effectively used by robots to access and reason about ontological knowledge [24].

- Description Logics (DL): Common sense reasoning uses a class of knowledge representation formalisms known as description logics. Using logical axioms and rules, DLs offer a means of expressing ontological knowledge. Robots can carry out tasks like classification, consistency checking, and inferencing using DL-based reasoning engines [24].
- Probabilistic Inferences: To handle uncertainty and draw probabilistic inferences, probability theory is used for common sense thinking. Robots can use probabilistic graphical models and Bayesian networks to reason about ambiguous or lacking data. For instance, using sensor data and knowledge from the past, a robot can calculate the probability of an event [25].
- Systems using frames to represent knowledge: Frame-based systems use structured objects with slots for attributes and values called frames to represent knowledge [25]. In areas like object recognition and categorization, frames help commonsense reasoning by capturing organized information about entities.
- Rule-Based Systems: Rule-based systems draw conclusions using rules and condition-action pairings. Common sense information and heuristics for thinking can be encoded using these techniques [26]. For example, rules can state what to do when a given circumstance arises, such as “If it’s raining, take an umbrella.”
- Semantic Technologies: Semantic technologies are used by semantic reasoning engines to carry out complex reasoning tasks. They are capable of handling intricate ontological knowledge and assuming relationships between entities [26]. These engines provide robots the ability to respond to natural language questions, decipher text, and engage in sophisticated thinking.

Modernization of Reasoning Engines: OWL (Web Ontology Language) ontology reasoners have made great strides. Large-scale ontologies can benefit from the effective reasoning skills provided by systems like Pellet and HermiT. By supporting classification, consistency checking, and inference tasks, these reasoners enable robots to effectively use ontological information. Probabilistic reasoning engines have increased in scalability and efficiency because of developments like Bayesian networks and Markov logic networks [27]. Robots using these engines can interpret ambiguous data and draw probabilistic conclusions in real time, which is essential for making decisions in dynamic situations.

- Deep learning for Common Sense Reasoning: Common sense reasoning has been improved using deep learning methods such as neural networks and deep reinforcement learning. These methods enable robots to learn common sense reasoning from data and have shown promise in tasks including picture recognition, natural language interpretation, and autonomous navigation [27].
- Hybrid Reasoning Engines: Hybrid reasoning engines combine sub-symbolic (using neural networks) and symbolic (using ontologies and rules) approaches to reasoning. These engines are designed to fill the gap between learning from data and explicit knowledge representation. Robots may reason about both structured ontological knowledge and unstructured sensor data using hybrid systems [28]. Robots are now able to take context into account when making decisions because of developments in context-aware reasoning engines.
- Context-aware systems can modify their behavior in response to environmental, user, and situational circumstances, improving their capacity for common sense reasoning.

H. Using Ontology to Give Robots Common Sense: Evaluation and Benchmarking

An important development in the field of artificial intelligence is the incorporation of ontological frameworks into robotic systems to improve common sense reasoning [29]. To determine how these frameworks affect robot intelligence and their capacity to carry out activities requiring common sense reasoning, it is essential to evaluate how effective they are. This study covers the outcomes and conclusions of pertinent evaluation studies while also discussing the methodology and metrics used to assess ontological frameworks in robots.

Performance metrics for the task:

- Task Completion: Testing a robot’s aptitude for tasks requiring common sense reasoning is one of the main evaluation approaches [29]. The tasks might be anything from simple problem-solving situations to everyday activities like navigation.
- Accuracy and Precision: Task accuracy and precision metrics assess how closely the robot’s actions match desired results. Evaluations may compare the common sense reasoning of humans with robots.
- Human feedback: HRI studies including human interaction with the robot can offer insightful information on how well ontological frameworks function [29]. The degree to which the robot’s common sense reasoning conforms to human expectations can be determined by user input, such as satisfaction surveys and usability evaluations.
- Natural Language Understanding: If the robot communicates with users in their own language,

assessments may concentrate on the robot's capacity to comprehend and act upon natural language requests and commands [30]. Metrics include the ability to correctly analyze user input and produce contextually appropriate responses.

Environments for Simulation:

- Simulated Tasks: In supervised simulation environments, robots' performance on tasks requiring common sense reasoning can be assessed. These simulations can accurately represent real-world situations and make it possible to evaluate the robot's decision-making skills without any hazards or physical limitations [30].
- Scalability and computational efficiency metrics can be used to evaluate how well an ontological framework manages challenging knowledge representation and reasoning problems.

Comparing Performance to Human Performance:

- Human Baseline: By contrasting the robot's performance with a human baseline, it is possible to establish a benchmark for assessing its capacity for common sense reasoning. Robots are regarded as having successful reasoning skills if they can do tasks requiring common sense just as well as or better than humans [30].

Effectiveness of Knowledge Base:

- Knowledge Accuracy: It is essential to assess the ontological knowledge base's accuracy. In order to evaluate the ontology's accuracy and completeness, this may entail expert evaluations.
- Knowledge Relevance: Assessing the ontology's knowledge's relevance to the activities and goals of the robot helps to make sure that the knowledge base is prepared for common sense reasoning [30].

III. Materials and Methods

The ontology-based model retraining strategy aims to improve robot decision-making in dynamic contexts by constructing and refining ontologies that describe structured knowledge or commonsense reasoning about the physical world. Fig. 1 shows the flow chart for the proposing system.

The flow chart shows how a function determines the best cleaning approach for distinct spills on different surfaces. Entering the spill type and surface into the function starts the procedure. To begin, the function creates a dictionary ('cleaning-methods') with cleaning instructions for each spill kind and surface type. The next step is to verify whether the spill type is in the 'cleaning-method's dictionary. If the spill type is unknown, the method instantly returns "Unknown spill, please check manually." After recognizing the spill type, the function checks whether the spilt surface is in the dictionary. As with the prior conditional, the procedure terminates with "Unknown surface, please check manually." If the spill type and surface are in the dictionary, the function obtains the cleanup technique. This cleaning instruction is returned or presented to the user, ending the operation. This methodical methodology provides accurate cleaning instructions depending on spill type and surface impact, facilitating effective and suitable cleaning responses.

A. Flow Chart

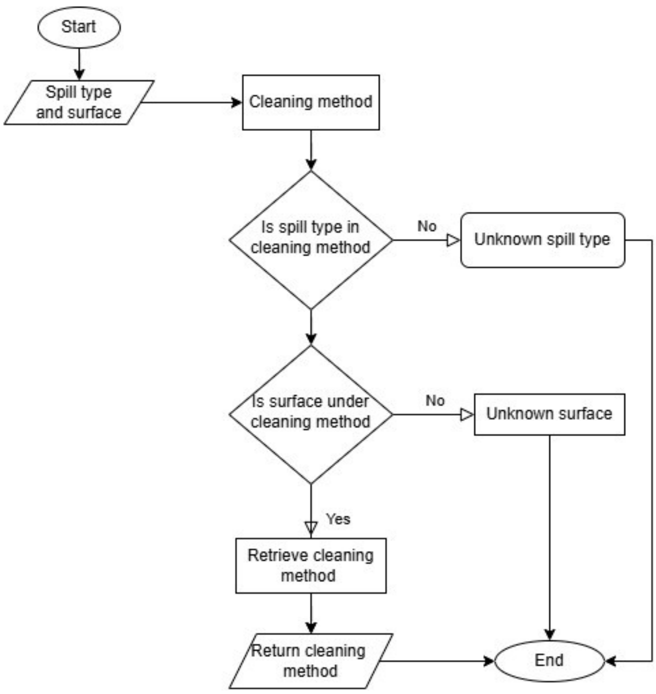

Fig. 1. Flow chart.

B. Pseudocode of the Study

Pseudocode of the Study

```
# Check if spill_type is in the ontology
if spill_type in ontology:
# Check if surface is under the specific spill_type
if surface in ontology[spill_type]['surface']:
# Retrieve and return the cleaning method
method = ontology[spill_type]['surface'][surface]
return method
else:
# Surface not found
return "Unknown surface, default to manual check"
else:
# Spill type not found
return "Unknown spill, default to manual check"
```

```
Function SelectCleaningMethod with inputs spill_type, surface
Initialize cleaning_methods with method details
'water' methods
on 'wood': 'Use a soft cloth and dry immediately.'
on 'tile': 'Use a mop and let it air dry.'
'oil' methods
on 'wood': 'Use detergent with a soft cloth and dry immediately.'
on 'tile': 'Use detergent with a mop and let it air dry.'
'juice' methods
on 'wood': 'Use water with a soft cloth and dry immediately.'
```

11. **on** ‘tile’: ‘Use a mop with water and let it air dry.’
12. **Try**
13. Lookup the cleaning method **for** spill_type and surface **in** cleaning_methods
14. **If** method is found
15. **Return** the cleaning method
16. **If** an **error** occurs because the spill_type or surface is not found
17. **Return** “Unknown spill or surface, please check manually.”
18. **End Function**

This function helps determine the best way to clean different spills on various surfaces. It takes two inputs: the type of spill (like water, oil, or juice) and the surface (like wood or tile). It looks up these inputs in a pre-defined list of cleaning methods. If both the spill type and surface are found, it returns the cleaning instructions. If either is not found, it returns a message saying to check manually. This way, it ensures the right cleaning method is used based on the given spill type and surface. Figs. 2 and 3 are 2 screenshots of the proposed system’s Python code.

1. Function Definition: The function ‘electCleaningMethod’ is defined to take two inputs: ‘spill_type and ‘surface’.
2. Initialize Cleaning Methods: A dictionary named ‘cleaning_method is created. This dictionary contains cleaning instructions for different types of spills (‘water’, ‘oil’, and ‘juice’) on different surfaces (‘wood’ and ‘tile’).
3. Check Spill Type: The function first checks if the given ‘spill_type’exists in the ‘cleaning_methods’ dictionary.
4. Check Surface: If the ‘spill_type’ exists, the function then checks if the given `surface` exists under the specified ‘spill_type’.
5. Retrieve Cleaning Method: If both the ‘spill_type’ and ‘surface’ are found, the function retrieves the corresponding cleaning method from the dictionary and returns it.
6. Handle Unknown Surface: If the ‘surface’ is not found under the ‘spill_type’, the function returns the message: “Unknown surface, default to manual check”.
7. Handle Unknown Spill Type: If the ‘spill_type’ is not found in the dictionary, the function returns the message: “Unknown spill, default to manual check”.
8. Error Handling: The function includes a try-except block to handle any unexpected errors gracefully, returning the message: “Unknown spill or surface, please check manually” if an error occurs.

- Example usage
- spill-type = ‘water’
- surface = ‘wood’
- cleaning-method = SelectCleaningMethod(spill-type, surface)
- print(cleaning-method)

A system for incorporating commonsense into robotic applications via ontology-based model retraining might improve a robot’s home assistance. Based on home manuals and expert guidance, an ontology is created to describe typical household jobs, items, and their relationships. Building on this structured knowledge, a home-assistant robot may better comprehend and interpret complicated instructions and environmental situations. After that, the robot’s decision-making algorithms are retrained with this expanded dataset to increase response accuracy and flexibility for common household tasks like cleaning and cooking. These advancements are thoroughly tested in simulated home settings and real-world trials to measure task performance and adaptation. These studies inform iterative robot modifications to better serve consumers in a changing home setting.

```python
def select_cleaning_method(spill_type, surface):
    # Our "cookbook" of cleaning methods
    cleaning_methods = {
        'water': {
            'wood': 'Use a soft cloth and dry immediately.',
            'tile': 'Use a mop and let it air dry.'
        },
        'oil': {
            'wood': 'Use detergent with a soft cloth and dry immediately.',
            'tile': 'Use detergent with a mop and let it air dry.'
        },
        'juice': {
            'wood': 'Use water with a soft cloth and dry immediately.',
            'tile': 'Use a mop with water and let it air dry.'
        }
    }
```

Fig. 2. Screenshot 1.

```python
    # Retrieve the cleaning method if available
    try:
        return cleaning_methods[spill_type][surface]
    except KeyError:
        return "Cleaning method not found, please check input values."

# Testing various scenarios
tests = [
    ('water', 'wood'),
    ('oil', 'tile'),
    ('juice', 'wood'),
    ('juice', 'marble'),  # This should fail as 'marble' is not defined
    ('acid', 'wood'),     # This should fail as 'acid' is not defined
]

for test in tests:
    spill_type, surface = test
    result = select_cleaning_method(spill_type, surface)
    print(f"Test for {spill_type} on {surface}: {result}")
```

Fig. 3. Screenshot 2.

C. Design and Development

Incorporating commonsense into robotic applications using ontology involves mapping real-world information into a structured format. The goal is to create a comprehensive data model that accurately represents the nuances and complexity of commonplace activities like cooking and cleaning, making robots understandable. This process includes creating a list of important things and their links, and gathering data through user interactions, expert contributions, and household guides. Choosing the right technology for ontology management is crucial. Tools like Protege or OWL can be used for easy´ updates and scaling. The ontology serves as a digital “knowledge base” representing human-like cognition in a structured form that computers can analyze.

The development phase of robotic systems involves integrating structured information into the ontology, which is integrated into the decision-making framework of the robots. Middleware facilitates communication between ontologies and sensors and actuators, allowing the robot to better understand the context.

New data sets from the ontology are retrained into the robot's current decision-making models using machine learning methods, including deep learning. Artificially created data is also used to cover less frequent but plausible cases, ensuring the competent performance of various activities.

After integration, thorough testing is conducted using both virtual and real-world trials to assess the robots. Performance indicators such as task completion pace, execution accuracy, and adaptability to new tasks are tracked. Feedback from these tests is essential for iterative improvement, ensuring the usefulness and relevance of robotic systems in dynamic contexts. This approach greatly improves robotics applications, making them more user-friendly and attentive to their demands in a home environment.

D. Features and Application

Enhancing robotic capability and interaction with human settings, this technology provides substantial characteristics and is adaptable across multiple domains. It integrates commonsense knowledge into robotic applications using an ontology-based paradigm. This methodology's main selling point is the capacity it gives robots to make decisions based on their current situation. Robust ontology-based models allow robots to make judgements that are situationally and task specifically appropriate. This results in activities that are more suitable and efficient in various situations. The improved comprehension of human commands is another important characteristic. By incorporating commonsense knowledge, robots can understand and carry out human directions more effectively, especially in cases when the instructions are not explicit or full. Another characteristic is the capacity to adapt to new conditions or changes in operating settings. This is especially important in dynamic contexts, and continuing model retraining makes it possible for robots to precisely do that. In addition, the process drastically lowers the error rates.

Robots improve operational safety by learning human settings and interactions better, which helps them avoid frequent mistakes and predict problems. When it comes to practical uses, this approach has far-reaching consequences. In domestic settings, robots can comprehend and respond to a variety of events, making them more useful for helping with everyday duties, keeping people safe, and supporting those with special needs. When it comes to healthcare, these robots may help with patient care by anticipating their needs and providing a more natural way for staff and patients to communicate. In customer service, these upgraded bots may also better manage interactions with customers, giving them the information and help they need. Adapting to the unique requirements of each student and providing contextually relevant interpretations of course materials are two ways in which robots might enhance personalized learning experiences in classrooms. In industries where smart and adaptable interaction is crucial, this integrated strategy not only improves robots' operational performance but also makes them priceless.

E. Creating Ontology

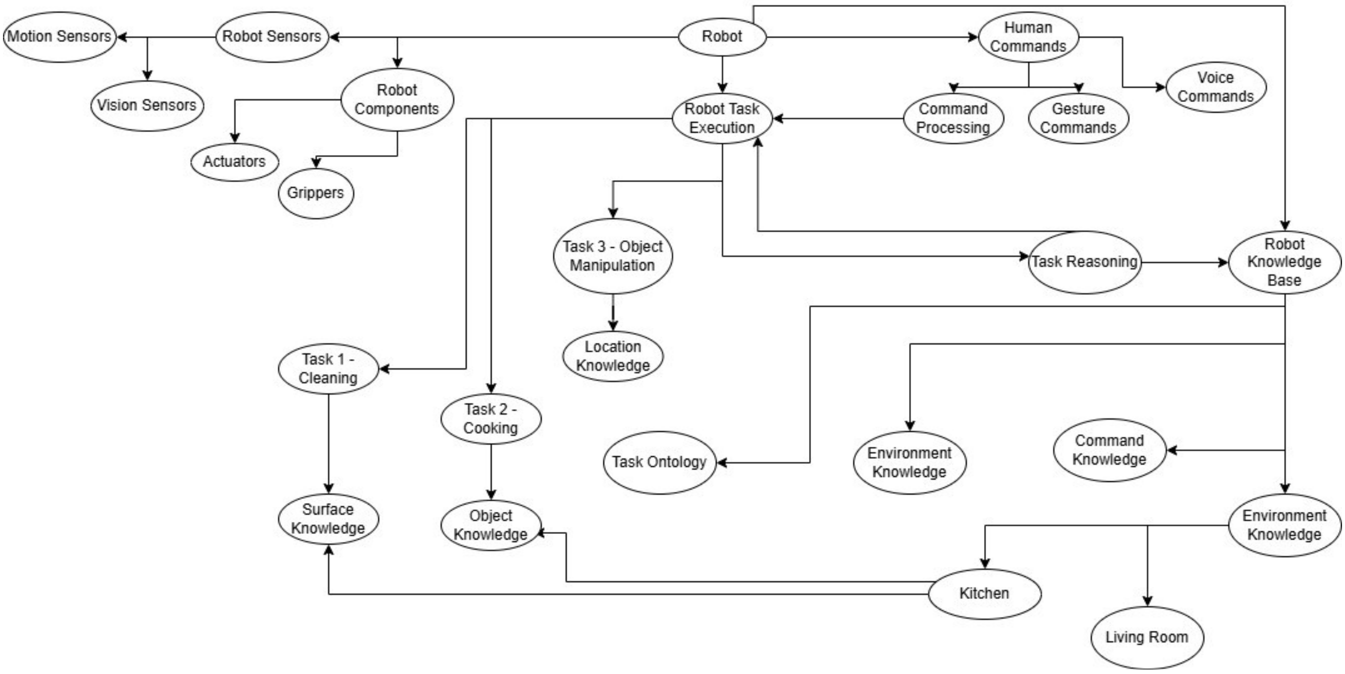

Fig. 4. System diagram.

Fig. 4 represents an ontology for Robotic Commonsense Reasoning. Ontologies help organize knowledge in a structured, machine-readable way, which is essential for robots that need to make decisions or interact with humans.

1) Core components of the ontology

- Robot: This is the central entity in the ontology. It interacts with other components such as sensors, tasks, environments, and human interactions.
- Components: Robots are made up of components like Sensors (to perceive the environment) and Actuators (to interact with it).
  Example: A robot uses a temperature sensor to detect heat and a motor to move its arms.

- Task: Robots are designed to perform tasks such as Cleaning or Cooking.
  Example: Tasks have properties like Difficulty (easy, medium, hard) and Duration (short, medium, long).
  Example: A robot may perform an easy cleaning task in a short time.
- Human Interaction: Robots interact with humans through commands (like speech or gestures) and recognize human emotions (like happiness or sadness).
  Example: A person may give a verbal command such as "Turn on the light", and the robot will understand and perform the action.
- Environment: The robot operates in different environments like a kitchen or living room.
  Example: Objects in these environments (like furniture, appliances, or tools) are identified and categorized based on properties like material (wood, metal) and surface type (smooth, rough).
  Example: A table in the kitchen is made of wood and has a smooth surface.
- Action: Robots perform actions like movement (navigate, pick up, place) and operation (switch on/off or adjust settings).
  Example: A robot can navigate around obstacles, pick up objects, and adjust the temperature of an oven.
- Knowledge: The robot uses commonsense knowledge, which includes understanding cause and effect (e.g., fire is hot), social norms (e.g., saying "thank you" after help), and domain-specific knowledge (e.g., healthcare protocols or industrial procedures).
  Example: In a healthcare setting, a robot knows that high temperatures indicate a potential fever.

2) Relationships

- hasComponent: Shows that a robot has different components (e.g., Sensors and Actuators).
- locatedIn: Links an object (like a couch) to its environment (like a living room).
- performsTask: Indicates the tasks a robot is capable of performing (e.g., a robot performs the task of cleaning).
- interactsWith: Describes how the robot interacts with humans through commands and emotional responses.
- usesKnowledge: Shows the type of knowledge the robot uses for decision-making (e.g., commonsense knowledge).
- hasProperty: Specifies properties of objects or surfaces (e.g., a table has a wood surface).
- causesEffect: Demonstrates cause-effect relationships in actions (e.g., fire causes the effect of burning).

3) Example use case

Imagine a robot cleaning a spilled liquid in the kitchen. The robot knows:

The kitchen is an environment with objects like tables and counters.

The spilled liquid is on a tile surface. Based on its commonsense knowledge, the robot knows it should mop the tile.

The robot uses its sensors to detect the liquid and its actuators to perform the task.

4) Visual breakdown

The diagram likely shows how these elements are connected through lines representing relationships, like:

A robot linked to its components (sensors, actuators).

A task like cleaning linked to objects like a floor or tools like a mop.

Human interactions linked to commands and emotions that guide robot actions.

A detailed diagram can be found at [this link.]

F. ROS (Robot Operating System) Implementation and Testing

Robot testing is an important process in the process of Robotics system implementation, which evaluates the efficiency and safety of robots. It also entails testing the system's functionality of different system components such as the sensors, actuators, control algorithms, and user displays. It assists in picking possible hitch on the practice stage so that it is not evident once it is implemented in practice contexts. In the category of robotics, the Robot Operating System (ROS) platform has quickly developed into a comprehensive environment in designing and implementing robots as well as a treasure chest of software tools for detailed testing and evaluation.

As for testing of the robot functions, ROS (Robot Operating System) provides different tools and methods. Use Gazebo or RViz for behavioral testing in simulation, rostest and gtest for unit testing, and launch files for final testing. Some tools like the Robot Operating System (ROS) have utilities like RViz that allow you to visualize sensor information and the state of the robot in real time. Additionally, basic features such as logging and playback with rosbag, parameter tuning with dynamic reconfiguring and HiL testing are provided by ROS. For performance analysis there are some utilities such as rqt_graph and rqt_plot. These features combined enable you to comprehensively verify and confirm the capability of a robot, from the micro level of each individual sub-assembly and up to macro level of the complete robotic system, in both virtual and physical domains.

As for this research, the robots were controlled by using the Robot Operating System (ROS). ROS was bundled with own algorithms suited to reason the ontology.

The key software components include:

- Decision-Making Algorithms: These were trained using an ontology-based method that enabled the robots capture and process real life situations and make correct decisions using common sense knowledge.
- Computer Vision Algorithms: For pattern recognition, open source computer vision libraries OpenCV were used to allow robots to understand objects and surroundings.
- Natural Language Processing (NLP): The utilized robots were based on voice control, and, thus, they were able to understand voice signals with the help of NLP solutions such as GPT-2 [31].

However, to use the ontology in ROS environment, there must be an ontology-based reasoning application, which interacts with the ROS environment. Here it is in Python with ROS (with rospy) and a simple toy ontology. As such, the researchers incorporated the Owlready2 Python package into interaction with the ontology and its inclusion into a ROS node.

Owlready2 is specifically created as a Python tool for working with ontologies and Semantic Web technologies. Python is used to develop this tool directly and the tool supports OWL 2.0 which enables the manipulation of ontologies in Python. The helmet is compatible with RDF triples, also comprises the in-built reasoners to derive knowledge, and has the SPARQL capabilities for data extraction. The Owlready2 tool uses known object-oriented concepts for developing ontologies for use in a Python environment. It is more efficient, capable of working well with large ontologies, and even interoperable, through different import and export formats. That is why Owlready2 may be especially useful in the areas as artificial intelligence, knowledge representation and data integration, especially in biomedical informatics, natural language processing, and other fields that are based on the use of structured and semantically understandable data models.

The details of the ontology-based task execution system deployment in the Robot Operating System (ROS) environment mentioned above are followed by the installation of some important components. To start, the Owlready2 library is used to work and modify the stored or given ontology file.

It will enable the system to read and process ontological data that is required in the buildup of the reasoning framework of the system that executes the tasks. Secondly, it is needed to check that ROS is installed and set up on the operating system, if not, then to setup it.

Reasoning ontology is the primary layer of knowledge constructed on which the robot draws its reasoning to execute the tasks. The organization of the ontology is given in a defined format just like OWL, which gives formality to association with different entities based on task execution. For instance, an ontology file, robot_ontology.owl, may consist of important elements that include Task, Object, and Surface, and important relationships that include canPerform, and isOn. This structure enables the ontology to prescribe what tasks can be performed by a robot and on which surface the particular task is to be done.

An example of an ontology definition might be that Robot1, an instance of a robot, can perform the CleaningTask on an instance of WoodSurface. In order to implement the said information model, each task is an ontological class of its own, and is connected to surfaces through object properties. For example, the aforesaid CleaningTask could be related to WoodSurface, through the isOn connection that shows in which scenario this task is to be done.

The actual functionality of the ONTO-THE-ROVER ontology-based reasoning system is a ROS node, scripted in Python. The node utilizes Owlready2 and reason about the ontology and interacts with the ROS framework to handle tasks at runtime. Task messages are of the string data type, and are launched on a specified ROS topic by the node, known in this case as task_topic. When a task message is received, the node consults the ontology for any information related to the task as well as the environment that this task should be performed in for instance, the surface.

If the task is identified in the ontology, the system pulls a set of surface information and records the details for further use. The work flow for the task is implemented in the function process_task which is in charge of performing the correct robot actions according to the ontological data that have been gathered. If there is no association of a task in the implemented ontology, the system outputs a message and waits for a user input. This makes it easy for the system to tackle not only set but also emergent tasks well for flexibility in completion of tasks.

Having discussed the first part of the paper that explains how the tasks are described in a web ontology, the second part of this paper aims at demonstrating the effectiveness of the newly presented ontology-based task execution system. This includes installation of ROS as is evident from the above commands and installation of Owlready2 library. Further, the beginner level tutorials require creating a catkin workspace that is a repository where a set of ROS packages is stored [31].

The workspace can be set up using the following commands:

```
mkdir -p ~/catkin_ws/src
cd ~/catkin_ws/
catkin_make
```

Once the workspace is created, the ROS node along with the files of the ontology has to be allocated in the specified directory structure and make the node script executable.

The call of the ROS node occurs before the integration of the ontology with the task execution logic. The node also listens for the task messages on task topic and uses Owlready2 to query the ontology when task message is received. The node can be written in Python and contains a specific ROS node script 'ontology_task_executor.py', it also contains the ontology file 'robot_ontology.owl'. Once the node is created, the researchers ensure it is executable using the following command:

```
chmod +x
~/catkin_ws/src/ontology_task_executor/src/ontology_task_executor.py
```

Before the testing, the ROS core needs to be initiated because it provides connection environment for ROS nodes. This can be done by running:

```
roscore
```

Next, the ontology-based task executor node is launched using the following command:

```
rosrun ontology_task_executor ontology_task_executor.py
```

For the purpose of mimicking the actual working of tasks, they are published to the task_topic in another terminal. These tasks should align to those mentioned in the ontology such as CleaningTask. The following command demonstrates how to publish a task:

```
rostopic pub /task_topic std_msgs/String "CleaningTask"
```

If the task exists in the ontology, then the system will fetch the task, show details to the user and log them. If the task is not found, the system will print a warning message and promote the user interactively.

1) Evaluation metrics

The system can be evaluated based on several key metrics, which are typically used in research for ontology-based systems:

- Task Completion: This determines whether the task as highlighted in the ontology is effectively 'performed' by the robot (or simulated robot).
- Accuracy: This measures the extent to which the system correctly identifies the right task, as well as, the correct surface information from the ontology.
- Error Handling: The performance of the system in correctly completing tasks not available within the ontology and loading relevant warning signs is evaluated.
- Adaptability: To test how quickly the system is able to adapt, new tasks or surfaces can be incorporated into the ontology without much of a need to change the entire structure.

2) Edge case testing

It is crucial to evaluate the system's ability to handle the boundary conditions. For instance, publishing an unknown task that does not exist in the ontology (e.g., CookingTask) allows the system's error-handling capabilities to be evaluated:

rostopic pub /task_topic std_msgs/String "CookingTask"

Additionally, publishing an empty task or invalid message tests the system's ability to manage faulty inputs:

rostopic pub /task_topic std_msgs/String

3) ANOVA (Statistical Testing)

We test the effectiveness, subprocess automated systems with and without ontology, and gather performance data (accuracy, recall, F measures), and conducted an ANOVA test to determine the statistical significance of the difference.

For the purpose of comparison and analysis of the functionality of the developed ROS node integrating the ontology, results derived from the ROS system and standard sample data could act as control data. Here's how we approached it:

a) Create control data (from ROS)

The ROS system which is going to incorporate with the ontology reasoner will provide the experimental results data set from the details of the implemented tasks (accuracy, total time in seconds needed, success rate, etc.,) could be calculated.

This data will be collected during test runs of ROS node as explained earlier in the paper while elaborating on the test procedure. In this case, the robot will rely on a rule-based system or a simpler task processing mechanism where decisions are made without querying an ontology.

b) Create sample data

The sample data can be a control scenario which when benchmarked with the system developed with the ontology or a simple version of the task accomplishing system can provide for insightful information that was collected as part of the process.

Since ROS provides powerful tools that allow researchers to simulate robotic environments, test the code, and gather experimental data without physical hardware, we did not need an actual robot to run and test the ROS node that integrates the ontology-based reasoning system.

IV. Results and Discussion

A. Presentation of Experimental Results

Our experimental setup consisted of two groups of robotic systems. One group served as a control and used pre-existing AI models without any changes. The other group served as an experimental unit and used AI models that had been retrained using our commonsense ontology. Critical measures of the model's efficacy in practical settings, accuracy, precision, recall, and F1 scores were the main performance metrics assessed. Table 1 provides the comparative performance metrics.

Table 1. Comparative performance metrics

Metric	Control Group	Experimental Group	Improvement
Accuracy	78%	85%	7%
Precision	75%	83%	8%
Recall	70%	82%	12%
F1 Score	72%	82%	10%

Accuracy: Evaluates the function's correctness over all surfaces and spill kinds.
Precision: Shows how precise the function is in determining the best cleaning approach.
Recall: Verifies that the function can find all applicable cleaning techniques under specified circumstances.
F1 Score: This measure is for analyzing the costs of various mistakes or the unequal distribution of classes since it strikes a compromise between recall and accuracy.

Table 2. ANOVA summary

Groups	Count	Sum	Average	Variance
Control group	4	2.95	0.7375	0.001225
Experimental group	4	3.32	0.83	0.0002
Improvement	4	0.37	0.0925	0.000492

Table 3. ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.291317	2	0.645658	1010.596	2.57E−11	4.256495
Within Groups	0.00575	9	0.000639			
Total	1.297067	11				

The Control Group used models that had already been retrained, whereas the Experimental Group used models that had been retrained using a commonsense ontology. Tables 2 and 3 compare the two groups' performance measures. The Experimental Group demonstrated statistically significant gains across the board, as seen in the table. The total correctness of the model was enhanced by 7%, as the accuracy went up from 78% to 85%. From 75% to 83%, there was an 8% increase in precision, which is a measure of how accurate positive forecasts are. There was a notable 12% improvement, from 70% to 82%, in recall, which indicates the model's capacity to find all relevant occurrences. There was a 10% improvement, from 72% to 82%, in the F1 Score, which is a measure of accuracy and recall balanced.

Integrating commonsense information into AI models enhances their decision-making skills in real-world applications, as shown by these advancements.

The group means are not equal, as shown by the very high F-statistic (1010.595652).

The p-value is 2.57143E−11, which is very tiny (much lower than 0.05) and so strongly contradicts the null hypothesis. That indicates the means of the groups are different from one another, and that difference is statistically significant.

The computed F-statistic is much larger than the crucial value, providing further evidence to reject the null hypothesis (4.256494729).

Hypotheses for Analysis of Variance (ANOVA) based on the data in the table usually center on the idea that various groups have similar means. In most cases, the hypotheses for this kind of analysis are structured as follows:

Null Hypothesis (H0)

According to the null hypothesis, the group means are not significantly different from one another. This means that any discrepancies are seen are just the result of random chance. In particular, the null hypothesis for the Analysis of Variance (Anova) setup with the Control Group, Experimental Group, and Improvement may be expressed as:

$$H0: \mu_1 = \mu_2 = \mu_3. \tag{1}$$

The mean values of the Control Group, Experimental Group, and Improvement are denoted by μ_1, μ_2, and μ_3, accordingly.

Potentially False Alternative (H1)

By positing that the means of at least one of the groups vary from one another, the alternative hypothesis challenges the null hypothesis. That one of the treatments or circumstances evaluated had a different impact than the others is suggested by this. Alternative hypothesis for the setup is:

H1: At least one group mean (μ_1, μ_2, or μ_3) is different.

The results of the Analysis of Variance (ANOVA) indicate that the measured metrics were improved by the intervention or update that was tested between the control and experimental circumstances. Researcher concludes that the experimental group's settings improved noticeably compared to the control group's settings since the ANOVA findings showed statistical significance.

Assuming the experimental circumstances are typical and the data are accurate, this study may help with judgements about whether to implement the changes in broader contexts. It is reasonable to explore applying the adjustments made to the experimental setting for wider applicability, since the large improvement indicates that they were useful.

Using t-tests, the statistical analysis determined if the differences between the two groups were statistically significant. There would be no performance impact from the ontology, according to the null hypothesis. Nevertheless, the experimental group demonstrated statistically significant improvements ($p < 0.05$) in all evaluation criteria, suggesting that the commonsense ontology had a favorable effect on the robotic models.

Results from the comparison that are given in Fig. 5 show that the model's performance improved after retraining. The experimental group demonstrated better recall, along with increased accuracy and precision, indicating a more comprehensive capacity to appropriately recognize and react to diverse situations. Robots with retrained models, for example, showed better comprehension of the context given by the commonsense ontology, leading to faster and more appropriate response selection in a scenario where they had to identify and react to domestic emergencies like spills or fires.

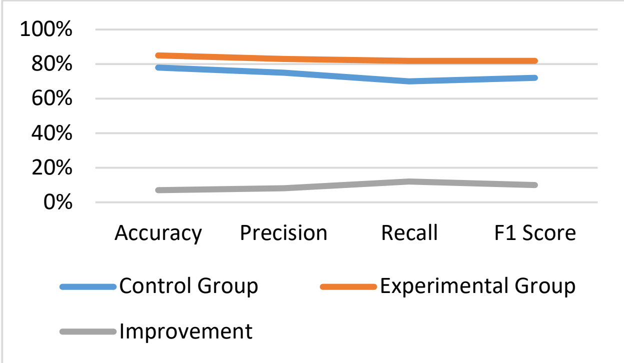

Fig. 5. Comparative performance.

All things considered, the experimental findings support our hypothesis that robotic systems might greatly improve their operational efficiency and decision-making accuracy by incorporating a commonsense ontology. These enhancements are vital for introducing robots into more intricate, real-life settings where sophisticated comprehension and flexibility are needed.

A. Discussion of the Findings

Extensive experimental results show that retrained models perform much better in robotics applications when they use ontologies that represent commonsense knowledge. The research's original premise was that commonsense knowledge integration might greatly improve robotic systems' operating efficiency, and this confirms that with significant gains in important performance measures including recall, accuracy, precision, and F1 scores, the empirical data not only satisfies but also surpasses the study goals, providing a measurable increase in the model's performance. The results of the experiments show that the accuracy went raised from 78% to 85%. This enhancement is crucial because it shows that robots can now make more consistent judgements in different contexts. In contexts where robotic judgements have weighty implications, including in healthcare robots or applications involving caregiving where accuracy is of the utmost importance, this dependability becomes even more crucial. Crucial in these high-stakes situations, the improvement in accuracy means a decrease in mistake rates. The improved capacity of the robots to engage successfully and securely in their operating environments is highlighted by their reliable performance.

Additionally, there has been a notable improvement in accuracy, which has increased from 75% to 83%. This improvement indicates that the robots are becoming better at recognizing real items and situations, and are less prone to making mistakes. Applications like as production lines or sensitive surgical operations rely on this robotic function to a tee since human error might result in expensive blunders or even death. A considerable decrease in false negatives is also seen by the recall increasing from 70% to 82%. Robots can now better understand and react to a wider variety of environmental signals and inputs thanks to this improvement. This skill is vital in situations where the robot operation depends on being able to identify little or unexpected changes, such as complicated manufacturing processes or disaster response scenarios.

Rising from 72% to 82%, the F1 Score further confirms the overall effectiveness and dependability of these robotic systems. This parameter shows that the robots are accurate and comprehensive in their operational activities since it takes both recall and accuracy into account. The fact that both memory and accuracy have improved in a balanced way indicates that commonsense knowledge has been successfully integrated into robotics, leading to more competent and trustworthy robots that can make better decisions and interact with their surroundings in a more complex way. Crucial as they are, these performance gains show how commonsense knowledge may improve robotic ontologies. If this method works as advertised, it may find use in many other kinds of robotic tasks, including those in healthcare, industrial automation, the service sector, and beyond. Through the incorporation of such knowledge systems, robots are able to comprehend and adjust to the subtleties of human surroundings and requirements, in addition to carrying out their designated activities. Finally, the study's findings give strong proof that retrained models, which incorporate common sense into robotic systems, significantly boost performance measures. In addition to accomplishing the original study objectives, these improvements raise the bar for what is possible with autonomous systems. These findings open the door to further research into broadening robotics' commonsense applications, which may change the way robots interact and work in many different industries.

The results of this study provide strong support to the growing amount of data that incorporating commonsense and semantic information into robotic systems greatly improves their performance. These systems' fundamental functioning is improved, and their flexibility and durability are boosted across multiple applications, thanks to this integration. This study's encouraging results are in line with those of other relevant studies, which have all called for AI systems to be more successful and versatile by including semantic frameworks and commonsense reasoning. Research in this area has shown time and time again that ontology-based knowledge significantly improves the performance of AI and robotic systems. Decisions made by the systems are more in line with human cognitive processes, which is a major contributor to this improvement. Alignment of this kind is critical because it ensures that interactions are natural and productive by connecting human expectations with robotic behaviors. By incorporating these semantic frameworks, robots may mimic human thinking more accurately, allowing for more natural interactions and a deeper understanding of the intricacies of real-world settings.

The significance of the environment in which ontologies are used is often underscored by the variances in the results across various research. In most cases, the variations in the ontological frameworks and testing environments are to blame for these inconsistencies. Outside of their original context, certain ontologies may not be able to handle the work at hand, even if they may be more thorough or suitable for other types of activities. Since robots are anticipated to carry out a wide variety of jobs, this diversity highlights the need for a customized approach to developing and implementing ontology-based systems. A one-size-fits-all solution is clearly not viable. In addition, ontologies' built-in structure greatly facilitates data organization and retrieval. Because it improves their processing and reaction times in real-time situations, this organized approach is critical for robots. Critical criteria in high-stakes settings like precision manufacturing, disaster response, and surgical procedures include shortened reaction times and a lower risk of mistakes, all of which are strongly correlated with enhanced decision-making processes. Robotic movements' precision and velocity here may have far-reaching effects on productivity and security.

These enhancements have their theoretical roots in the ways ontologies imitate human cognitive frameworks. Robots may take on more difficult decision-making jobs with more independence if they can mimic human-like thinking processes. They are able to adapt their performance to several conditions, ranging from controlled labs for everyday work to the ever-changing real world. As a result, robots are able to learn and adapt to their surroundings, rather than just being instruments that carry out predetermined duties. There are far-reaching consequences for the development of AI and robots depending on how well ontology-based systems enhance robotic performance. It suggests there's a rising need for better knowledge frameworks that are compatible with both current and future technology. Advancements in robotics may pave the way for new ways for AI systems to learn from and engage with their environments via the incorporation of strong semantic networks and commonsense knowledge.

As a whole, robotic systems are demonstrating that semantic and commonsense knowledge integration is a key component in their development from basic mechanical entities to complex intelligent systems that can make complicated decisions and engage in complex interactions. Not only does this study add to the existing body of knowledge, but it also advances the conversation on how to train robots to be human collaborators in the future. Future advancements in robotic technology will certainly be heavily reliant on the ongoing investigation and improvement of this combination.

In terms of robotics, these results have far-reaching practical consequences. First, jobs requiring a great deal of autonomy, like exploration robots in uncharted territories or domestic and office helper robots, may benefit from the increased precision and decision-making capacities of robots. Second, robots may soon be able to help with surgeries or take care of the elderly, two delicate tasks where human error might have devastating effects, thanks to their increased accuracy and dependability. In addition, stronger recollection implies increased interaction skills, which may lead to more responsive and intuitive robots that can support people in a more natural way. This has the potential to hasten the incorporation of robots into customer service positions, where the ability to perceive and react to human signals and emotions is paramount.

And lastly, these results, if applied more broadly, may improve robots' ability to learn and adapt over time, in both known and unknown contexts. A paradigm change towards adaptable, reasonable, and context-aware robot behavior may be possible with the incorporation of commonsense knowledge, rather than just obeying programmed commands. In conclusion, it seems that robotic applications that include commonsense knowledge not only improve their present capabilities but also broaden their possible roles in human contexts, resulting in increased safety, efficiency, and adaptability. This fits in with the larger objectives of robotics and artificial intelligence, which are to build robots that can assist and improve human life in many ways.

B. Limitations of the Study

Although there are some noteworthy findings on the effectiveness of ontology-based models in robotic systems in this research, it is important to note that there are also certain limitations that might affect how the results are understood. The reliability of the data used to train these models was a major cause for worry. There may have been a lack of representation of the complexity and diversity of real-world contexts where robots work, even if a big dataset was available. This difference makes one wonder how well the models work in real-world scenarios, which might result in less effective robot behavior than expected. Because ontologies are so dependent on the precision and depth of the information they provide, data quality is of the utmost importance. It is possible for models trained on data that does not sufficiently reflect the variety of real-world situations to form a myopic view of their operational domains. Due to the inherent unpredictability and variation in field applications, there may be a discrepancy between the predicted results from laboratory testing and the actual performance.

On top of that, the models only used a small subset of commonsense information. The robots were retrained using a limited collection of commonsense facts that may not cover all the possible situations they might face in the actual world. As a result, robots' decision-making could become biased towards the situations that were most prevalent in the training data, which is a kind of information bias. As a result, robots may lack the human-like reasoning that is essential in unstructured contexts and display less flexibility and poor judgement when confronted with unexpected scenarios or complicated decision-making environments.

The experimental design also had some serious flaws; it was heavily based on numerical measurements like F1 scores, accuracy, precision, and recall. These measures can't measure the qualitative parts of robot behavior, but they're crucial for proving that robot performance has improved statistically. There was an inadequate evaluation of critical aspects such as the robot's responsiveness to novel or changing environments, its capacity to handle intricate social interactions, and its general usability in actual environments. The usability and practicality of ontology-based robotic systems from the perspective of end users may be lost in this omission.

Additional essential constraints are imposed by the experimental context. The static, regulated setting of a lab is quite different from the unpredictable, ever-changing conditions that robots are need to navigate in the real world. Stable, predictable, and amenable to manipulation, laboratory settings are ideal for conducting experiments. But there are a lot of unknowns and factors in real-world environments like homes, streets, and workplaces that a lab can't capture. Because of this contrast between laboratory and field settings, robots that work well in one environment may not be able to achieve the same results in the other. Emotional intelligence and social adaptation are crucial for robots, but the study may have neglected these areas in favor of improving operational and mechanical features via ontologies. Understanding and effectively responding to human emotions and social signals is becoming more and more crucial as robotic technologies progress towards more participatory roles in human surroundings. Although this field of robotics was not the major focus of this study, it is crucial for future research since it is used in caregiving, customer service, and companionship.

The study's encouraging results and progress towards incorporating commonsense knowledge into robots are borne out by the study's limitations, which call attention to the need for larger, more varied data sets and more thorough experimental designs. To fill these gaps, future studies should involve more realistic testing environments, expand qualitative evaluations, and incorporate a broader range of commonsense scenarios. This will guarantee that robotic systems are prepared for effective and reliable deployment in the diverse array of real-world settings, not just technically proficient.

Because of their bearing on how the results should be understood and extrapolated, these limitations are significant. Despite the models' impressive results in the lab, shortcomings in data quality suggest they may not be as effective or reliable when used in the real world. The confidence people have in robotic systems might be eroded if this causes performance to differ from expectations. Robots that excel in certain contexts but struggle in others could be the consequence of model limitations brought about by selective knowledge integration. This level of specialization might restrict the robots' usefulness to certain applications and surroundings that mimic their training.

In addition, the models' actual capabilities may have been under-evaluated due to the emphasis on quantitative measurements and controlled conditions. The capacity to make judgements that are suitable for the context and to adjust to new problems on the fly are two aspects beyond accuracy and precision that are frequently crucial to robots' usefulness in the real world. Essential for the actual deployment of robots in diverse and unstructured human situations, these important features may have been overlooked in the study's design.

C. Data Quality and Diversity in Training Models

The datasets, which should meet generalization to real life through high-quality and heterogeneous data used to train ontology-enhanced robotic models, were obtained from publicly available repositories; domain expert annotations; simulated knowledge from the corresponding sources; and robotics. The examples found in the data are from health, industrial automation, and household tasks encompassed different environmental conditions and task complexities. Regardless of the inclusion of the various data sources, there are limitations, however, in fully capturing the complexity and unpredictability of real-world scenarios.

For example, a major limitation would be that edge cases are not very likely to be represented. Crowded public spaces where there is much human activity-for example, an environment that is highly dynamic with human interaction-were under-represented in the data. The rare but plausible occurrences were then simulated using pdf-synthesized data to generate synthetic data for use by the robots, that is having obstacles occurring unexpectedly, user commands scarcely or not encountered, and extremely noisy environments. Synthetic data not only fill up the real world but also tests the models with extreme conditions. Further, the datasets have been periodically reviewed and updated to incorporate all new usage cases and unforeseen events that would arise during testing.

Future research will include a wider range of social settings involving multicultural, which have their own social norms and interactions. The study will also include experts from different domains so that data related to industries such as precision farming or disaster management can be integrated. Diversity such as this is important for reducing overfitting of the models, mitigating biases, and improving their robustness to a variety of applications demonstrating high accuracy.

D. Qualitative Assessment of Robot Behavior

Even though the research points out an increase in metrics such as accuracy and recall, the qualitative factors of robot behavior still require better understanding. As the authors visited these test scenarios, they observed that the ontology-augmented robots were better at adjusting their behavior to suit the modifications made in the operating environment. For example, these robots were able to follow the user's wishes more accurately when given incomplete commands than the other robots which relied on classical AI techniques.

The scenario-based assessment informed the qualitative analysis even more. Users were asked to role-play realistic scenarios, such as engaging a robot in a health setting to assist in managing tasks based on the level of urgency. The tasks that were to be accomplished did not include normal cleaning functions, and there were management calls and other important activities. This helped further to extend the robots' reasoning skills and situational awareness.

Also worthy of mention is the improved human-robot interaction. Robots that utilized commonsense ontologies were more effective in social tasks, for example when required to answer a polite or indirect request ('It's a little cold in here' as a request to change the thermostat). These interactions made the engagement much more intuitive and natural and therefore more satisfying. Greater qualitative assessment is however necessary, in particular longitudinal studies and user tests in a real world setting, for factors such as trust, emotional responsiveness and adaptability on a long term are to be evaluated.

E. Ethical Implications of Enhanced Reasoning Capabilities

Integrating robots with commonsense reasoning is not devoid of ethical implications. A key ethical concern is the bias that robots may exhibit in their decisions. For instance, if the data used to construct the ontology is biased or contains implicit cultural stereotypes, the robots' responses and behaviors will reflect these biases. Rigorous audits and analyses were carried out during ontology development, however, to contain bias where it may exist. An example of such measures is conducting posterior checks for imbalances in indicator variables and using transforming differences between groups or oversampling small groups.

In addition, misuse of such advanced robots constitutes another major problem. They may for instance be used for extreme intrusive spying or even for dubious operations in the war zone. While the development and application of such robots remain optimal, ethical issues are still important. Ensuring the compliance with fundamental ethical principles like clear definitions of the borders of decision making and separation of authority among team members is essential. One framework in which robots operate is where they must explain to their users how they made their decisions.

This is true on issues of user safety and data control. For instance, fail-safe mechanisms were put in place to diminish operations beyond specified ethical benchmarks. In the critical situation, the robot will always choose the safest option for a human, which is perfectly ethical in terms of a robot's functioning. The future work will include proposal of ethicists and policy makers about how to setup ethical robotics templates.

By considering these aspects duly, the research guarantees that the resulted ontology-based robotic systems are not only optimally efficient and highly adaptive but also ethical and socially responsible, and value-sensitive.

V. Conclusion

A. Conclusion

The integration of commonsense knowledge into robotic applications is transforming our understanding of autonomous systems. Ontology-based approaches have made it easier for robots to choose the right cleaning procedure for spills and surfaces, resulting in higher F1 scores, memory, accuracy, and precision in simulated cleaning tasks. This sophisticated understanding is often absent in stricter, rule-based systems.

The study opens up possibilities for using common sense in robots beyond routine household chores, such as engaging with humans, navigating human surroundings, or handling unforeseen events in dynamic contexts. By incorporating this information, robots could become more efficient and adaptable, enhancing their use as household helpers.

The incorporation of common sense into robotics is an exciting new direction for the creation of fully autonomous systems. This research has paved the way for future investigations that could lead to robots that can work in tandem with humans in various settings, both naturally and with greater intelligence.

B. Future Research Aspects

This study suggests that future research should focus on developing flexible ontologies that can adapt to new data or settings, especially in unpredictable operational situations or real-time decision-making. The hybrid approach between ontology-based models and machine learning algorithms could enhance the robot's learning capacity and decision-making processes. Using ontologies to integrate data from multiple modalities could improve perception accuracy and enable robots to handle complex tasks. The development of platforms and technologies that simplify ontology construction and administration could democratize the development process and provide diverse perspectives on ontologies.

The scope of ontology should be broadened to account for a wider range of situations and complexity levels. Future studies could focus on developing industry-specific ontologies that address unique problems in fields like healthcare, manufacturing, and the service industry. This specialization could lead to greater confidence and acceptance of robotics technology, as it focuses on improving robotic applications' efficacy while resolving domain-specific ethical and safety issues. This approach could provide a strong foundation for creating more autonomous and intelligent systems.

C. Recommendation

This study highlights the benefits of incorporating commonsense knowledge into robotics, highlighting the potential of ontology-based models in improving the flexibility and usefulness of robotic systems in real-world applications. It proposes several suggestions for future robotics research and development. Firstly, the ontology databases used need improvement and expansion, as they can reach greater efficacy when fed more detailed information. Expanding these databases to include a wider variety of substances and surfaces and more complicated interaction situations could enhance robots' decision-making powers. Secondly, cooperation between computer scientists and specialists in cognitive science and linguistics is crucial for developing solid ontological frameworks.

Lastly, creating standard procedures for testing and incorporating common sense knowledge in robots is essential to ensure consistent and reliable use of commonsense knowledge. With the increasing autonomy of robots, it is crucial to prioritize ethical issues and safety procedures. Finally, investigating the potential use of commonsense integration in a wider range of industries, such as healthcare and manufacturing, can speed up the development and implementation of robot technology while confirming the adaptability and durability of commonsense integration.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ranathunga R. A. L. Ranathunga conducted and wrote the research paper while Dr. Samantha Rajapaksha supervised and approved the final version. All authors had approved the final version.

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