IoT-Enabled Agroecology: Advancing Sustainable Smart Farming Through Knowledge-Based Reasoning

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Abstract: The global increase in population necessitates enhanced food security, yet current agricultural practices are inadequate in feeding everyone and are detrimental to the environment. Consequently, agriculture faces the task of increasing production while minimizing resource usage and prioritizing sustainability. To assist farmers, new technological tools using AI, Robotics and IoT have been developed in a new field called Smart Farming. Unfortunately, these tools are primarily employed in unsustainable farming practices, such as mono-cropping. However, sustainable methods like Agroecology exist, which involve observing how plants interact with their environment to devise crop management strategies that work harmoniously with nature, requiring minimal resources and ensuring sustainability. In this paper, we propose an Internet of Things (IoT) platform that utilizes an ontology and a set of rules to provide farmers with recommendations for optimizing crop development while adhering to agroecology principles. This platform employs Knowledge-based reasoning to correlate crop requirements with local environmental data obtained through a wireless sensor network deployed on the farm. It can suggest crop layouts, crop calendars, detect relevant events, and manage irrigation. Our system has been tested in a simulated environment and yielded promising results, leaving ample room for future improvements and developments.

1 INTRODUCTION

1.1 Context

By 2050, it is projected that the global population will grow to approximately 9 billion, according to estimates. In order to ensure food security worldwide, the Food and Agriculture Organization (FAO) of the United Nations suggests that food production needs to increase by approximately 60% by that time (Ranganathan et al., 2018). In response to this growing concern, the agricultural industry is being transformed by Smart Farming (SF) technologies, also known as Precision Agriculture (PA), with the aim of enhancing productivity and sustainability. These SF tools utilize information and communication technologies (ICT) like Artificial Intelligence (AI), Internet of Things (IoT) platforms, and Robotics to offer modern and sustainable solutions (Walter et al., 2017).

IoT plays a crucial role in revolutionizing agricultural practices. IoT is a network of physical objects or devices that are embedded with sensors, actuators and connectivity capabilities, allowing them to collect and exchange data with other devices and systems over the internet. After the perception of data, they are processed with different algorithms using big data analytics methods and AI to make a decision about actions to implement. This interconnected system enables real-time monitoring, control, and automation of various processes and tasks (Elijah et al., 2018). One use case example involves the deployment of IoT sensors in crop fields. These sensors can collect data on soil moisture levels, temperature, humidity, and other environmental parameters. The collected data is transmitted to a central platform or system via the Internet. Farmers and agricultural experts can then access this data remotely and make informed decisions about irrigation, fertilization, and pest control. For example, an IoT platform can decide to open or not an

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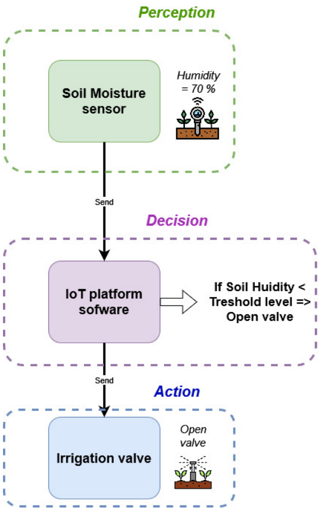

Figure 1: Simple IoT platform for Smart Farming.

irrigation valve regarding the value of the soil moisture sensor attached to it as depicted in figure 1. By leveraging IoT in this manner, farmers can optimize resource usage, improve crop yields, and reduce environmental impact through precise and data-driven farming techniques (Misra et al., 2020). IoT platforms commonly handle more substantial quantities and diverse arrays of data, encompassing locally acquired data from sensors and remotely acquired data, such as satellite observations. It is also noteworthy to acknowledge the increasing usage of emerging smart sensors that incorporate AI analysis. These advancements enable the direct interpretation of complex data, such as sound or images, at the source of data collection (Chollet et al., 2022).

Regrettably, IoT, similar to numerous Smart Farming techniques, is predominantly employed to enhance production using fewer resources while disregarding the ecological consequences of inherently unsustainable farming practices (Bronson, 2018). Hopefully, true sustainable farming method exist such as Agroecology. Agroecology is an agricultural technique that relies on careful observation of the crop-growing environment to collaborate with it rather than oppose it (Altieri, 2018). In particular, it encompasses various techniques such as crop rotation to safeguard against soil nutrient depletion (Ball et al., 2005), intercropping to encourage beneficial plant interactions and deter pest and insect development (Gebru, 2015), and the utilization of genetically diverse crop varieties that are well-suited to particular climatic conditions (Hajjar et al., 2008). An actual illustration of Agroecology can be seen in the ancient agricultural practice known as the Three Sisters farming strategy, which was discovered by Native Americans

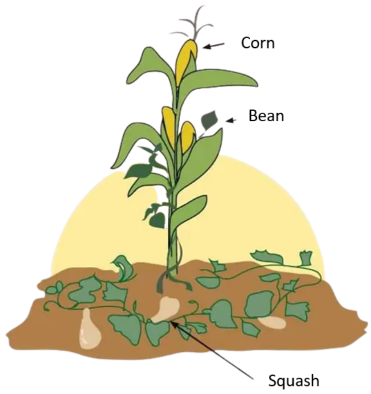

Figure 2: Three sisters planting method.

thousands of years ago. Remarkably, this method continues to be employed by a significant number of rural small-holder farmers in South America today (Lopez-Ridaura et al., 2021). It involves intercropping three main crops: corn (maize), beans, and squash. These crops are grown together in a mutually beneficial way. The corn provides a trellis for the beans to climb, while the beans enrich the soil with nitrogen, a fertilizer, through nitrogen fixation. The squash serves as a ground cover, shading the soil and reducing weed growth while retaining moisture. The process is depicted in Figure 2. This interdependence among the three crops creates a sustainable and productive farming system. Therefore, the core principles of agroecology are observation and interpretation through knowledge of the environment and plant biology. Those are difficult processes to implement in real-life scenarios for farmers who wish to transition to sustainable farming as they require an important amount of time and workload.

1.2 Proposal

To facilitate the transition of farmers towards agroecology, our research endeavors to deploy an Internet of Things (IoT) platform to acquire an extensive range of environmental data from various sources. This encompasses the utilization of both conventional and intelligent sensors for local data acquisition, as well as accessing global weather databases for remote data retrieval. Subsequently, the IoT platform undertakes the task of interpreting these data in accordance with agroecological principles, thereby proposing actionable measures to farmers for effective farm management. For example, sensor management (layout and maintenance), crops spatial distribution, rotation, provisional schedule, irrigation procedure, and event detection (pest development). In this paper, we take

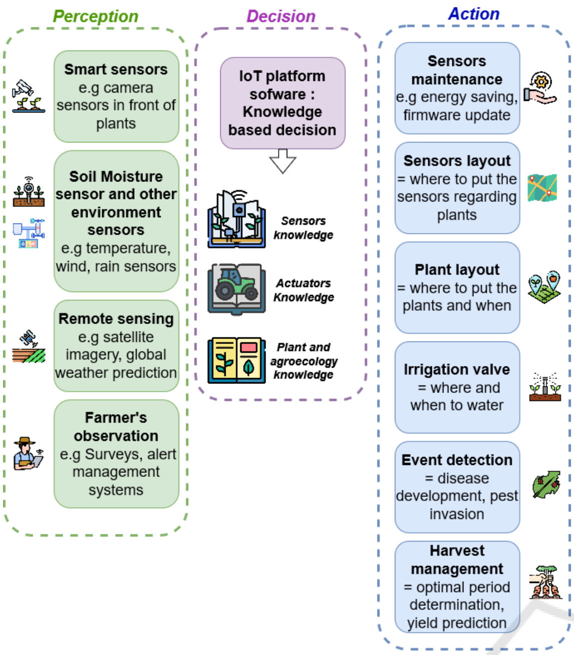

Figure 3: Overall view of the IoT platform.

a focus on the decision process. For the system to make the best decision, it needs to have knowledge about agroecology, crops, and sensors while managing a vast amount of data. Knowledge is defined as the explicit functional associations between information and/or data items. To allow computer systems to understand agroecology, we need to use knowledge engineering, which is the process of developing knowledge-based systems in a field (Kendal and Creen, 2007). Knowledge Engineering, also known as Knowledge Representation and Reasoning (KRR), proposes numerous tools to achieve the desired goals, such as ontology. Ontologies have demonstrated their effectiveness in handling organized and structured data. Consequently, the primary objective of this study revolves around the establishment of a knowledge base (KB) utilizing an ontology for Agroecology IoT platforms. The performance of this knowledge base will be assessed through the examination of various case-study scenarios. The overall view of the IoT platform is depicted in figure 3.

1.3 Structure of the Paper

Section 2 of this paper is dedicated to the definition of knowledge engineering and a brief state of the Arts for Knowledge-base regarding agriculture and IoT. The third section describes the architecture of our system and the ontology-building process. Afterward, we'll use our ontology in different use-case scenarios described in section 4. Finally, we will share our conclusion and future work orientation in section 5.

2 RELATED WORK

2.1 Definition

Knowledge Engineering refers to the process of designing, creating, and managing knowledge-based systems. It involves capturing, representing, organizing, and reasoning with knowledge to develop intelligent systems that can perform tasks, make decisions, and solve problems. Knowledge is base on data and information as depicted in figure 4 (Kendal and Creen, 2007).

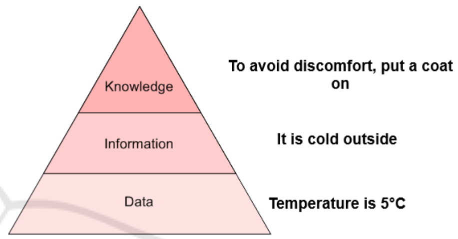

Figure 4: Data, information, and Knowledge.

Ontology, on the other hand, plays a significant role in Knowledge Engineering as a key component of knowledge representation. An ontology is a formal and explicit specification of concepts, relationships, and properties within a particular domain. It serves as a shared vocabulary or conceptual framework that enables effective communication and understanding among humans and computer systems. In Knowledge Engineering, ontologies provide a structured and standardized way to represent and organize knowledge. They define the entities, their attributes, and the relationships between them, allowing for clear conceptual modeling and knowledge representation. By defining a common vocabulary and formal semantics, ontologies facilitate knowledge sharing, integration, and interoperability between different systems and domains. A fully developed and populated ontology, containing a comprehensive collection of individuals, rules, and properties, is commonly referred to as a knowledge base. In technical terms, the knowledge base consists of two components: the Tbox (Terminological Box) and the Abox (Assertion Box). The Tbox represents the ontology itself, where information is stored, while the Abox encompasses the rules and properties associated with it. Ontologies enable intelligent reasoning and inference over the represented knowledge. They allow for the application of logical rules and automated reasoning techniques to derive new knowledge or make deductions based on existing knowledge through the use of a reasoner. A reasoner is a tool that enables the deduction of logical conclusions based on a given set of facts, thereby facilitating the classification process within an ontology. For instance, if we define an instance V as a Car, and the class Car is a subclass of Vehicle, the reasoner can infer that V is also a Vehicle. In more intricate scenarios, certain reasoners can incorporate SWRL rules (Semantic Web Rule Language) (O'connor et al., 2005). SWRL is a logic description language that allows the combination of diverse rules to construct more intricate axioms. The official documentation provides a basic example to define the syntax: : *hasParent(?x1,?x2) ˆ:hasBrother(?x2,?x3)* then *:hasUncle(?x1,?x3)* . By combining the two axioms, namely, :hasParent and :hasBrother, the hasUncle relationship can be applied to individuals, thus establishing the individual X1 as the child of X2 and the nephew of X3. This reasoning capability helps in solving complex problems, making intelligent decisions, and generating logical outputs from input information (Staab and Studer, 2010).

2.2 State of the Art

In this section, we will highlight various Knowledge Bases that mainly utilize ontologies and are specifically designed for the domains of IoT, agriculture, or both.

2.2.1 Knowledge Base for IoT

The widespread presence of smart devices in Internet of Things (IoT) applications has led to a significant challenge in achieving interoperability due to the diverse and heterogeneous nature of these "things." The other issue with IoT is the vast amount of data that have to be fusion together to make an effective decision. Both of these issues can be solved with Knowledge Engineering and ontologies. This area of research has been widely studied over time, and good surveys have been done by the authors in (Szilagyi and Wira, 2016), (Bajaj et al., 2017), (Graf et al., 2019).Two notable observations can be drawn from the literature: Firstly, ontologies developed in the IoT domain often focus on specific application areas, addressing the unique requirements and characteristics of those domains. Secondly, a significant portion of these ontologies is built upon the Semantic Sensor Network recommendation proposed by the World Wide Web Consortium (W3C) (Neuhaus and Compton, 2009). Briefly, in a traditional sensor network, sensors collect raw data and transmit it to a central processing unit for analysis. However, in a semantic sensor network, additional metadata and semantic annotations are associated with the sensor data. This metadata provides contextual information about the data, such as the sensor type, location, time of measurement, and the observed phenomenon but also maintenance data such as battery level or firmware version. By incorporating semantic annotations, SSNs enable enhanced data interpretation, discovery, and integration.

2.2.2 Knowledge Base for Agriculture

Knowledge in Agriculture has been a widely explored area of research. Their main aim is to model botanical knowledge about cultivated crops, and environmental knowledge about various ecosystems and farming practices. Firstly there is general purposes ontology: The Food and Agriculture Organization of the United Nations (FAO) developed AGROVOC, which is recognized as the most extensive and comprehensive semantic resource in the agricultural domain (Caracciolo et al., 2013). AGROVOC serves as a controlled vocabulary, encompassing 35,000 concepts and 40,000 terms. Its scope extends beyond agriculture to include domains such as food, nutrition, fisheries, forestry, and the environment, aligning with the FAO's wide-ranging purview. AGROVOC is a multilingual resource, available in 27 languages, including English, Arabic, and Chinese. Furthermore, AGROVOC adheres to the Linked Open Data Schema (LOS), ensuring compatibility with modern data integration practices. Despite being utilized in numerous case studies, AGROVOC exhibits certain limitations. For instance, it lacks the ability to identify specific types of fertilizers, diagnose crop diseases, or classify soil types, which restricts its coverage across various domains. Furthermore, while AGROVOC serves as a vocabulary system or thesaurus, it falls short of being a complete ontology. Other noteworthy general purposes agricultural ontologies are the Crop ontology (Shrestha et al., 2011) , CIARD Ring (Pesce et al., 2010), Planteome (Cooper et al., 2018). To explore this domain further, the authors in (Drury et al., 2019) have proposed a comprehensive survey. Apart from general purpose ontology, a large number of ontologies have been constructed for specific domains within the Agricultural scope, like the potatoes ontology which focuses on the cultivation of this vegetable from seeding to distribution (Haverkort and Top, 2011) or the wheat ontology to model its phenotype (Nédellec et al., 2020). Other specific ontologies focus on agricultural practices like vertical farming (Sivamani et al., 2014), or aquaponics (Abbasi et al., 2022) or even general organic farming in (Abayomi-Alli et al., 2021). Most of those specific ontologies, can be found in a large repository called Agroportal (Jonquet, 2017).

2.2.3 Knowledge Base for Agricultural IoT Platforms

The objective of knowledge bases in the context of IoT and agriculture is to establish connections between information relative to IoT device hardware and data, and agricultural knowledge necessary for effective farm management. Two notable studies, conducted by the authors in (Bhuyan et al., 2022) and (Ngo et al., 2018), present comprehensive surveys of such ontologies. One prominent ontology widely used in Agricultural IoT is AgOnt (Hu et al., 2011), which introduced a foundational model for this domain. Additionally, the recently developed OAK system proposes a comprehensive knowledge base, demonstrating promising results but highlighting scalability limitations (Ngo et al., 2020). Furthermore, numerous use-case-specific IoT and agricultural knowledge bases exist, catering to specific needs such as managing orchid farms (Kaewboonma et al., 2020) or coffee plantations (Suarez et al., 2022).

2.3 Limitation

Knowledge-base systems are extensively employed in the fields of IoT and agriculture primarily for sensor data management. These systems facilitate the fusion of diverse data sources and enable the control of fundamental systems like irrigation or ventilation. However, there is a notable scarcity of applications that combine plant phenotype ontologies with sensor data to make informed decisions. In the meantime, our research indicates that only one ontology, proposed by the authors in (Soulignac et al., 2019), focuses on agroecology principles. Regrettably, we could not identify an ontology that specifically integrates both agroecology and IoT aspects. Hence the purpose of this paper.

3 ARCHITECTURE PROPOSAL

3.1 Scenario

A farmer desires to initiate the implementation of Agroecology in one of his fields. In order to do so, he must cultivate crops that align with the ecosystem and climate of the field and its surroundings. To make the best decision about what to plant, where to plant and when to plant, the farmer interrogate our Knowledge Base named Permonto, which focuses on Agroecology. By providing the field's location, dimensions, and optionally the desired crop types, the

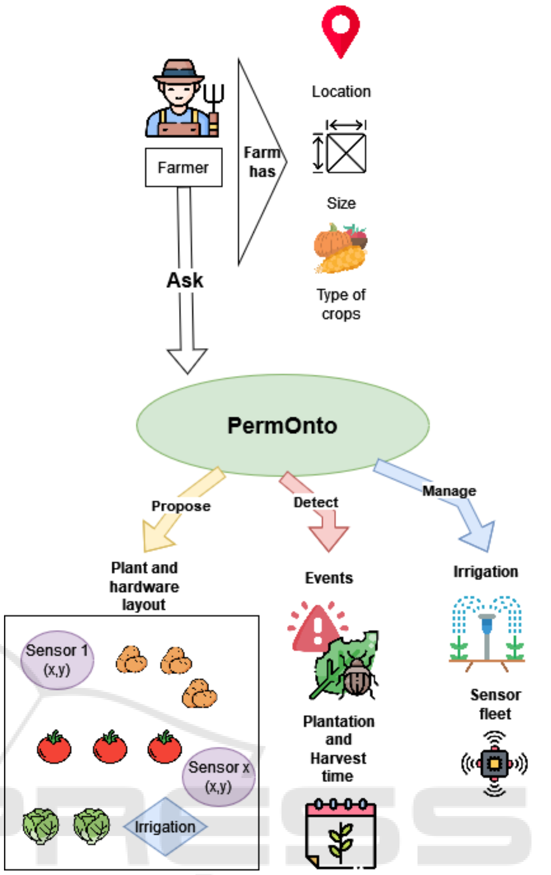

Figure 5: Permonto platform.

farmer queries the system. Subsequently, the system retrieves climate data for the specified location over a certain period of time, as well as information about the soil type in the region on different server over the internet. Based on these details, the system suggests an intercropping arrangement that adheres to Agroecology principles by proposing the best associations. Simultaneously, the system recommends a layout for the hardware, meaning the irrigation valves and the sensors to gather additional data about the local ecosystem. Once the crops are planted and the necessary hardware is set up, the system manages irrigation precisely in accordance with the climate and the specific requirements of each plant during their growth. Additionally, intelligent sensors detect various events and propose corresponding measures. Leveraging the available data, the system also predicts the optimal harvest time for each crop type. Finally, at the conclusion of a farming cycle, the system proposes a new layout for crops and hardware. This proposal takes into account both remote data and the locally measured data, and previous crops layout, enabling the system to continuously improve itself with each iteration of the growing period.

3.2 Environment Development

Our work revolves solely around software, and the hardware components are regarded as theoretical instances for now. We used a computer with 16 GB RAM and a I7 8th generation processor running Ubuntu 20.04. To construct our ontology, we used Protégé 5.5 Software. Protégé software offers a comprehensive and adaptable platform for ontology development. Its user-friendly interface, flexibility, robust features, collaborative capabilities, open-source availability, and seamless integration make it the ideal choice for projects of any size or complexity (Musen, 2015). We used the Ontology Web langage (OWL) with SWRL for our ontology. You can find our ontology on the Agroportal database. To interact with our Ontology we developped a simple application using Python and notably Owlready2 library. It is a module for ontology-oriented programming in Python 3. For more comprehensive details about our project and ontology, including aspects that may not be explicitly covered here, you can visit our GitHub page. There, you will find additional sources and information that provide a deeper understanding of our system.

3.3 Structure of the Ontology

In this part we will describe the Ontology we created. It is depicted in figure 6. Like any ontology, it is an explicit but partial representation of a targeted conceptualization. The assumptions made for our ontology may therefore be valid in certain contexts and not in others where the ontology is not intended to be used. This is why we refer to ontological commitment to indicate the assumptions made in an ontology and the implicit adherence to these assumptions by the users of that ontology (Kendal and Creen, 2007). Our goal in this endeavor is to develop an ontology that enables the inference of relationships between plants based on agroecology principles and data gathered from sensors. This ontology is centered around three primary components: the farm and its constituent growing fields, the plants, and the IoT devices.

3.3.1 Farm

The class *farm* regroup the farmers, the field, and the agricultural procedure. *Farmers* are regarded as the key agents responsible for executing an action effectively. The agricultural procedure class describes the fundamental actions that farmers have at their disposal, such as *planting*, *harvesting*, and *applying_countermeasures* in response to detected events. The *field* class ultimately symbolizes an individual

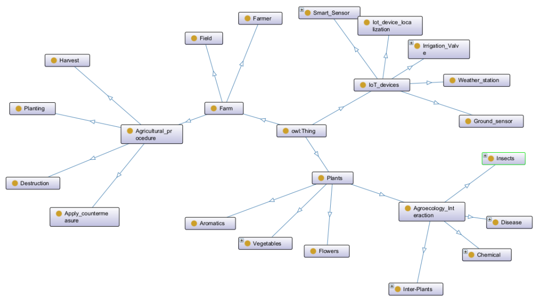

Figure 6: Global representation of Permonto and its main classes.

plot of land within a farm. A field possesses a *location* indicated by GPS coordinates and is associated with various environmental data. This includes local data obtained from sensors, such as *temperature*, *humidity*, *wind_speed*, *rain_level*, *soil_type*, *sun_exposure*, *ground_temperature*, and *ground_humidity*. Additionally, remote data pertaining to the same parameters is retrieved from a global weather database as long as *predicted_weather* data. Furthermore, the field encompasses the crops and IoT devices described in the remaining sections of the ontology.

3.3.2 Plants

Within the plant class, there are four subdivisions: vegetable, *aromatic*, *flower*, and *Agrocecology_interaction*. The flowers, aromatics, and vegetables subclasses provide detailed information about the biological traits of plants. This includes their respective families, water requirements, temperature range (minimum and maximum), preferred soil types, and other significant characteristics. These characteristics, provided as examples, have already been incorporated into numerous ontologies related to plant biology, such as AGROVOC, and are readily accessible for reference. Our primary emphasis was on the Agroecology interaction class, where we aimed to model the advantages and disadvantages of each plant in relation to various ecosystem parameters. This was done to enable our system to identify the most favorable plant interactions. One specific interaction we focused on was the "three sisters" associations, as mentioned in the paper's introduction. By assigning properties of *need* and *provide* to the plants, we can depict their positive influence on the surrounding environmental factors. By implementing this approach across a wide range of plant species, our system can independently uncover valuable plant interactions on a large scale. The interaction of three sisters is modeled in Figure 7.

Another instance of interaction we modeled was the pest protection mechanism. For instance, tomato

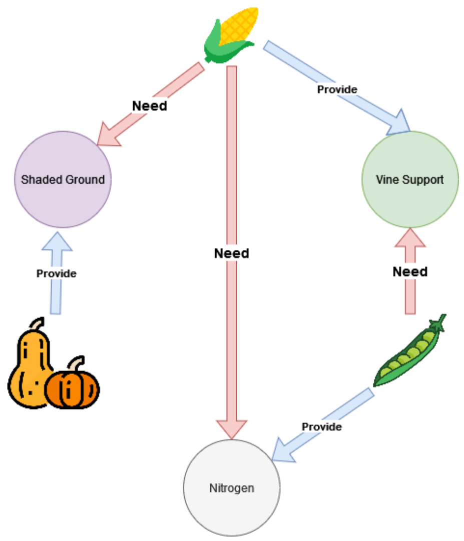

Figure 7: Three sisters modelisation in the ontology.

plants are highly susceptible to aphids, which are small insects that feed on their leaves. However, marigold flowers act as a natural repellent for aphids. By representing these facts through properties such as *menaced_by* and *protect_from* on the Aphids class, as depicted in Figure 8, our system can deduce that planting tomatoes alongside marigold would offer protection against aphids.

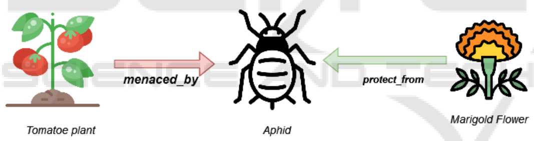

Figure 8: Aphids relations.

3.3.3 IoT Devices

The final major class in our ontology pertains to *IoT_device*. We have incorporated four device types: *ground_sensor*, *weather_station*, *smart_sensor*, and *irrigation_valve*. Each device is associated with a specific location within the farm and operates on battery power. The weather stations provide information on air temperature, air humidity, wind speed, and overall farm rainfall levels. The ground sensors measure sun exposure, soil temperature, and ground temperature within a 5-square-meter radius. Each ground sensor is linked to specific crops based on its location in the field. The smart sensors observe crops within a designated 10m radius and can identify the development of pests (such as aphids or slugs) or diseases (like mildew or Botrytis). The smart sensor also has two extra parameters, the firmware version and the accuracy of the inferences. Indeed, as explained by the authors in (Chollet, 2022), Smart sensors need firmware over-the-air update when their accuracy drops below a certain point. The irrigation valve also has an effective 20m radius and is similarly connected to specific crops.

3.4 Data Fusion

Once our ontology is populates with individuals sensors plants and field, the value from the sensor will be stored in the different classes. Doing so we perform Data fusion. It involves combining data from multiple sources to create a comprehensive and accurate representation of information. By integrating diverse data, such as sensor readings or database information, data fusion improves accuracy, completeness, situational awareness, and robustness. It enables the discovery of hidden patterns and correlations, leading to better decision-making (Khaleghi et al., 2016).

3.5 Rules Implementation

Once the Agroecology model, which qualifies the data, has been incorporated into the ontology, it becomes necessary to establish rules to standardize the ontology. These rules serve as the basis for automating the farming procedure. An example of a rule we implemented pertains to the irrigation process. In this rule, plants and sensors are linked to an irrigation valve based on their location. If a sensor detects that the soil's water level is below the required amount for a specific plant, the valve will open until the sensor detects the appropriate water level. Additionally, an extra layer of reasoning is included to consider the rain prediction parameter sourced from a weather database for the next 24 hours. If the prediction indicates a high likelihood of rain, the irrigation valve will not be opened. Another example of rule we implemented was the ones regarding the smart sensors. When a pest development is detected, on one plant, the farmer is requested to apply a counter measure on it. On the hardware side, if the battery of a sensors drops below a certain threshold, farmer is requested to replace it. The rules we have written do not rely on exact values but rather on fuzzy values, which are based on the principles of fuzzy logic (Chen et al., 2001). This means that parameter values are qualified using fuzzy notions such as "strong," "very strong," "a little bit," "little," etc. These fuzzy values are utilized to infer knowledge from the written rules, allowing for a more nuanced and flexible approach to reasoning.

4 USE-CASE EXPERIMENTATION

4.1 Simulator Building

To validate our model, we created a straightforward command-line interface (CLI) tool. This tool allows us to input data and obtain query results regarding various procedures. By utilizing this CLI tool, we can assess the effectiveness of our model based on the generated outputs.

4.2 Irrigation Management

For this experiment, we selected two fields: one planted with tomatoes and the other with potatoes. Each field is equipped with a single irrigation valve responsible for managing the water supply to all the plants within it. Additionally, there are four ground sensors in each field, strategically placed in quarters. The layout can be visualized in the provided figure9.

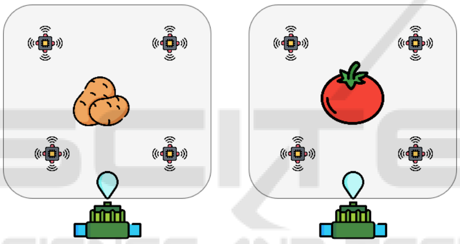

Figure 9: Irrigation procedure.

In the first scenario, we observed that the measured ground soil moisture level on all the sensors was *low*, and the weather prediction for the next 24 hours indicated *very_low* precipitation. As a result, we noticed that only the irrigation valve in the tomatoes field opened. This behavior is because tomatoes require water when the available moisture level is *low*, while potatoes necessitate water when the level is classified as *very_low*.

In a different configuration, we adjusted half of the ground sensors in the potato field to a *very_low* moisture level, while the other half remained at a *low*. As expected, the irrigation valve only opened for the corresponding half of the potato field.

Lastly, we set all the ground sensors to a *very_low* moisture level, but the "*rain_prediction*" parameter was set to *very_high*. As expected, no irrigation valve opens as they wait for raining.

4.3 Pest Development

In this scenario, we deployed a *smart_sensor_camera* to monitor a lettuce field and another one positioned in front of a tomato field. During the initial test, we simulated a *pest_detection_event* specifically for slugs in the lettuce field. Our system's response consisted of two actions: first, it prompted the farmer to remove the slugs and apply organic slug poison, and secondly, it recommended planting Lavender around both the lettuce and tomato fields. This recommendation was based on the high susceptibility of both crops to slug infestations, and Lavender's natural repellent properties against these insects. This process is described in figure 10.

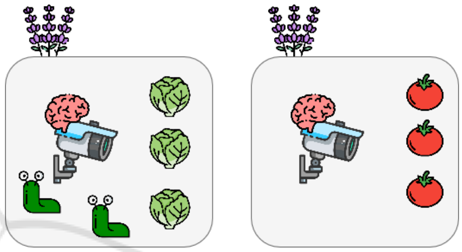

Figure 10: Pest development.

4.4 Firmware Update over the Air for Smart Sensors

We also performed a test to evaluate the accuracy of the smart sensors. In this test, we intentionally set the "accuracy" parameter of a smart sensor to an "insufficient" level. As a result, the system automatically initiated a Firmware Update Over The Air (FUOTA) procedure, as previously explained.

4.5 Calendar Estimation

To assess the capability of our system in determining the optimal planting periods for different crops based on farm location, we conducted simulated tests in two cities: Marseille in the south of France and Lille in the north. We queried the system to determine the ideal timing for planting tomatoes in each location. The system retrieved temperature data from previous years for both cities and compared them against the minimum temperature requirement for tomato plants. Based on these parameters, the system advised initiating tomato planting from early April in Marseilles while recommending waiting until the end of May in Lille.

4.6 Crops Layout

In our final scenario, we aimed to demonstrate the system's ability to identify known beneficial plant interactions based on the provided information. We requested the system to propose a crop layout for a field measuring 2m by 8m, specifying our desire to plant corn, squash, peas, tomatoes, and basil. Utilizing the range parameter of each plant, which represents the space it requires on the ground, the system generated a layout map. It strategically positioned squash, corn, and peas together to foster beneficial interactions among them. Simultaneously, the system separated the tomato field from the corn to avoid potential competition. Instead, it recommended planting basil alongside the tomatoes to provide shade for the soil. By considering these factors and employing the range parameter, the system successfully proposed a crop arrangement that optimizes beneficial plant interactions within the given field. Each plant was given by coordinates, we represented the layout in figure 11.

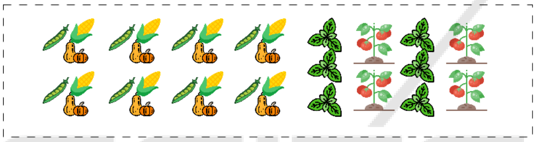

Figure 11: Crops Layout.

5 CONCLUSIONS

The proposed knowledge base demonstrates promising outcomes, enabling farmers to effectively manage essential stages of the farming process. These include crop layout, care tasks (such as irrigation and pest detection), and optimal harvest timing, all in concordance with agroecology principles. Additionally, the knowledge base facilitates the seamless integration of IoT devices, allowing farmers to harness the generated data effortlessly. Moreover, the model possesses the capability to identify advantageous crop interactions based on agroecology principles. To advance this research, it is crucial to incorporate further knowledge from farmer experiences into the ontology. Furthermore, aligning our ontology with existing plant-related knowledge sources like AGROVOC would enable the discovery of novel beneficial relationships between plants, specific to their respective environmental contexts. In conclusion, this knowledge-based system holds great potential for farmers seeking to transition towards sustainable farming practices with the aid of IoT technologies.

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