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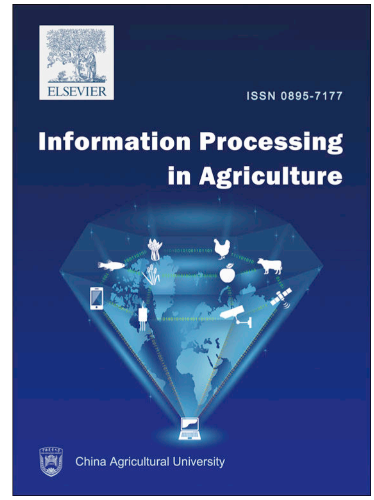

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Rabiya Abbasi, Pablo Martinez, Rafiq Ahmad

PII:	S2214-3173(21)00093-7
DOI:	https://doi.org/10.1016/j.inpa.2021.12.001
Reference:	INPA 346

To appear in: *Information Processing in Agriculture*

Received Date:	19 March 2021
Revised Date:	24 November 2021
Accepted Date:	7 December 2021

Please cite this article as: R. Abbasi, P. Martinez, R. Ahmad, An ontology model to represent aquaponics 4.0 system's knowledge, *Information Processing in Agriculture* (2021), doi: https://doi.org/10.1016/j.inpa.2021.12.001

An ontology model to represent aquaponics 4.0 system's knowledge

Rabiya Abbasi, Pablo Martinez, Rafiq Ahmad*

Aquaponics 4.0 Learning Factory (AllFactory), Department of Mechanical Engineering, University of Alberta, 9211 116 St., Edmonton, AB, T6G 2G8, Canada

*Corresponding author. Tel.: +1 (780) 4927180

E-mail address: rafiq.ahmad@ualberta.ca

Abstract

Aquaponics, one of the vertical farming methods, is a combination of aquaculture and hydroponics. To enhance the production capabilities of the aquaponics system and maximize crop yield on a commercial level, integration of Industry 4.0 technologies is needed. Industry 4.0 is a strategic initiative characterized by the fusion of emerging technologies such as big data and analytics, internet of things, robotics, cloud computing, and artificial intelligence. The realization of aquaponics 4.0, however, requires an efficient flow and integration of data due to the presence of complex biological processes. A key challenge in this essence is to deal with the semantic heterogeneity of multiple data resources. An ontology that is regarded as one of the normative tools solves the semantic interoperation problem by describing, extracting, and sharing the domains' knowledge. In the field of agriculture, several ontologies are developed for the soil-based farming methods, but so far, no attempt has been made to represent the knowledge of the aquaponics 4.0 system in the form of an ontology model. Therefore, this study proposes a unified ontology model, AquaONT, to represent and store the essential knowledge of an aquaponics 4.0 system. This ontology provides a mechanism for sharing and reusing the aquaponics 4.0 system's knowledge to solve the semantic interoperation problem. AquaONT is built from indoor vertical farming terminologies and is validated and implemented by considering experimental test cases related to environmental parameters, design configuration, and product quality. The proposed ontology model will help vertical farm practitioners with more transparent decision-making regarding crop production, product quality, and facility layout of the aquaponics farm. For future work, a decision support system will be developed using this ontology model and artificial intelligence techniques for autonomous data-driven decisions.

Keywords: Aquaponics 4.0; Industry 4.0; Ontology modeling; Knowledge modeling; Decision support system.

1. Introduction

The gradual decrease in farmlands due to ongoing trends of increasing population, rapid urbanization, anomalous environmental changes, diminishing water supply, and resulting food security issues have attracted much attention towards vertical farming (VF) practices [1]. In principle, VF is a simple concept that involves growing crops in vertically stacked layers. It is essentially a controlled-environment agriculture model, which aims to optimize indoor soilless farming techniques such as hydroponics, aquaponics, and aeroponics. As one of the modern VF methods, aquaponics has the potential to be the future of agriculture as a sustainable farming method with high yield and low water consumption. Aquaponics is the combination of a recirculating aquaculture system (RAS) and a hydroponics system (soilless growing of plants), that work together in an integrated environment [2]. Being a symbiotic process, the design and management of an aquaponics system are challenging, when scaling it up to a commercial level. However, through the introduction of automation, smart strategies, and connectivity, the aquaponics system's feasibility can be strengthened.

With the advent of agriculture 4.0—the agricultural counterpart of Industry 4.0—modern vertical farms can leverage disruptive digital technologies such as the internet of things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), wireless sensor networks (WSN), big data and analytics (BDA), autonomous robot systems (ARS) and ubiquitous cloud computing (UCC) to achieve sustainable intensification. Aquaponics 4.0 system is a digital farm based on a smart farming concept that uses all these technologies to bring improvements in systems' design and operation by ensuring autonomous monitoring and control and intelligent data-driven decisions in the fast-processing pervasive environment [3]. The realization of aquaponics 4.0 brings flexibility and adaptability to the system; however, it requires efficient data integration and information flow among different domains. Data can be of two types: i) data created by people, which are mainly distributed through the Web (social networks, emails, online television, online broadcasting, etc.) or available in form of books, documents, and computer files; and ii) data generated by multiple heterogeneous sources such as sensors, IoT devices and suggested services. This mixed traffic of data needs to be stored, categorized, mined, and processed to extract useful knowledge and utilize it to solve complex real-world problems such as managing complex processes. The continuous evolution of digital technologies, however, has led to complex systems' architectures – generating enormous volumes of data with diverse formats. The exponential increase in data size is causing interoperability issues making data integration and knowledge extraction complex and difficult [4].

Recent research has shown that semantic web technology (SWT) plays a key role in solving the problems of data heterogeneity, interoperability, interpretation, and integration [5,6]. To ensure reliable semantic modeling, knowledge management, and data integration, ontologies are considered promising tools. Ontologies are used to store information from multiple sources and provide an automatic process known as *reasoning* to infer new knowledge that has not been explicitly incorporated [7]. They are commonly employed in the development of a knowledge base - one of the building blocks of a decision support system. Besides, ontologies have appeared as an alternative to relational databases (RDB) and are considered as more powerful than RDB because; i) accessibility of the data is simple in ontologies – it is easy to define changes, and 2) Inference of new knowledge from existing models is carried out using reasons in ontology, whereas in RDB one needs to create every single link manually to infer new knowledge – making RDB difficult to manage in case of knowledge modeling of big data [8].

So far, no attempt has been made to develop an ontology model for the aquaponics 4.0 system. Therefore, this study aims to create an ontology "AquaONT" for the aquaponics 4.0 system by utilizing web ontology language (OWL). AquaONT stores aquaponics 4.0 knowledge gathered from domain experts, literature, databases, and IoT devices installed at the farm. It also builds the semantic relevance among fundamental elements of an indoor soilless vertical farm, such as optimal environmental parameters, system configuration, and product qualitative aspects. It can provide the optimal solution for the operation of IoT devices based on contextual data received from the farm, updates on crop quality along with respective causes and treatments, and design configuration of grow beds concerning crop characteristics, when integrated with the suitable interface. The practical implementation of AquaONT in the context of engineering design (parametric design automation of aquaponics grow beds based on crop characteristics) can be found in a study which is the extension of this work and hence, it is suggested to have a look at it [9]. Overall, the current work can be used as a semantic framework to build agricultural applications that will allow vertical farming practitioners to access each dimension of aquaponics knowledge for more precise decision-making regarding crop production and facility layout in aquaponics farms. In summary, the main contributions of this paper are listed as follows.

- Review of the knowledge modeling approaches and current state-of-the-art ontology models in the agriculture sector.
- Description of the domain-specific concepts and sub-concepts of aquaponics 4.0 farm and relationships between them.
- Populating the respective knowledge domains with data and information from multiple sources to enable automatic decision-making related to various aspects such as process, design, environment, and quality control.

The rest of the paper is organized as follows. Section 2 presents a detailed literature review focusing on the general concepts of an aquaponics 4.0 system, knowledge modeling, and research contributions related to ontology-driven smart systems and agricultural ontologies. The research methodology used to develop AquaONT is discussed in Section 3 followed by its detailed formulation in Section 4. The implementation and validation of AquaONT are presented in Section 5. In Section 6, a detailed discussion of the work is provided. Finally, the concluding remarks and future directions are presented in Section 7.

2. Literature review

2.1 Aquaponics 4.0 historical landscape

The historical interaction between industrial revolution and aquaponics evolution is depicted in Fig.1. Aquaponics technology was first implemented towards the end of the 19th century where indigenous tools were used to develop the system and can be referred to as aquaponics 1.0 [10]. Intensive research was conducted afterwards to determine the efficiency of aquatic plants at filtering and consuming the nutrients in wastewater from aquaculture farms and several electrical devices such as water pumps, aerators, and fish feeders were installed, which can be marked as aquaponics 2.0 [11]. Around the 1970s, technologies like robotics, information technology (IT), embedded systems, and software engineering were integrated with the aquaponics system to enable precision farming, which can be marked as aquaponics 3.0 [12]. The research regarding the implementation of industry 4.0 concepts in aquaponics systems started towards the end of 2016 [13]. This can be marked as the beginning of aquaponics 4.0—a digital aquaponics farm that involves remote monitoring and control of ecosystem parameters, a high degree of automation, and intelligent decision-making to ensure high crop yield and quality.

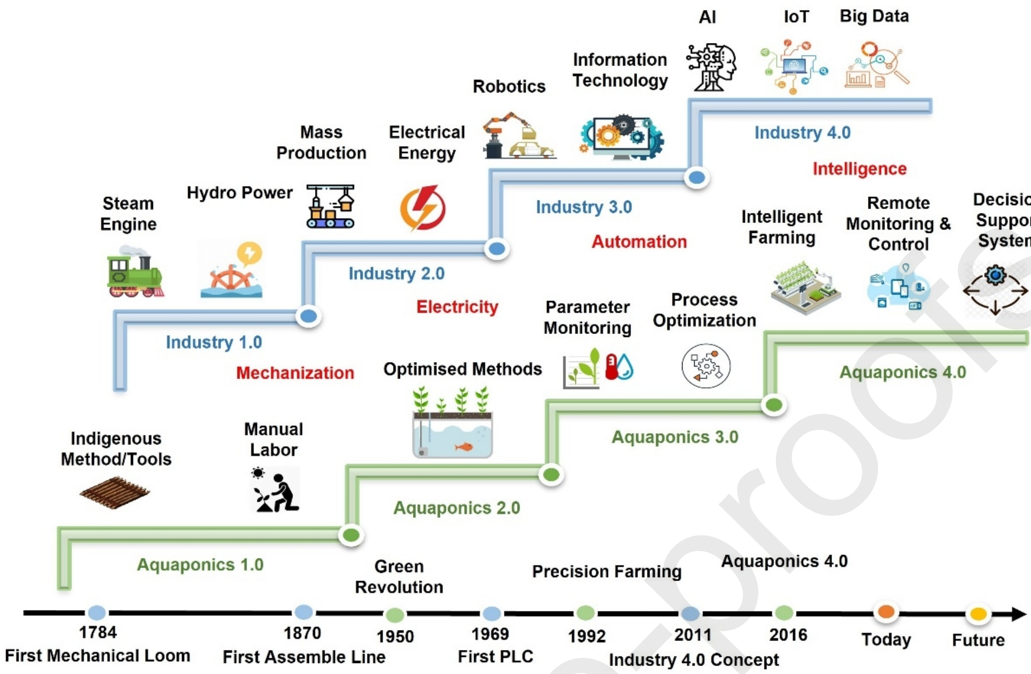

Fig. 1 Roadmaps describing the interaction between the industrial and aquaponics evolution.

Applications of various Industry 4.0 technologies in aquaponics system are reflected in Fig.2. The realization of such a high level of digitization requires efficient data integration and information flow along with knowledge management so that the system can vary and adapt its behaviors to different scenarios based on past experiences and learning capabilities [14].

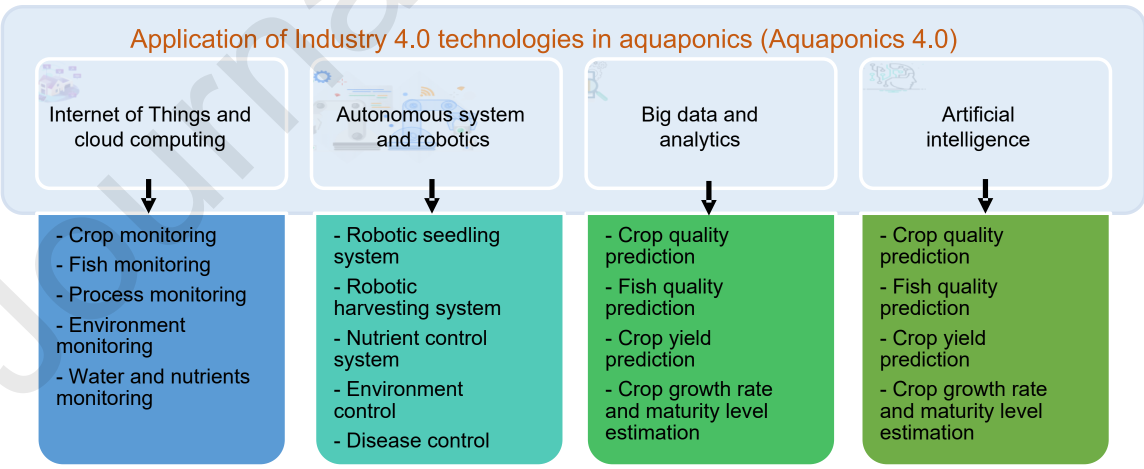

Fig. 2 Aquaponics 4.0—Applications of Industry 4.0 technologies in an aquaponics system.

2.2 Knowledge modeling conceptual overview

According to Davenport et al., knowledge is a high-value form of information combined with experience, context, and interpretation that is applied to decisions and actions [15]. To store and represent this knowledge, modeling techniques are employed [16]. Based on fundamental theories of knowledge base technology, knowledge modeling and manipulation techniques can be classified into four groups such as 1) linguistic knowledge base; 2) expert knowledge base; 3) ontology; and 4) cognitive knowledge base, and their detailed description can be found at reference [17]. For situations in which large data acquisition systems are used, i.e. aquaponics 4.0 systems, ontologies are employed as they support the creation of customized rich web-based data platforms and ease data accessibility to interested parties. Therefore, for this study, an ontology-based knowledge modeling and manipulation technique is employed to model knowledge of the aquaponics 4.0 system.

2.3 Overview of ontology modeling

Ontology is a branch of metaphysics that is related to the philosophy of the "being". Ontology can be defined as a formal, explicit specification of a shared conceptualization, where “conceptualization" refers to an abstract model of some phenomena in the world that can be identified by its relevant and explicitly defined concepts and constraints [18]. Ontologies provide mechanisms to represent shareable heterogeneous data among domains, in the form of knowledge models that vary due to the complex and dynamic nature of a system. An ontology is typically formulated as a tuple, $\mathrm{O} = \{\mathrm{C}, \mathrm{I}, \mathrm{OP}, \mathrm{DP}\}$, where C (concept) is a set of instances, I (instance) is the object in the domain, OP (object property) is the relationship between two concepts or instances, and DP (datatype property) links instances with literals (integer or string) [19]. Most researchers classify the ontologies in four categories: 1) application ontologies; 2) domain ontologies; 3) representation ontologies; and, 4) generic ontologies based on generality levels and conceptualization [20–23]. In this study, a domain ontology is proposed, representing the concepts that are valid only in a specific domain—the aquaponics domain. Detailed insights into ontology, its architecture, related computational tools such as SWRL and SPARQL can be found at [24–28]. To develop an ontology model, Protégé[1] is employed, which is an open-source ontology editor and framework developed at Stanford University [29].

[1] https://protege.stanford.edu/products.php#desktop-protege.

2.4 Ontology-driven smart systems

The recent advancements in big data, IoT, and cloud computing have spurred the rise of artificial intelligence (AI) in various sectors such as agriculture, aquaculture, manufacturing, healthcare, etc. AI is all about data analysis, which is roughly classified into two categories: data-driven and rule-based [30]. Traditionally, many smart devices and services use a set of rules for situation recognition and inference. These rules are extracted from the long-term experiences and knowledge of human experts (human learning). Semantic modeling (ontology) is a representative technique for this approach - performed on already-built semantic models (a set of rules in semantic language) and new data [31]. Today, the focus is more on data-driven approaches such as machine learning and deep learning - extensively used in image recognition and natural language processing because of their high accuracy. Both approaches, however, have their drawbacks and benefits. In semantic modeling, rules should fit the real phenomena consistently. The rules may become obsolete if circumstance changes dynamically and drastically. In machine learning, assumptions are made on the data reflecting the whole phenomena we are interested in. The analysis becomes meaningless if assumptions made are not satisfied [32].

Recently, ontologies are increasingly being used in combination with machine learning and deep learning techniques to model smart ecosystems such as smart homes, smart farms, smart factories, power grids [20,33–36]. The main applications include solving the interoperability issues, detecting the cyber-attacks, remote monitoring and controlling of system's parameters and entities, analysis of big data, creating and analysis of digital twin models, prediction of patient's disease, checking the accountability of AI systems, improving the monitoring of industrial operations, enhancing the flexibility of control solutions in human-robot collaborative cells, and optimizing the design parameters for maximum reliability and minimum cost. Examples of how ontology and machine learning or deep learning technologies are used in these applications are context modeling, semantic filtering, automatic ontology population, utilization of background knowledge stored in ontology models, developing intelligent decision support systems, and ontology-based learning and applications. Table A1 given in Appendix A provides a summary of relevant publications, where ontologies are used in combination with digital technologies.

The idea of combining machine learning, AI, and ontology modeling techniques is relatively new in the agricultural field and hence, there are only a few studies available, which are mentioned towards the end of section 2.5. Most of these studies have either focused on enabling smart services (monitoring and control) in IoT-based farming systems or detection of cyber-attacks using ontology models. None of these studies has directly used machine learning in combination with ontology modeling. There could be various reasons for that: i) Agricultural data is vast and scattered and no unified model is available to keep that data in one place, ii) Agricultural sector is a slow adopter of technology, owing to the increasing complexity of IT (information technology), and iii) Presence of complex biological processes, environmental parameters and living organisms. Therefore, the notion of presenting examples of different domains (table A1), where ontology is used in combination with smart technologies is to highlight the significance of the ontology modeling approach and how it can be used in different capacities to bring improvements in a variety of systems.

2.5 Agricultural ontologies

Ontologies have been a dominant research area for the representation, storing and management of agricultural knowledge. For instance, AGROVOC, initially published in the early 1980s is the renowned agricultural thesaurus [37]. AGROVOC is the amalgamation of a controlled RDF vocabulary with around 32000 concepts covering several areas of interest, such as food, nutrition, farming, fisheries, forestry, and the environment. Another prominent ontology model is crop ontology (CO), which was designed to provide a structured and controlled vocabulary for significant crops' phenotypes for food and agriculture research [38]. Several ontologies are developed to represent specific aspects of a crop or a system. For example, Aree et al. proposed an ontology model for Thai rice, aiming to present a plant ontology prototype and specify crop growth data [39]. In the study by Maleerat et al., domain ontology based on agricultural expertise retrieval framework “ARGIX” was constructed in Protégé with the idea of improving the performance of information retrieval using simple query terms and association rules mining method for inference [40,41]. Suresh et al. developed a farming ontology with extensible vocabulary to support the dataset with agricultural aspects related to production, geography, and meteorology [42]. Hifza et al. extended this ontology to include several other classes, such as water, pesticide, nutrients, and seed to assist farmers in decision-making related to rice crops [43]. To represent the technical knowledge of the agriculture operations field, Elcio et al. presented a formal task ontology model [44]. The field operations associated with task agents, agent roles, input resources, task and sub-task decomposition, control-flow, task concepts, attributes, and relations were defined. Most recently, Aydin et al. proposed a generic ontology-based data acquisition model to create data acquisition forms based on model-view-controller (MVC) design pattern, with the notion to publish and use agricultural open data platforms [45]. A tool OWL2MVC was developed that integrates the hazelnut ontology to illustrate the proposed model's effectiveness for generating data acquisition forms.

Ontologies are also developed to enable smart farming services. For instance, Chukkapalli et al. developed a member farm and co-op ontologies for a connected cooperative smart farming ecosystem to provide a more accurate and data-driven dimension to precision agriculture [35] AI applications are employed to use the information gathered from the cloud for diagnosing the critical conditions of the farm such as crop diseases, soil condition, water level, etc. Sai et al. developed a smart farm ontology (incorporates users, sensors, and systems in a farm) for implementing an attribute-based access control (ABAC) to evaluate access control requests in farms dynamically[46]. Sivamani et al. proposed a vertical farm ontology (VFO) model to enable a smart service based on ubiquitous sensor networks [47]. Their research concentrates more on the monitoring and controlling of the internal and external environment parameters. This work was extended to link VFO with web services aiming to assist different entities related to hardware, user, service, and environmental factors [48]. In the study by Kim et al., an ontology using context modeling technique is designed for an intelligent service in a vertical farm by integrating several environmental and control factors, which were validated for different scenarios [49].

The contributions mentioned above have established the philosophical foundations in representing agricultural knowledge, but most of the models are designed for soil-based methods. For soilless VF, such as hydroponics, aquaponics, and aeroponics systems, limited or no research is conducted in relation to knowledge representation through ontology models. Moreover, the current models are limited to the representation of knowledge concerning a single product type and its growth data, monitoring, and controlling of environmental parameters, usage of pesticides, and seed plantation. Nevertheless, no heed has been paid to integrate and specify the heterogeneous metadata related to crop quality and soilless VF design. With these observations in mind, this work aims to present an ontology model for representing and storing multidimensional knowledge of an aquaponics 4.0 system with a notion to use it for developing further applications using machine learning models, which will assist aquaponics practitioners in decision-making related to aquaponics farms.

3. Methodology for ontology development

To represent and model the essential knowledge of the aquaponics 4.0 system, an ontology is developed. There are multiple methodologies to create an ontology from scratch. In this study, the *"methontology"* approach is employed to formulate and evaluate AquaONT. This approach presents a well-structured framework to develop ontologies from scratch by enlisting and tracking the activities necessary in an ontology development process [50]. These activities are classified into six stages: ontology specification, knowledge acquisition, knowledge conceptualization, knowledge formalization, ontology evaluation, and ontology verification and validation, which are presented in Fig.3.

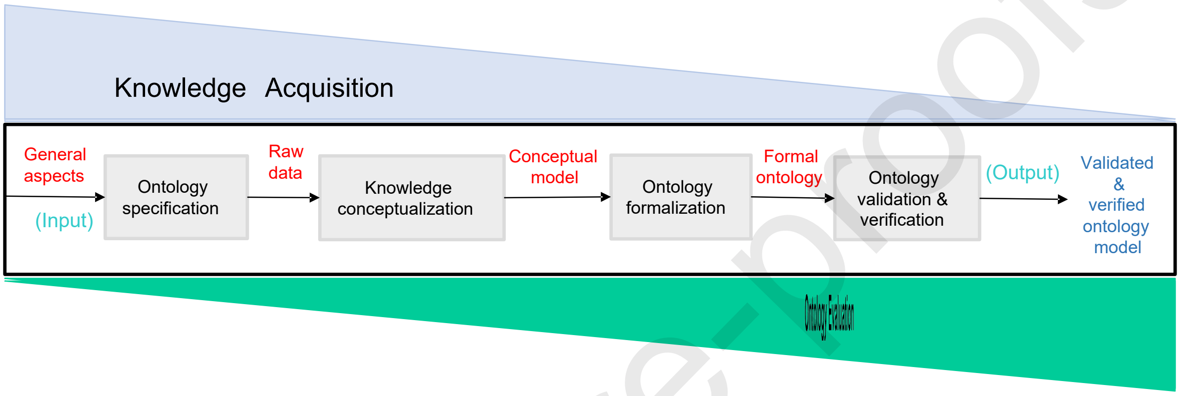

Fig. 3. Methontology approach for ontology development, adapted from [50,51]

First, ontology's scope is specified in the ontology specification stage by describing and assembling the general aspects such as ontology domain, the purpose of ontology, its intended users, level of formality, and several key terms. A conceptual model is then developed in the second phase – involving organization and modeling of the raw data gathered in accordance with the scope during the knowledge acquisition stage in a more formal and structured form. A glossary of terms (GT) describing physical and conceptual objects related to each knowledge domain is created in tabular or graphical form. A conceptual model (taxonomy) is converted to a formal model (computable) in the ontology formalization phase, using an ontology editor such as Protégé. Domain-specific concepts and sub-concepts are defined in this stage. Finally, to test the correctness and coherence and detect the incompleteness, inconsistencies, and redundancies, formal ontology is evaluated. The evaluation process is carried out during each phase, between the phases, and at the end and it involves validation and verification [51]. Verification refers to "building the system right" and involves a technical process that ensures that the ontology is built correctly as per the requirements established during the specification phase [50]. Whereas, validation refers to "building the right system." It ensures that the ontology corresponds to the system that it represents and guarantees that the designed ontology performs correctly with an acceptable level of accuracy by checking the quality of the solutions when the system is queried [50]. The validated and verified ontology model is then used in different applications for automatic decision-making.

4. Formulation and evaluation of AquaONT

Following the steps mentioned in section 3, formulation, and evaluation of AquaONT is carried out. Each stage is comprehensively described in the following sub-sections.

4.1 Ontology specification

An informal ontology specification document written in natural language and describing the clear and concise purpose and scope of an ontology was generated for AquaONT before its formalization, see Table A2 in Appendix A. The purpose of AquaONT was specified in this document, which is to structure, model, and store the aquaponics 4.0 system's knowledge, and use it to enable data-driven decisions for farmers by developing a functional decision support system. These decisions will be related to determining the optimal growth environment, assessing the system configuration based on product characteristics, and evaluating the quality of products based on the environment-based contextual data.

4.2 Knowledge conceptualization

To organize and store the gathered knowledge, a conceptual model representing the upper-level hierarchy of AquaONT is developed, see Fig.4. The resources used to gather the knowledge for AquaONT include i) literature, which provided the information about optimal environmental parameters, optimal growth parameters, qualitative aspects of the product, and standard operation of the aquaponics farm; and ii) the aquaponics 4.0 system established as a learning factory (AllFactory) at the University of Alberta, which provides real-time contextual data [52]. For AquaONT, six knowledge domains are identified for creating a conceptual model such as consumer product, production system, production facility, ambient environment, product quality, and contextual data. The common dependencies among and within knowledge domains are identified as the relationships and are illustrated in the model. Several GT e.g., Crop, Fish, Digital_System, Qualitative_Value_Assessment, and relationships between these terms, e.g., Product_Quality "is_Determined_by" Quality_Aspects, are identified for AquaONT.

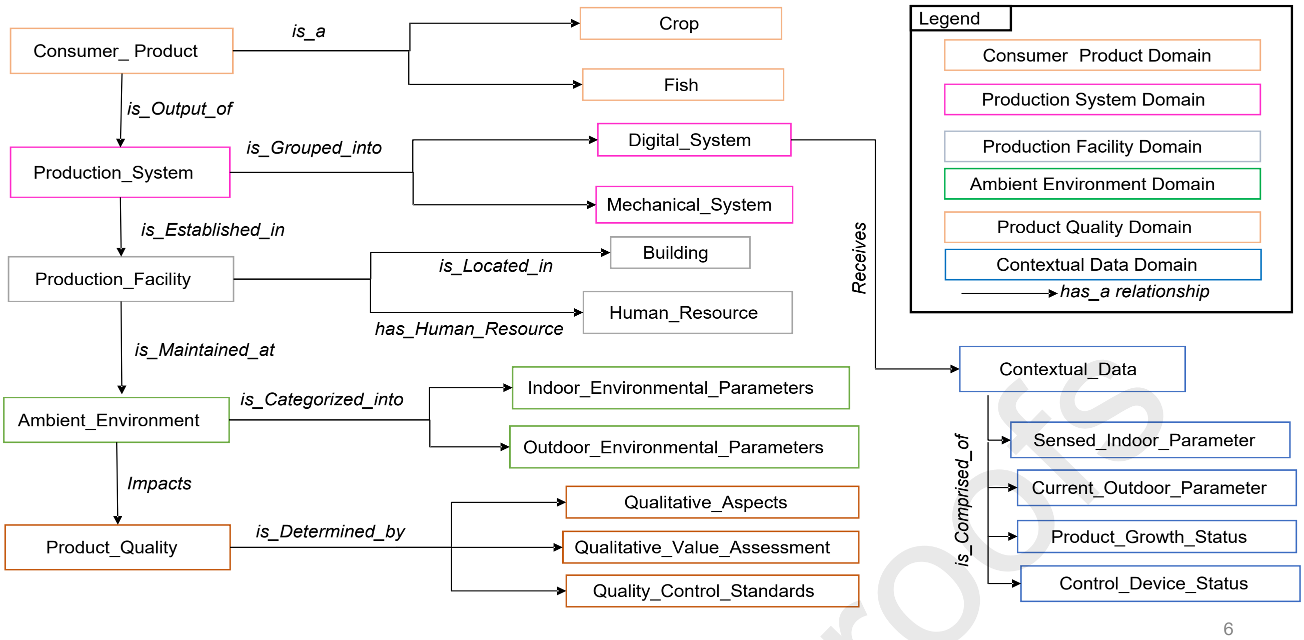

Fig. 4. Conceptualization tree for the upper-level ontological model of AquaONT

4.3 Ontology formalization

The upper-level ontological knowledge model developed for AquaONT during the conceptualization stage is formalized and implemented using Protégé 5.5. Six “classes” or “concepts” were created for the six knowledge domains mentioned in the previous subsection, and accordingly, “subclasses” were formed, see Fig A.1 of Appendix A. The relationships between these classes and subclasses were specified using “object properties.” Instances of classes are modeled using “individuals,” and attributes are stipulated using “data properties.” In the next sub-sections, all the contents are distinctly presented and explained.

4.3.1 Domain-specific concepts

Consumer product concept

A product is the outcome of any production system. In an aquaponics 4.0 system, the notion of the Consumer_Product class is to provide an abstract view of the type, growth status, and growth parameters of ready-to-harvest crops and fish, which are primary products in this case [53]. The hierarchical tree-like structure of this class is shown in Fig.5. Crop as an indispensable part of any aquaponics system is further defined to include subclasses such as Crop_Growth_Parameters (optimal humidity, light intensity, water temperature, air temperature, pH, carbon dioxide (CO_2), etc.), Crop_Type (leafy green vegetables such as lettuce, basil, mint, cabbage, and cilantro), and Crop_Growth_Status (the growth rate of a specific crop from seed to ready-to-harvest crop). The second product in the aquaponics system is fish, which plays a vital role in supplying nutrients for the healthy growth of plants in the RAS. The subclasses Fish_Species (fishes used in aquaponics system), Fish_Growth_Parameters (water pH level, ammonia content, amount of dissolved oxygen, etc.), and Fish_Growth_Factors (growth rate, feeding rate, stocking size, etc.) are specified under the class Fish.

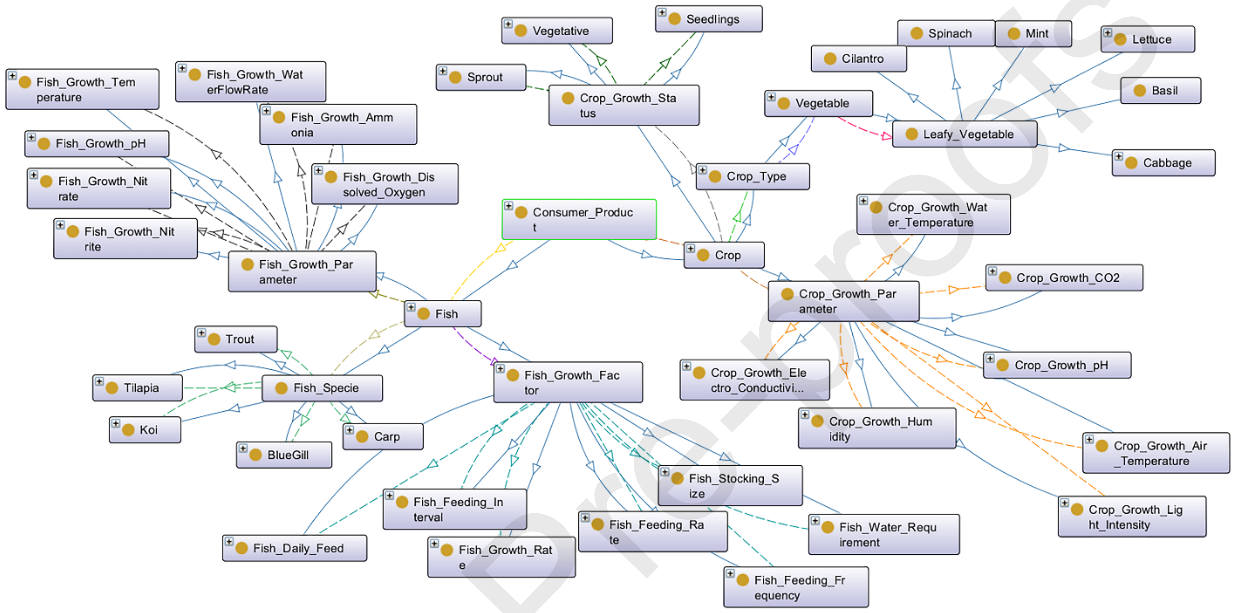

Fig. 5. Consumer product concept showing knowledge elements of crop and fish

Ambient environment concept

For the healthy growth of crops and fish in an indoor aquaponics 4.0 system, it is necessary to ensure that environmental parameters (water and atmospheric) are within the optimum range [55]. The Ambient_Environment concept is modeled in this regard to specify the threshold of indoor influenceable environmental parameters according to the tolerance range of crop and fish considered under the subclasses Optimal_Water_Parameters and Optimal_Atmospheric_Parameters. The hierarchical diagram of this concept is given in Fig.6. In an aquaponics system, the living organisms can exist only if water and atmospheric parameters such as temperature, pH, electroconductivity, ammonia, dissolved oxygen, nitrate and nitrite level, water hardness, light intensity, humidity, and CO_2, water level, water flowrate, alkalinity, and salinity are within the optimal range or else they may perish [55].

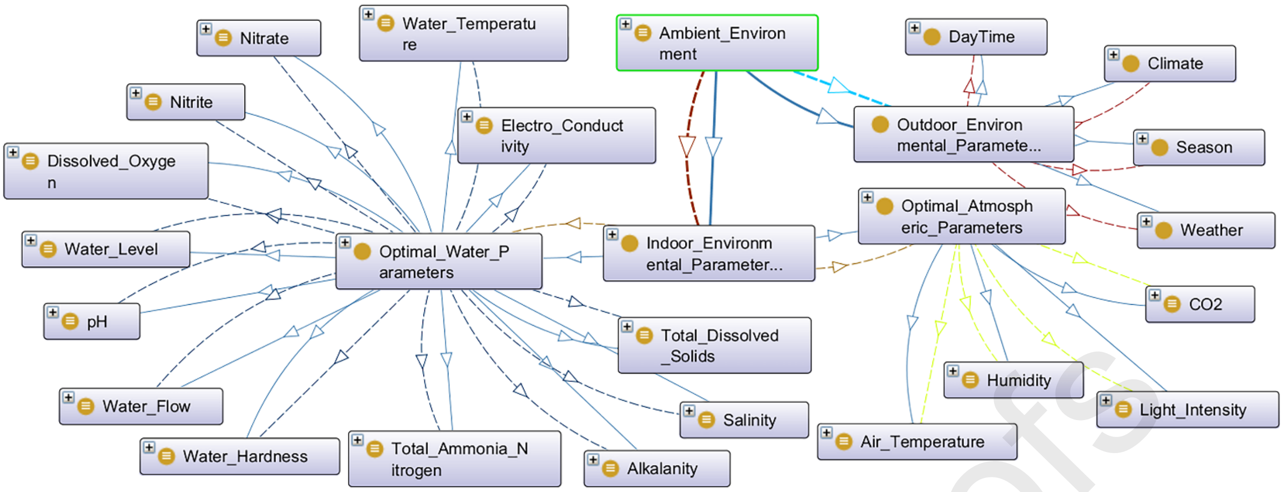

Fig. 6. Ambient environment concept showing a variety of atmospheric and water parameters

Contextual data concept

The IoT-based system has many heterogeneous environments that consist of several devices generating context information/data. Therefore, it is necessary to integrate, store and share this information between system entities for which ontologies are used [56]. The contextual information is usually gathered from sensors through proper connectivity channels and is utilized to enable data-driven decisions [14]. Hence, contextual information plays a vital role in a ubiquitous environment. The Contextual_Data concept in AquaONT specifies the set of environmental parameters and crop growth status at a particular location at a scheduled time interval. The hierarchical structure of this concept is shown in Fig.7. Three subclasses are identified for this concept include Sensed_Indoor_Parameter, Current_Outdoor_Parameter and Current_Product_Status. The instances of these subclasses are populated by importing cloud data of farm in ontology model using transformation rules.

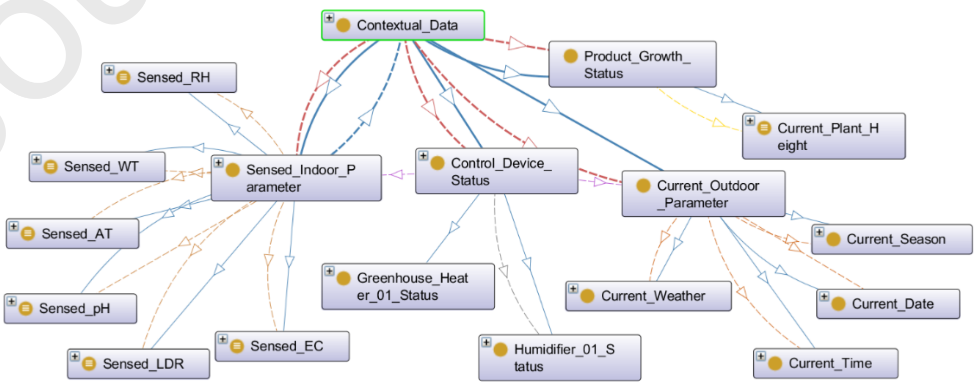

Fig. 7. Contextual data concept showing real-time data that is imported in AquaONT

Production system concept

An indoor aquaponics 4.0 system consists of various mechanical and electrical components. The Production_System concept is devised to model the knowledge of these components under the subclasses Digital_System and Mechanical_System, shown in Fig.8. The mechanical system of the aquaponics 4.0 farm is comprised of NFT (nutrient film technique) grow channels for plant growth represented under subclass Hydroponic_Unit and the fish tanks for fish habitat and biofilters for the breakdown of ammonia mentioned under subclass Aquaculture_Unit. The design of these systems is dependent on the physical characteristics of plants and fishes, such as height and width [9]. The subclass Digital_System lists sensors, controllers, and other electronic and network devices that are employed in an aquaponics 4.0 farm to achieve autonomous services, such as remote monitoring and control [57].

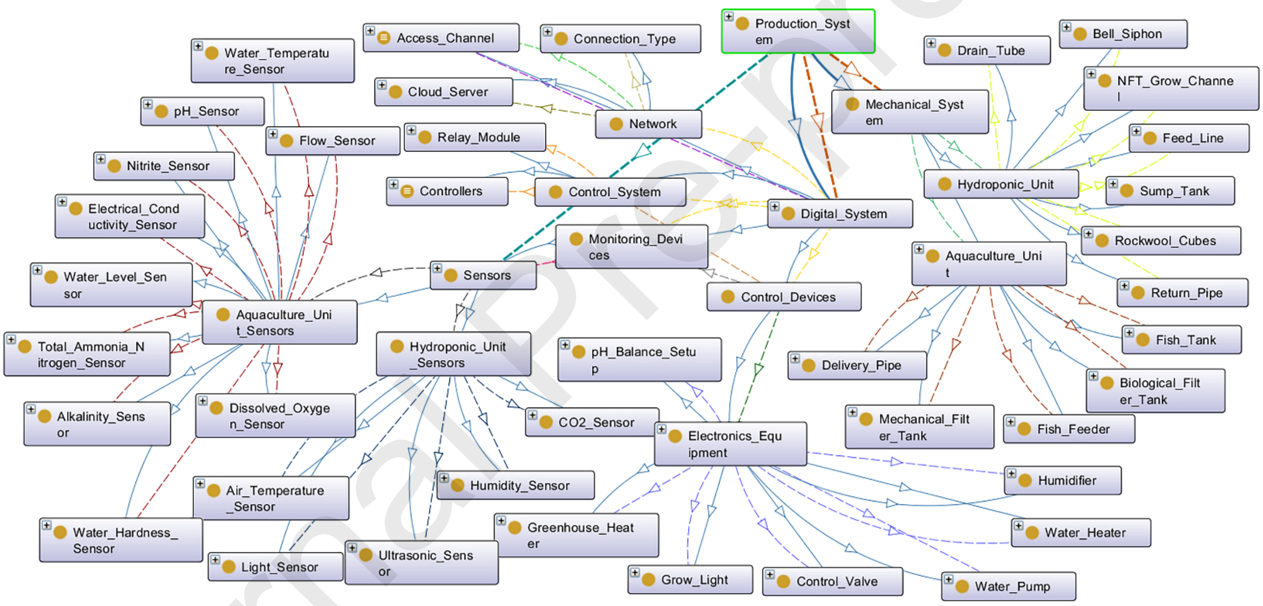

Fig. 8. Production system concept with digital and mechanical components in aquaponics 4.0 farm

Product quality concept

The Product_Quality concept models and stores the qualitative product aspects, quality control standards, and quality assessment criteria and links these attributes with the knowledge represented under Consumer_Product, Production_System, and Ambient_Environment classes. The diagram showing the hierarchical structure of this concept is depicted in Fig.9. The Subclass Qualitative_Aspects represents the quality attributes of both fish and crops such as products' physical aspects (size, shape, color, structure, transparency or turbidity, etc.) and nutritional value (well-balanced ratio of carbohydrates, fats, proteins, minerals, etc.) as standardized by local and international food associations [58]. The Quality_Control subclass defines the set of procedures adopted to ensure that product meets the desired quality standards set in subclass Qualitative_Aspects. It involves two main areas; product inspection and product handling. The last subclass defined under this concept is Qualitative_Value, which classifies the product as a good or bad quality product by comparing the information from product inspection with qualitative aspects.

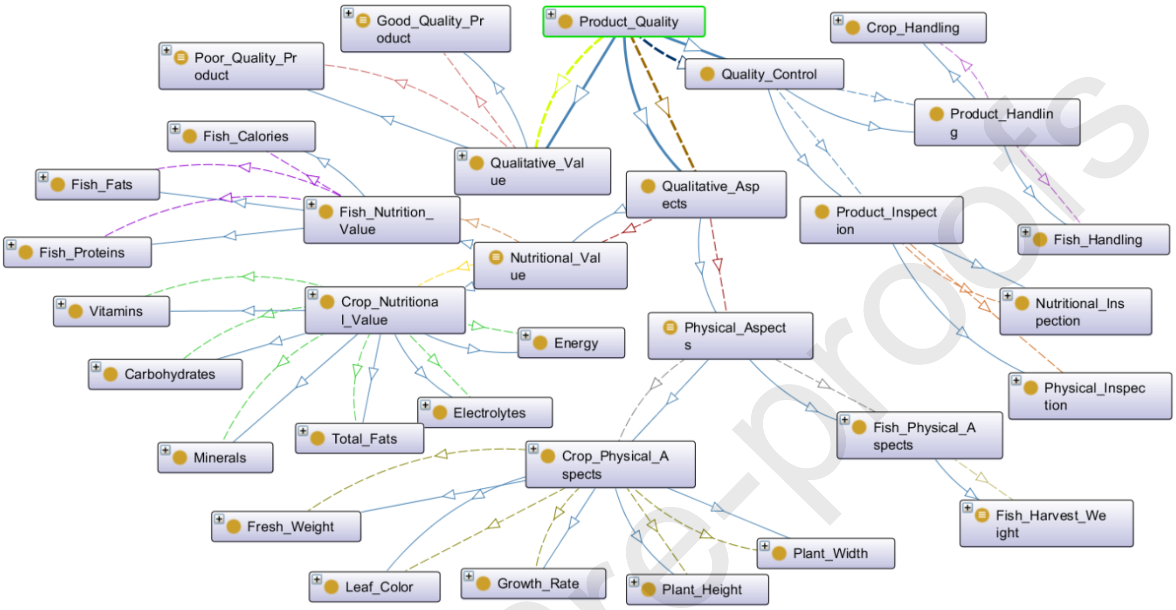

Fig. 9. Product quality concept showing potential elements related to qualitative aspects

Production facility concept

The main purpose of an indoor aquaponics 4.0 system is to increase crop yields by maintaining optimal conditions, even in the middle of the urban areas [58]. Production_Facility concept shown in Fig.10 is designed to specify the location of the aquaponics 4.0 farm.

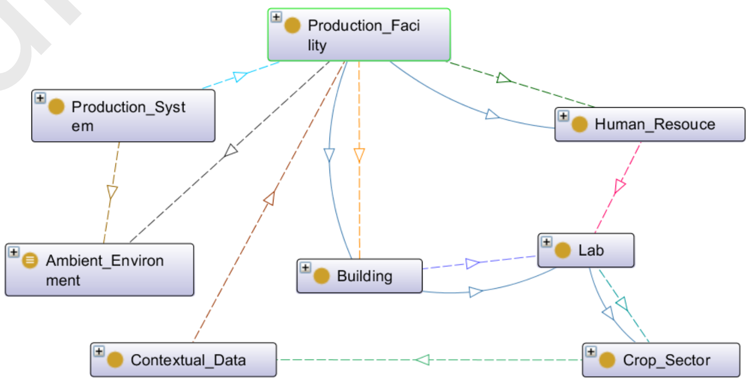

Fig. 10. Production facility concept showing the interactions of farm facility and other domains

In this study, the production facility is the AllFactory. The crop grow area in the facility is divided into multiple sections referred to as crop sectors to grow a variety of crops. For instance, Sector_01 is allocated to grow lettuce, and Sector_02 is assigned to grow cabbage. Each crop sector has its digital system composed of sensors, control devices, controllers, and network access points.

4.3.2 AquaONT instances

For AquaONT, a total of 310 instances/individuals are defined for different classes and subclasses. For example, the instances defined for Ambient_Environment class are Optimal_Light_Intensity, Optimal_Humidity, Optimal_Temperature, and so forth. Likewise, to classify the product quality, instances defined are Good_Quality_Crop (crop meeting the required qualitative aspects) and Poor_Quality_Crop (crop lacking the desired qualitative aspects). To further express the outstanding quality issues, potential causes, and recommended solutions in the context of poor-quality lettuce, instances are specified as shown in Fig.11. Instances are also defined for subclasses of Production_Facility, Consumer_Product, Production_System, and Contextual_Data concepts. For the Contextual_Data concept, the instances are real-time data coming from sensors and control devices. For the Production_System concept, the defined instances give information about operating voltages, equipment identifiers, suppliers along with a sector-wise description of all the sensors, devices, and control architecture installed in the AllFactory. The list of instances of some other classes is given in Fig A.2 of Appendix A.

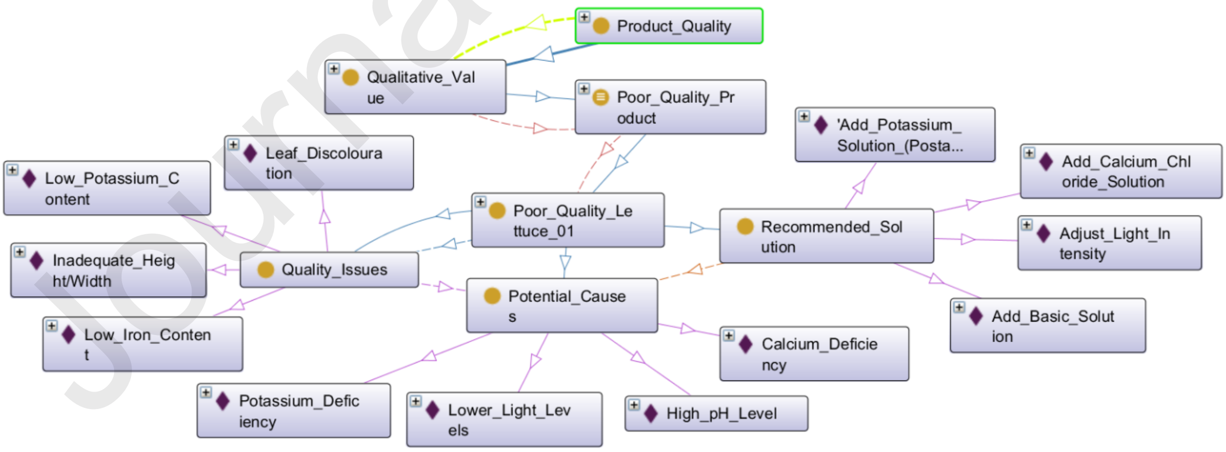

Fig. 11. Instances for subclasses of Product_Quality concept specifying qualitative requirements.

4.3.3 Object and datatype properties

The domain-specific concepts defined for AquaONT are related to each other, and their relationships are represented through the property module, which consists of two types of properties viz object property and the datatype property. Object properties represent the ontological relationships that link different classes (concepts) together [60]. In AquaONT, 139 object properties are defined to represent all the interactions between classes and subclasses. Fig A.3 and A.4 in Appendix A show object properties of AquaONT and relationships between classes and subclasses respectively. Object property assertions are also applied to develop relationships between different instances [87]. For example, in AquaONT, to determine the solution, causes, and quality issues of a poor-quality product, the instances of subclass Recommended_Solution are linked with the instances of Quality_Issues through object property is_Recommended_for, and instances of Quality_Issues are linked with instances of Potential_Causes through is_Consequence_of. The second type of property is the datatype property that links an instance to an RDF literal. RDF literals can be in the form of Boolean or integer values, as well as string variables [60]. For AquaONT, 53 datatype properties are created, and they are used with 575 different literals. The list of datatype properties of AquaONT is given in Fig A.5 of Appendix A with Fig A.6 shows the relationship between some of the instances and attributes.

4.3.4. Standards, restrictions, and rules

After creating the instances for subclasses of domain-specific concepts, these are assigned numerical and qualitative values through datatype properties. These values conform to the standards defined in literature or local bodies. For example, in AquaONT, the optimal values for instances of Ambient_Environment class were taken from the literature [10]. The value of Optimal_Light_Intensity is PPFD (photosynthetic photon flux density) 600-900 nm wavelength and in terms of PAR (photosynthetic active radiation), it is 5 to 17 mols/m2/day. For other indoor environmental parameters, the values of instances are defined in the same way. Likewise, for assessing the qualitative aspects of the products, the data was taken from the Health Canada database [61]. To enable the knowledge retrieval process, the real-time data from AllFactory is then compared with these standard values using a data query engine. Restrictions refer to the constraints in the ontology model. In ontologies, there are three main types of restrictions that can be placed on classes: quantifier restrictions, cardinality restrictions, and “hasValue” restrictions [29]. In AquaONT, only cardinality constraints are imposed using the object restriction creator to limit the number of sensors employed to get variable data. In Protégé, rules are usually written in the

SWRL editor, which is a built-in development environment to work with SWRL. As multiple scenarios occur at the aquaponics farm, for which rules are created within the AquaONT model.

4.4 Ontology verification and validation

Different types of built-in reasoners are available to evaluate an ontology model in Protégé for its consistency and coherence. The most used reasoners for ontology evaluation are "Pellet" and "HermiT" [62]. For AquaONT, both reasoners are tested with selection based on the empirical results obtained. After testing, HermiT v.1.4.3.456, a Protégé built-in reasoner, is employed for verification and validation of AquaONT because it processed the ontology in 2098 ms - lower than for "Pallet", which is 3450 ms. The computation is done with no errors, showing the consistency and coherence of AquaONT. To further verify it, the DL queries were created and executed after the reasoner classification [63]. Examples of DL queries and corresponding results for AquaONT are shown in Fig.12.

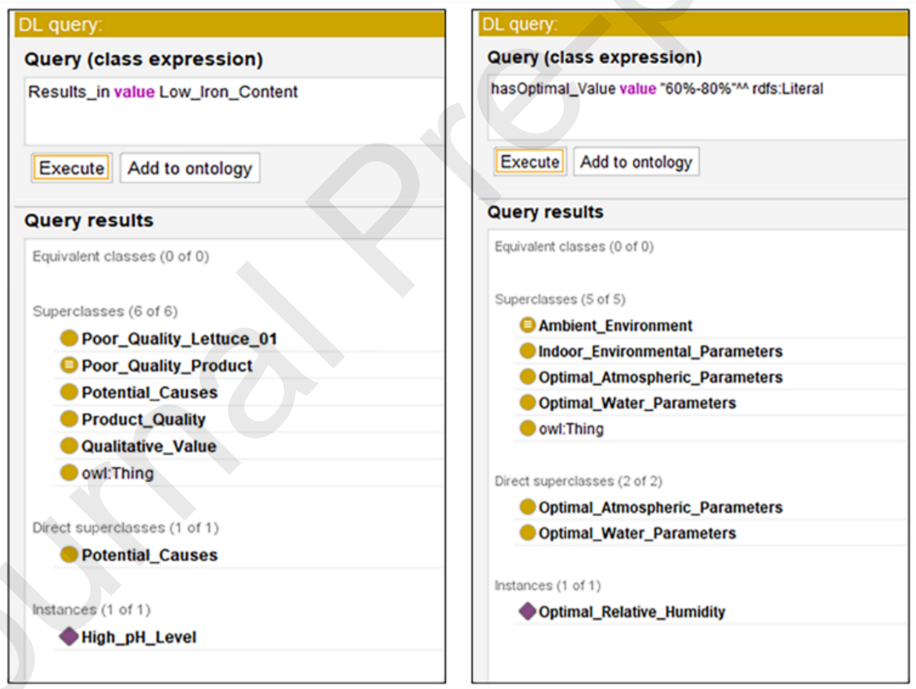

Fig. 12. DL queries for verification of AquaONT

The first DL query is about finding the potential cause of one of the quality issues mentioned in the query (class expression) tab. The result shows that the potential cause of Low_Iron_Content of lettuce is High_pH_Level, which is an individual in AquaONT. The second DL query is related to checking whether the given value of humidity is optimal or not. The result of this search shows that 60%–80% is the Optimal_Relative_Humidity, which is an individual of humidity. Nevertheless, it is also possible to search for AquaONT according to other scenarios. The results of these queries depict the correctness of the captured knowledge and requirements set during the specification stage. Likewise, the validation of AquaONT was performed, which is discussed in section 5.

5. Validation and Implementation of AquaONT

As stated, AquaONT is developed to capture and store the essential knowledge of the aquaponics 4.0 system, which then can be retrieved and used in other applications to make informed decisions for a variety of applications related to aquaponics systems, from systems' design and preparation to systems' control and monitoring. A framework in which AquaONT is currently utilized is shown in Fig.13. This framework has two primary purposes: 1) The first one is to structure how the data is acquired and stored in the ontology model as it populates its instances and to validate that the appropriate knowledge is being retrieved; and, 2) The second one is to give an insight that how AquaONT can be integrated with the aquaponics 4.0 farm through an interface (decision support system) to control operations and ensure intelligent decision-making regarding design, quality, among others as required by the user. The framework consists of four building blocks including 1) data generation and communication, 2) knowledge representation and modeling, 3) knowledge extraction and validation, and 4) knowledge application and decision-making.

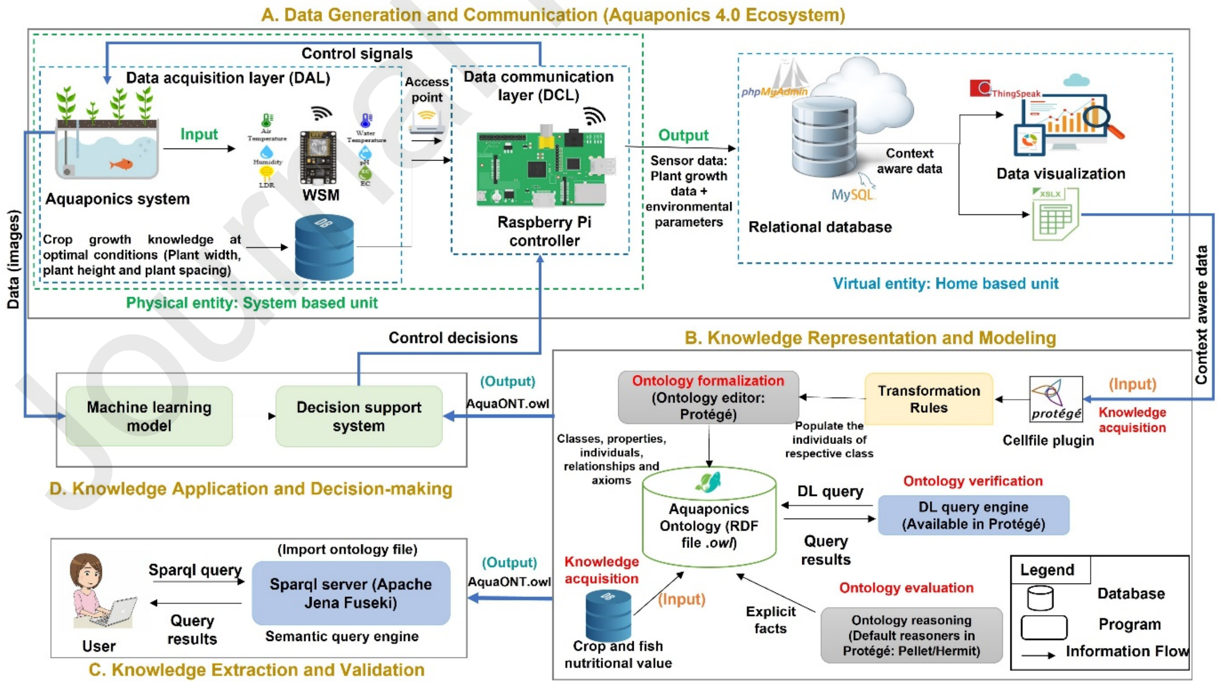

Fig. 13. Overview of the implementation of AquaONT in aquaponics 4.0 systems

An aquaponics 4.0 system reflects a context-rich environment that has entities that generate data related to indoor environmental parameters and crop growth characteristics. Hence, the real-time data from these entities is gathered and transmitted to an accessible cloud database, which along with other databases such as for product quality populate the instances of AquaONT concepts. The existing and inferred knowledge can be extracted from AquaONT and applied to enable autonomous decision-making and control farm operations through an interface, which is part of future work (the fourth building block of the framework). A variety of test cases in relation to the aquaponics 4.0 farm and the capacity of AquaONT mentioned in section 1 were then considered to validate the accuracy of ontology. To achieve this, AquaONT was uploaded in Apache Jena Fuseki 3.16.0, which is a SPARQL server to retrieve the desired information using the SPARQL query language. These test cases are explained below.

Test case 1

One primary function of AquaONT is that it will allow users to keep track of indoor environmental conditions at the farm. In case, if conditions are not adequate, AquaONT will tell users what to do in that scenario. To validate this, we have performed a simple test case using the historical data of the aquaponics 4.0 farm (AllFactory) available on the cloud [3]. The farm has different crop sectors, with each sector has a distinct crop with its particular atmospheric parameters and water conditions. This means each crop sector has its set of wireless sensors and control equipment. The historical data used is related to the growth of Little Gem Romaine Lettuce, which is located in sector 1. A sector can be defined as a location where vertically stacked NFT grow channels are being kept and sector 1 is the place where Lettuce is being grown. The cloud data is imported in AquaONT, which is then compared to the knowledge stored in it, and the required information is retrieved by running SPARQL queries. One simple example of this test case is shown in Fig. 14. Let's say a user wants to know what to do under certain indoor temperature conditions. For instance, the temperature value in the farm has exceeded 18℃. The query and corresponding results for this case are shown in Fig.14.

From the results, it can be seen that AquaONT has given several suggestions to a user on what to do in a particular scenario. For example, it has suggested a user turn off the heater in sector 1, which is represented by GHH01:OFF. This is because the optimal temperature to sustain the aquaponics 4.0 ecosystem is 18℃–30℃ and for the healthy growth of the lettuce crop, the temperature should be kept between 16℃–19℃. Whereas, the temperature in the farm at the moment is 24℃, higher than needed for the growth of Lettuce. A similar pattern is followed for other temperature values (lower and optimal temperature) to see if the AquaONT is giving the correct information that corresponds to real-world phenomena. Every time, the query produces the same results for the given conditions, proposing the validation of AquaONT. These results, later on, can be integrated with some applications such as expert systems or decision support systems to control the environmental conditions at the farm. In addition to that, these results can also allow new farmers or aquaponics startups to get information on which type of sensors and electronic equipment is most suitable for their aquaponics 4.0 farms before building the physical system.

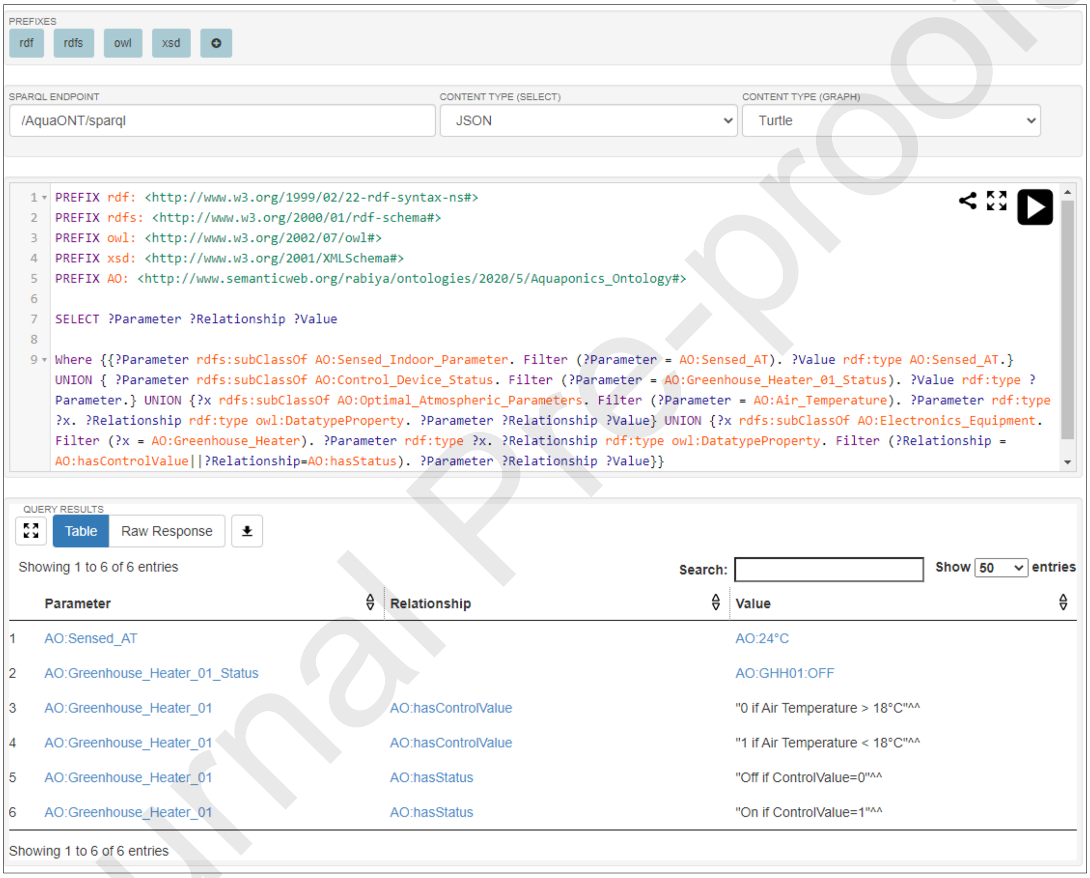

Fig. 14. Test case 1—SPARQL query 1 and results (Temperature variations in aquaponics 4.0 farm)

Test case 2

To further validate AquaONT, another simple test case is conducted considering a different class and scenario. This test case reflects another primary function of AquaONT, which is to allow users to get information on different qualitative aspects of crops or fish involved in the process. A simple example of this test case is shown in Fig.15. When considering growing a certain crop in an aquaponics 4.0 farm, a few elements are important to be known beforehand: i) what quality issues in lettuce crop any practitioner can encounter; ii) what can be the causes of the particular quality issue, and iii) what treatments should be employed to solve this particular quality issue. Each crop has standardized qualitative aspects in terms of nutritional value and physical characteristics recommended by local food authorities that need to be met to ensure a marketable product. Hence, the answers to all these questions can be found through the knowledge stored in AquaONT, which is imported from literature, databases, and food agencies. Running simple queries, results show the potential quality issues for selected crops, i.e. quality issues for the lettuce crops in Fig.15. For each potential quality issue, AquaONT provides the user with information on the cause and treatment of that issue. For instance, one potential quality issue of the lettuce crop is inadequate length or width at a certain period of its growth cycle or at the time of harvesting. The primary cause of this issue could be lower calcium content in the nutrient solution, for which the suggested treatment is to add calcium chloride. This kind of information will guide a user on what necessary steps should be taken before start growing the lettuce crop.

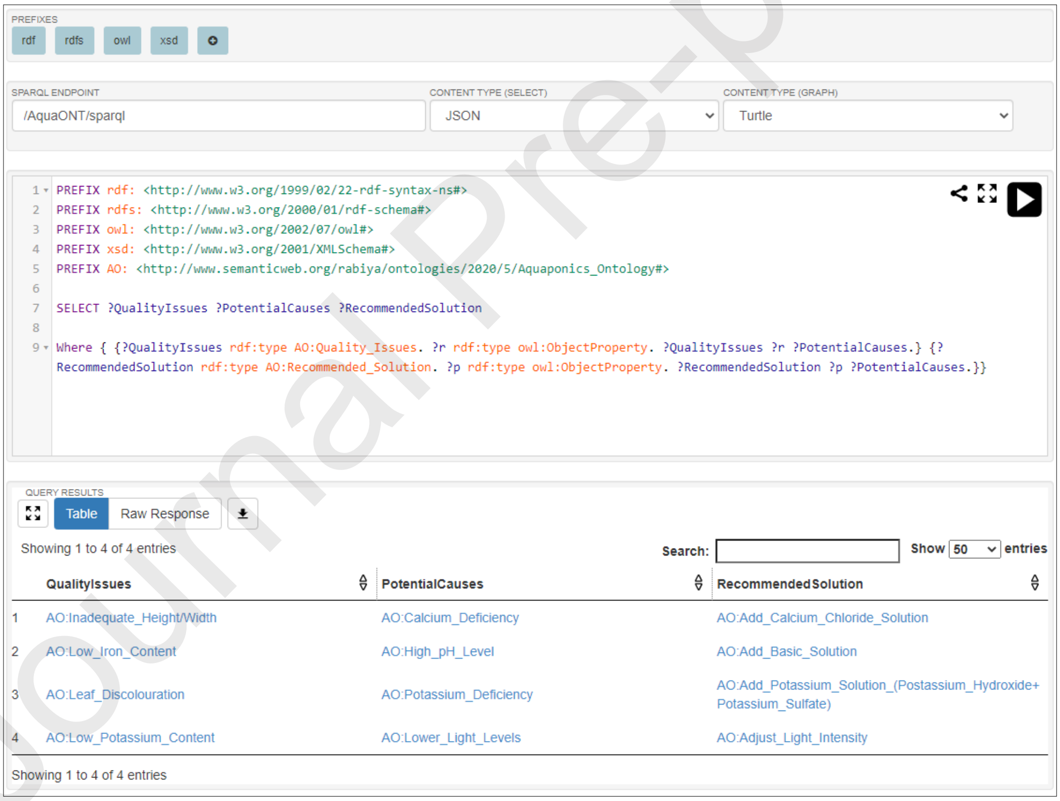

Fig. 15. SPARQL query 2 and results for test case 2

Another scenario for this case study could be if a user is already growing a certain crop in an aquaponics 4.0 farm and wants to compare the quality of the crop with the standards available. Let's say that this user has a crop inspection system installed at the farm, from where it is gathering real-time data on crop height and width. This data can be populated in the instances of AquaONT. Upon running the query, the user will get information on whether the crop is of adequate dimensions or not along with causes and treatments. For this scenario, a proper interface is needed with which AquaONT needs to be integrated.

The aforementioned test cases and queries are created considering the capacity of AquaONT mentioned in section 1 in order to search and extract useful knowledge of real-time events happening at the farm. Upon analysis of final results after query execution, it was observed that AquaONT provides accurate information each time the particular query is executed, which proposes the validation of AquaONT. Further, these results can be utilized to reconfigure and supervise the aquaponics 4.0 system accordingly by integrating AquaONT with an external interface or application.

6. Discussion

Driven by rapid advancements in AI due to big data, IoT, cloud computing, machine learning and deep learning, the agriculture sector is shifting towards a smart farming ecosystem to balance the increase in food demands. Not only that, modern farming techniques such as hydroponics, aquaponics, and aeroponics are being employed to increase crop yield, optimize plant growth, and improve crop quality. Within the scope of this study, we focused on the aquaponics system, that couples RAS with hydroponics. Research has shown that the design and management of an aquaponics system are complex due to the presence of living organisms such as plants and fishes, complex biological processes, and diverse environmental parameters [10]. To deal with these issues, the concept of aquaponics 4.0 is introduced in this paper. Aquaponics 4.0 system is a digital farm based on Industry 4.0 technologies. It consists of smart sensors and IoT devices that bring automation in the system and provide data-driven applications to improve farming practices with minimal human and natural resources and enable farmers to make optimal decisions for the farms.

Developing such a highly digitized system, however, requires efficient data integration and knowledge management. With its growing number of devices and their diversity, along with the big data from divergent sources, the reality of IoT is challenging current approaches and technologies for smarter integration of data, applications, and services in the agricultural domain. Providing interoperability among IoT devices and other heterogeneous big data sources is one of the most fundamental requirements to support object addressing, tracking and discovery, and information representation, storage, and exchange. While the Web is seen as a convenient platform for integrating things, the Semantic Web Technologies

(SWT) can further improve its capacity to understand things' data and facilitate their interoperability along with enabling the knowledge management and data exchange in a machine-interpretable way. This synergy between SWT and IoT domains gives rise to the birth of a new appellation; known as the semantic web of things (SWoT) [4]. To develop this semantic web stack for IoT, metamodels such as ontologies play a key role in facilitating semantic integration and aggregation of data generated by different sources. Moreover, ontologies can connect and qualify unstructured, semi-structured or structured data formats without any need for standardization. They streamline the process of identifying core concepts, improving classification results to collate critical information.

Considering the complexity of the aquaponics 4.0 system with different data sources and the unavailability of a unified knowledge model, AquaONT — aquaponics 4.0 ontology — is proposed in this paper. AquaONT is designed to store and model the knowledge of the aquaponics 4.0 system. It gives a full description of concepts concerning remote monitoring and controlling of environmental parameters, production facility layout based on crop selection, and product quality to analyze the quality issues and suggest the desired treatments. AquaONT also enables semantic interoperability among multivariate data sources. The knowledge from AquaONT can be retrieved and used to make intelligent decisions regarding farm operations and system design by integrating it with an external interface (decision support system). The final service and quality of application, however, depends on the quality of the knowledge base, which is usually constructed from ontology models [64,65].

With a unified knowledge model for aquaponics 4.0 system, such as AquaONT, it is possible to get insights on what are the optimal environmental parameters for growing different types of crops, what are the optimal growth parameters for fish, and what are the optimal water and atmospheric parameters for sustaining aquaponics 4.0 farm. This information will assist farmers in deciding which sensors and IoT devices are most suitable for their farm and their choice of the crop before building it. This will in turn allow farmers to avoid wasting money on the wrong sensors and IoT devices. Even if the farm is already running and growing a certain crop, AquaONT will assist in finding out if the parameters are within the range by collecting the data from sensors and comparing it with standard values. If integrated with some external interface, the knowledge from AquaONT can be exploited to control parameters and processes in the aquaponics 4.0 farm.

In aquaponics systems, the design of grow bed is directly dependent on the type of crop to be planted [9]. Each crop has certain width and height at optimal water and environmental conditions that impact the design of grow beds in terms of the spacing between plants and between channels. Hence, the same configuration of grow bed cannot be used for different crops. The correct design configuration of grow bed enables plants to absorb the right amount of nutrients, ensuring healthy crops, high crop yields, and enhanced farm productivity [66]. With the AquaONT-driven decision support platform, it is possible to visualize the impact of crop characteristics on grow bed design that assists farmers to decide on what design configuration of an aquaponics grow bed is suitable for their crop choice and space availability before building a physical system. Such an ontology-driven platform can also enable parametric design automation by retrieving the data from the ontology model and integrate it with some CAD software. This kind of platform can save a lot of money by preventing farmers from choosing the wrong materials and saves a lot of time as a new design of the system can be built with just one click due to parametric modeling. Another significance of AquaONT is that it can provide information on quality issues, causes and recommended treatments for different crops and fish species, which will assist farmers to take necessary steps before building a system to avoid quality issues.

At the moment, AquaONT can only be applied to NFT based aquaponics 4.0 farms that grow leafy green vegetables such as lettuce, spinach, parsley, basil, and cabbage. But it can easily be expanded to include aspects and knowledge of other aquaponics 4.0 systems such as deep-water culture (DWC) and media-based aquaponics. For this purpose, the "Production_System" class will be modified to include subclasses, instances and attributes related to the design configuration of aquaculture and hydroponic units. For instance, DWC uses more water for the hydroponics portion of the equipment with a ratio of about seven times as much water for plants as for the fish [67]. Hence, the design of grow bed, the capacity of fish tanks, and the specifications of biological and mechanical filters will be different from that of NFT-based aquaponics 4.0 system. This information is required to be modeled in AquaONT before using it for different aquaponics systems. The rest of AquaONT classes for different aquaponics setups will remain the same if leafy green vegetables are to be grown. In case, other crops such as fruits, root and flower vegetables are to be considered, then all other classes of AquaONT will have to be expanded. Overall, the concepts of AquaONT can be extended and reused in different aquaponics 4.0 systems.

Other approaches such as empirical and theoretical, can be utilized to model the aquaponics 4.0 system [68]. These modeling techniques serve different objectives. For instance, an empirical approach that uses statistical models can be employed to perform analysis on historical data from previous experiments. This approach is useful to estimate potential factors affecting fish and crop production in the aquaponics systems, which can further be used in future experiments - making the utilization of costly research assets more effective. A theoretical approach such as mathematical modeling or system dynamic (SD) modeling can be employed to understand and optimize the farm for effective management and control of complex processes. The theoretical approach offers various benefits over the statistical approach. For instance, with theoretical models, it is possible to perform process simulation considering the hypothesis, comparative analysis of simulation results with observed data, evaluation of proposed model and hypothesis, and optimization of the system, whereas statistical models just confirm the hypothesis with no clear evidence of underlying processes [68]. Developing a theoretical model, however, requires different parameters that usually comes from the empirical model [68]. A theoretical approach such as SD modeling is widely employed in literature to model the aquaponics system with many aims. These include understanding the dynamic behavior of different aquaponics processes such as crop and fish growth, waste production and filtration, greenhouse climate and hydroponics; evaluating the performance of multis-stage RAS; and estimating the energy-efficient greenhouse parameters [69–71]. SD modeling has proven an effective tool as it provides a simulation platform to represent real-world entities in the form of equations, which allows to understand and anticipate changes in complex systems. There are also few drawbacks of this modeling approach. For instance, to develop a complete dynamic model for a system, sub-models of all the contributing entities have to be built and then integrated to ensure process synchronization, which is a time-consuming process. In case, if a new entity must be added later on, a new dynamic model has to build for this entity and link with other sub-models. Moreover, different sub-systems and their dynamic models introduce complexities driven by time and spatial scales and multiple interactions among the factors [72]. With ontology modeling, however, it is easy to expand ontologies by incorporating new entities as classes and linking them with existing classes. But to exploit the full potential of the ontology model, it needs to be integrated with an external interface.

While ontologies offer various advantages concerning storing knowledge and solving interoperability issues, they also face various challenges. For instance, knowledge is described as a priori in ontology models, making them less adaptable to systems where the notion is to predict and analyze behaviors of different environments and users [73]. These challenges can be resolved by integrating machine learning techniques with the ontology models in different applications. This is because machine learning supports the prediction and analysis of systems using classification, clustering, and association identification techniques – bringing adaptability in ontology-driven systems. However, one problem with machine learning models is that they struggle to explain the rationale for decision making, where multi-domain semantic modeling and rule-based reasoning can excel [32]. The idea of using cloud data and underlying essential semantic knowledge with learning algorithms preserves the interoperability and re-usability of classification processes and brings intelligence to systems.

However, combining machine learning and ontology modeling is not sufficiently addressed in the agricultural domain, but there are several applications available in other domains, which are explained in section 2.4. These applications focus on improving cybersecurity, patient monitoring, design improvement, digital twin analysis, etc. Regarding ontology-driven IoT and AI systems for the agriculture sector, only a few studies are available which are explained towards the end of section 2.5. These applications mainly focus on cyber-attack detection and monitoring and controlling of IoT based farms. The reason behind limited research work in the agricultural sector in the context of ontology-driven AI systems or a combination of ontology modeling and machine learning approaches could be the complex dynamics of agricultural operations and the presence of complex biological processes. In this essence, AquaONT is a first step towards introducing an ontology model that can be integrated with machine learning models to bring intelligence in aquaponics 4.0 farms by autonomously managing the farm operations and providing solutions for farm design.

7. Conclusions

An ontology model "AquaONT" is presented to model and store the knowledge of the aquaponics 4.0 system – a digital farm that uses smart technologies to improve the system's design and operations. AquaONT provides information for optimal operation of IoT devices by comparing contextual data coming from a farm with standard/ideal data from experts, taking corrective actions on qualitative issues of crop and fish, and design configuration of grow beds based on crop characteristics, when integrated with the suitable interface. This information can assist farmers and users in clear decision-making regarding IoT devices, sensors, and other components necessary for farm development. To achieve remote control of the aquaponics 4.0 farm's operation, AquaONT can be integrated with the external interface, which will exploit the AquaONT knowledge to control the electronic devices installed at aquaponics 4.0 such as heaters, lights and fish feeders or humidifiers, etc. The knowledge of AquaONT can be extracted and used to get an insight into crop characteristics and their impact on the design of aquaponics' grow beds, which can be used to make a decision support platform for parametric design automation.

We will develop an autonomous decision support system in future work by integrating AquaONT and intelligent techniques such as machine learning, deep learning, and computer vision for controlling farm operations and crop quality. Moreover, it is also possible to investigate the monetary benefits of parametric design automation of grow beds.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors acknowledge the financial support of this work by the Natural Sciences and Engineering Research Council of Canada (NSERC) (Grant File No. ALLRP 545537-19 and RGPIN-2017-04516).

Appendix A: Supplementary Model Information

1. Summary of different ontology-driven smart systems (Table A1)

Table A 1. Review on ontology-driven smart systems (Integration of ontology and AI techniques)

Sr. No.	Model	Domain	Purpose	Significance	Approach	Citations
1.	A semantic framework consisting of "RAInS" and "SAO" ontologies is developed for AI systems.	AI	AI system design and implementation	Provide a visual interface for designing accountability plans and managing accountability records.	Modeled the accountability information relevant to the design stage of the AI system.	[74]
2.	A deep learning-based NLP ontology population system is developed.	Biology	Systems and processes analysis	Automatic population of the Biomolecular Network Ontology (BNO).	Used the popular deep learning algorithm "Word2vec" to learn word embeddings using a shallow neural network	[75]
3	An ontology model "OntoSenticNet" is proposed consisting of a composite deep learning classifier.	Text analysis	Sentiment mining	Deep learning-based text mining with ontology-based information.	Used semantic information in ontologies for explaining deep text mining, using neural attention and word embeddings.	[76]

4	A lightweight dynamic ontology "LiO-IoT" using machine learning technique is proposed for IoT systems.	IoT	Fulfilling the requirements of IoT systems.	Ensure semantic interoperability among IoT devices and reducing complexity and introducing dynamicity in the ontology.	Used machine learning technique (clustering) to provide dynamic semantics automatically for including additional concepts.	[77]
5	A novel ontology model "SOHO" is proposed for human-robot collaboration.	Robotics	A flexible representation of collaborative production processes	Enhance the flexibility of control solutions of robot-based systems.	Employed context-based approach for ontology design.	[78]
6	A smart ontology-based IoT framework is proposed for the early detection of COVID-19 in patients.	Healthcare	Covid-19 detection and remote patient monitoring.	Control the spread of the coronavirus.	An ontology-based biosensor is developed using sensory 1D biomedical Signals (ECG, PPG, temperature, and accelerometer) and machine learning techniques such as feature extraction and classification.	[34]
7	A novel approach is proposed for generating ontology using a deep learning model.	Cyber security	Ontology learning and application for cyber-attack detection.	Improve intelligent intrusion detection for cybersecurity.	Used deep neural network and supervised classifier gradient boosting decision tree (GB) for ontology learning and application.	[79]
8	A decision support system is developed using ontology and machine learning techniques to predict disease and suggest solutions.	Healthcare	Prediction of diabetes stage in patients	Improve the healthcare diagnostic system.	Used ontology containing data such as disease symptoms, causes and treatments, Naive Bayes algorithm, and decision tree for identifying disease stage.	[80]
9	An ontology model is proposed for cyber-security of self-recovering smart grids.	Smart Grids	Monitoring and restoration of the operability of the Smart Grid power systems.	Ensure sustainability and functioning of power systems in the event of destabilization	Used conceptual bases of self-recovery of perspective energy systems in the conditions of information confrontation are employed to develop an ontology model.	[33]
10	An ontology model is proposed to represent Digital Twin (DT) in the context of a cyber-physical system (CPS).	Cyber-physical system	Analysis of DT through knowledge representation.	Highlights the main concepts involved in the development of DT.	Used concepts already existing in the literature, such as the IoT-Lite ontology.	[81]
11	A smart fisheries ontology is developed, and an Attribute-Based Access Control System (ABAC) is implemented to evaluate access requests in farms.	Aquaculture	Protect the internet-connected sensors from potential cyber-attacks and propose AI applications to aid the owners to effectively manage their fish farms.	Secure and efficient smart fisheries ecosystem.	Used an ecosystem consisting of virtual and digital entities and their interactions to develop an ontology model, which is then used to implement ABAC.	[46]
12	A method based on natural language analysis and big data ontology is proposed for metadata analysis,	Big data	Analysis of metadata records in big data.	Improve the efficiency of all stages of big data processing	Used data created by human experts and generated by electronic devices to populate the instances of the ontological big data model.	[82]
13	A decision support system based on ontology-based text mining, self-organizing maps (machine learning algorithm), reliability and cost optimization is developed for design	Design	Identification of manufacturing faults and optimization of design parameters	Enhanced design reliability and reduced manufacturing costs.	Used ontology-based text mining approach to extract hidden knowledge in warranty database, data mining approach SOM to link information with manufacturing data, and	[83]

	improvement using warranty data.				statistical analysis for re-evaluation of parameters for cost analysis and design changes.	
14	A system "PALS (Privacy via Anomaly-detection System)" is developed based on ABAC and ontology model to execute access control decisions for smart homes.	Smart home	Detect the intrusions in the smart home.	Enable users to control devices at home by providing them with the ability to change the access control policy.	Used context-sensitive policies that were created based on online privacy policies available from cloud service providers like Google Nest suite of products.	[36]
15	Innovative ontology matching system is developed that finds complex correspondences by processing expert knowledge from external domain ontologies and by using novel matching methods.	Smart grids	Identify and solve interoperability issues within smart grids.	Improve performance of smart grids.	Used innovative graph-based matching methods and innovative mapping algorithms.	[84]
16	A novel ontology-based neural network model "OntoLSTM" is proposed for manufacturing time series classification.	Smart factory	Enhancing deep learning model by using semantic.	Improve products, processes, and decisions.	Used a core manufacturing process ontology to design deep neural networks.	[85]
17	A methodology for the combination of ontology-based knowledge management and machine learning for the classification of multiple spatial data sources.	Nature conservation	Determination of the grassland indicators wetness and alkalinity.	Improve interoperability, reproducibility and exchange of data.	Used a decision tree classifier (DT) approach in combination with ontological formalism to generate classification procedures and results.	[86]
18	A roadmap is presented combining ontology and machine learning approaches for intelligent building monitoring.	Energy consumption	Intelligent monitoring of building energy consumption	Enhanced energy utilization.	Used nearest neighbour algorithm to predict the electricity consumption based on raw data along with knowledge data related to occupancy.	[87]

2. Ontology specification document for AquaONT (Table A2)

Table A 2. Ontology specification document for AquaONT describing the scope and purpose

Ontology Requirement Specification Document	
1	**Purpose**
	The purpose of AquaONT is to structure, model and store the aquaponics 4.0 system's knowledge, and use it to enable data-driven decision making for farmers by developing a functional decision support system.
2	**Domain**
	Agriculture – Smart Indoor Soilless Farming – Aquaponics 4.0
3	**Scope**
	The ontology has to focus on the aquaponics 4.0 system – which is a digital farm based on a smart farming concept. The level of granularity is directly linked with the indoor vertical farming terminologies.
4	**Implementation Language**
	The ontology has to be implemented in OWL 2 web ontology language.
5	**Intended End-Users**

	User 1. A farmer who wants to build a new indoor aquaponics 4.0 farm and wants to get information on the growth parameters of crops and fish. User 2. A person who wants to understand the impact of crops on the design configuration of aquaponics grow beds before building a physical farm for his/her startup. User 3. Researchers who want to build further applications such as decision support systems, and expert systems. User 4. Industrial practitioners who want to find out the causes of poor crop quality in their aquaponic farm.
6	**Intended Uses**
	Use 1. Develop a decision support system. The ontology model will be used to develop a system for crop quality monitoring and control. Use 2. Search for aquaponics 4.0 system information. A farmer will look for general information about the management of the aquaponics 4.0 system. Use 3. Search for optimal ranges of environmental and water parameters for the sustainability of aquaponics 4.0 farm. Use 4. Build an interface to enable parametric design automation. The ontology will be used to develop an application to visualize the impact of crop type on the design configuration of grow bed.
7	**Ontology Requirements**
	a. Non-Functional Requirements 1. The ontology must be based on the international and Canadian food standards in existence or under development. **b. Functional requirements** 1. Optimal ranges of environmental parameters: light intensity, humidity, temperature, etc. 2. Optimal ranges of water parameters: pH, DO, TDS, water level, flow rate, nitrogen level etc. 3. Types of crops: leafy green vegetables such as lettuce, basil, spinach, mint etc. 4. Optimal growth conditions for crop survival: environmental plus water parameters. 5. The growth cycle of each crop: seedling, sprouting, vegetative and plant. 6. Species of fish suitable for the crops considered: Tilapia, catfish, trout etc. 7. Optimal growth conditions for fish survival: environmental plus water parameters. 8. The growth cycle of each fish: fingerlings and mature fish. 9. NFT grow channel configuration: standard widths, lengths, and heights available in the commercial market. 10. Specifications of fish tanks, mechanical filters, and biological filters. 11. Specifications of sensors and electronic devices installed at the farm for monitoring and controlling. 12. Crop and fish quality specifications and control standards determined by international and Canadian food agencies.

3. A formal model of AquaONT showing classes and subclasses (Figure A.1)

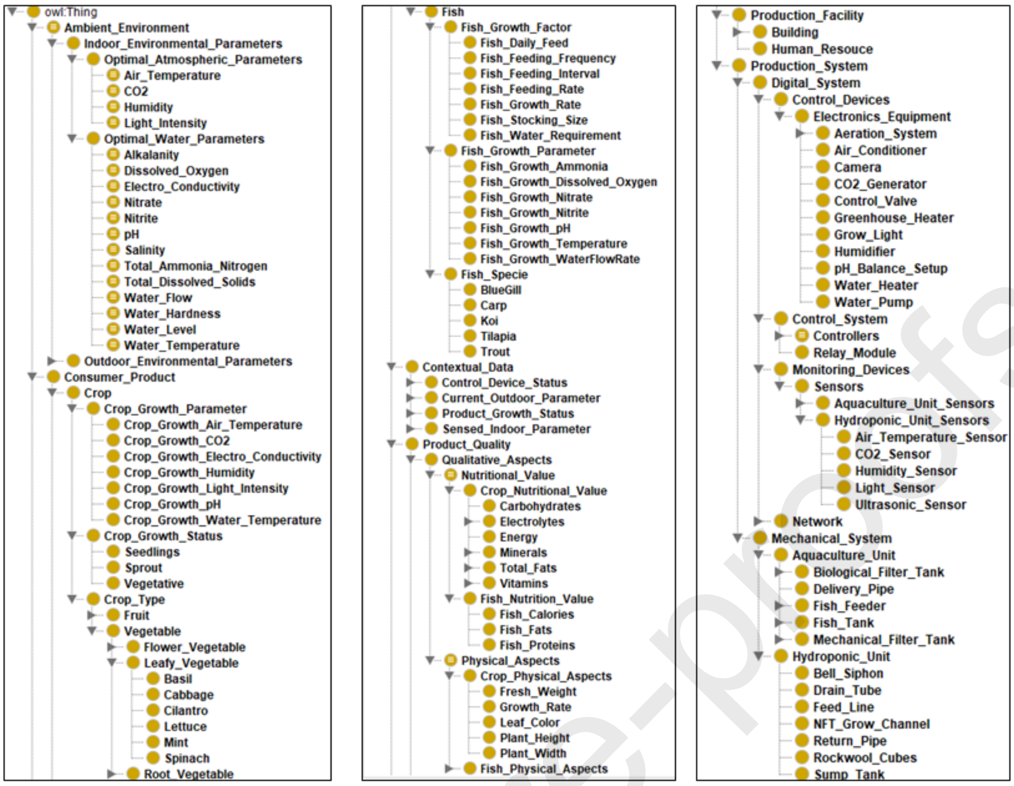

Fig A. 1. AquaONT formal model implemented on Protégé showing classes and subclasses

4. AquaONT instances for different classes and subclasses (Figure A.2)

Concept	Class	Subclass	Subclass	Instances
Contextual_Data	Sensed_Indoor_Parameters	AO:Sensed_Indoor_Parameter	AO:Sensed_pH	AO:6.7
		AO:Sensed_Indoor_Parameter	AO:Sensed_AT	AO:24°C
		AO:Sensed_Indoor_Parameter	AO:Sensed_WT	AO:25°C
		AO:Sensed_Indoor_Parameter	AO:Sensed_LDR	AO:478Lumens
		AO:Sensed_Indoor_Parameter	AO:Sensed_EC	AO:1000µS/cm
		AO:Sensed_Indoor_Parameter	AO:Sensed_RH	AO:80
Consumer_Product	Crop	AO:Crop_Growth_Parameter	AO:Crop_Growth_CO2	AO:Lettuce_Growth_CO2
		AO:Crop_Growth_Parameter	AO:Crop_Growth_Water_Temperature	AO:Lettuce_Growth_WaterTemperature
		AO:Crop_Growth_Parameter	AO:Crop_Growth_Electro_Conductivity	AO:Lettuce_Growth_Electro_Conductivity
		AO:Crop_Growth_Parameter	AO:Crop_Growth_pH	AO:Lettuce_Growth_pH
		AO:Crop_Growth_Parameter	AO:Crop_Growth_Humidity	AO:Lettuce_Growth_Humidity
		AO:Crop_Growth_Parameter	AO:Crop_Growth_Light_Intensity	AO:Lettuce_Growth_Light_Intensity
		AO:Crop_Growth_Parameter	AO:Crop_Growth_Air_Temperature	AO:Lettuce_Growth_AirTemperature
	Fish	AO:Fish_Growth_Parameter	AO:Fish_Growth_Dissolved_Oxygen	AO:Tilapia_Growth_DO
		AO:Fish_Growth_Parameter	AO:Fish_Growth_WaterFlowRate	AO:Tilapia_Growth_WFR
		AO:Fish_Growth_Parameter	AO:Fish_Growth_pH	AO:Tilapia_Growth_pH
		AO:Fish_Growth_Parameter	AO:Fish_Growth_Nitrate	AO:Tilapia_Growth_Nitrate
		AO:Fish_Growth_Parameter	AO:Fish_Growth_Temperature	AO:Tilapia_Growth_Temperature
		AO:Fish_Growth_Parameter	AO:Fish_Growth_Nitrite	AO:Tilapia_Growth_Nitrite
		AO:Fish_Growth_Parameter	AO:Fish_Growth_Ammonia	AO:Tilapia_Growth_Ammonia
Production_System	Mechanical_System	AO:Hydroponic_Unit	AO:NFT_Grow_Channel	AO:NFT_Grow_Channel_01
		AO:Hydroponic_Unit	AO:Sump_Tank	AO:Sump_Tank_01
		AO:Hydroponic_Unit	AO:Drain_Tube	AO:Drain_Tube_01
		AO:Hydroponic_Unit	AO:Return_Pipe	AO:Return_Pipe_01
	Digital_System	AO:Hydroponic_Unit_Sensors	AO:Humidity_Sensor	AO:Humidity_Sensor_01
		AO:Hydroponic_Unit_Sensors	AO:CO2_Sensor	AO:CO2_Sensor_01
		AO:Hydroponic_Unit_Sensors	AO:Ultrasonic_Sensor	AO:Ultrasonic_Sensor_01
		AO:Hydroponic_Unit_Sensors	AO:Air_Temperature_Sensor	AO:Air_Temperature_Sensor_01
Product_Quality	Crop_Nutritional_Value	AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Vitamin_C_Content
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Carbohydrates_Content
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Calcium_Content
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Vitamin_A_Content
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Total_Fats_Content
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Protein_Content
	Crop_Physical _Aspects	AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Fresh_Weight
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Leaf_Color
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Plant_Width
		AO:Leafy_Vegetable	AO:Lettuce	AO:Lettuce_Plant_Height

Fig A. 2. AquaONT instances for different classes and subclasses

5. Object properties of AquaONT (Figure A.3)

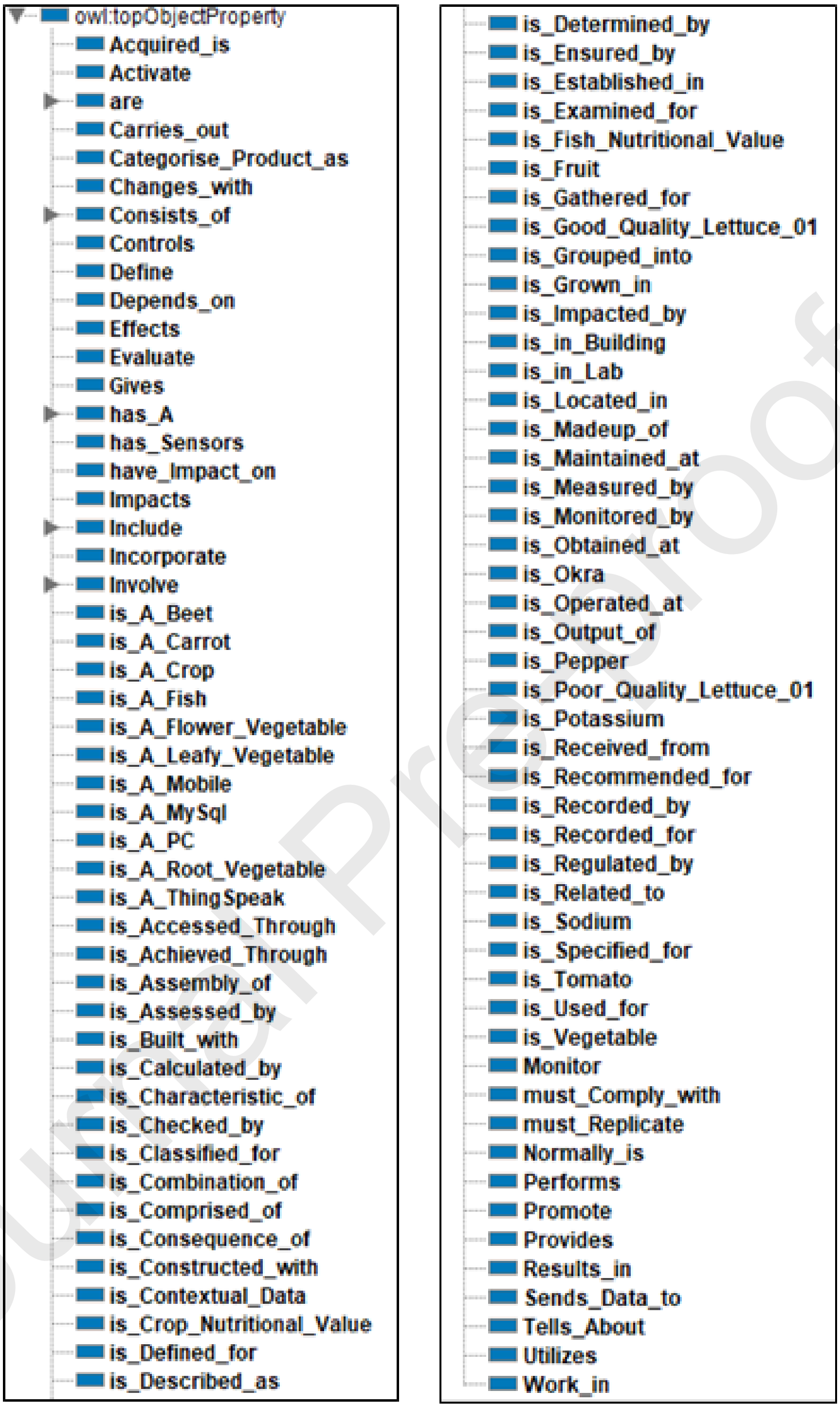

Fig A. 3. Object properties of AquaONT formal model

6. Object properties showing relationships between classes and subclasses (Figure A.4)

Domain	ObjectProperty	Range
AO:Contextual_Data	AO:Acquired_is	AO:Sensed_Indoor_Parameter
AO:Arduino	AO:Collects_Data_From	AO:Sensors
AO:Controllers	AO:Commonly_Used_are	AO:Arduino
AO:Sensors	AO:Generally_are	AO:Aquaculture_Unit_Sensors
AO:Sensors	AO:Generally_are	AO:Hydroponic_Unit_Sensors
AO:Humidity_Sensor	AO:Gives	AO:Sensed_RH
AO:Humidity	AO:Impacts	AO:Humidity_Sensor
AO:Fish_Growth_Factor	AO:Incorporate	AO:Fish_Daily_Feed
AO:Fish_Growth_Factor	AO:Incorporate	AO:Fish_Feeding_Frequency
AO:Fish_Growth_Factor	AO:Incorporate	AO:Fish_Feeding_Interval
AO:Control_System	AO:Controls	AO:Control_Devices
AO:Product_Inspection	AO:Define	AO:Nutritional_Inspection
AO:Product_Inspection	AO:Define	AO:Physical_Inspection
AO:Qualitative_Value	AO:Depends_on	AO:Indoor_Environmental_Parameters
AO:Crop_Growth_Parameter	AO:Normally_Include	AO:Crop_Growth_Air_Temperature
AO:Crop_Growth_Parameter	AO:Normally_Include	AO:Crop_Growth_CO2
AO:Crop_Growth_Parameter	AO:Normally_Include	AO:Crop_Growth_Electro_Conductivity
AO:Crop_Growth_Parameter	AO:Normally_Include	AO:Crop_Growth_Humidity
AO:Crop_Growth_Parameter	AO:Normally_Include	AO:Crop_Growth_Light_Intensit
AO:Optimal_Water_Parameters	AO:Mainly_Include	AO:Total_Dissolved_Solids
AO:Optimal_Water_Parameters	AO:Mainly_Include	AO:Water_Flow
AO:Optimal_Water_Parameters	AO:Mainly_Include	AO:Water_Hardness
AO:Optimal_Water_Parameters	AO:Mainly_Include	AO:Water_Level
AO:Optimal_Water_Parameters	AO:Mainly_Include	AO:Water_Temperature
AO:Optimal_Water_Parameters	AO:Mainly_Include	AO:pH
AO:Optimal_Atmospheric_Parameters	AO:Mainly_Involve	AO:Humidity
AO:Optimal_Atmospheric_Parameters	AO:Mainly_Involve	AO:Air_Temperature
AO:Optimal_Atmospheric_Parameters	AO:Mainly_Involve	AO:CO2
AO:Crop_Physical_Aspects	AO:are_Evaluated_by	AO:Fresh_Weight
AO:Crop_Physical_Aspects	AO:are_Evaluated_by	AO:Growth_Rate
AO:Crop_Physical_Aspects	AO:are_Evaluated_by	AO:Leaf_Color
AO:Crop_Physical_Aspects	AO:are_Evaluated_by	AO:Plant_Height
AO:Crop_Nutritional_Value	AO:is_Assessed_by	AO:Minerals
AO:Crop_Nutritional_Value	AO:is_Assessed_by	AO:Vitamins
AO:Crop_Nutritional_Value	AO:is_Assessed_by	AO:Carbohydrates
AO:Crop_Nutritional_Value	AO:is_Assessed_by	AO:Electrolytes
AO:Crop_Nutritional_Value	AO:is_Assessed_by	AO:Energy
AO:Crop_Nutritional_Value	AO:is_Assessed_by	AO:Protein
AO:Aquaculture_Unit_Sensors	AO:Considered_are	AO:Alkalinity_Sensor
AO:Aquaculture_Unit_Sensors	AO:Considered_are	AO:Dissolved_Oxygen_Sensor
AO:Aquaculture_Unit_Sensors	AO:Considered_are	AO:Electrical_Conductivity_Sensor
AO:Aquaculture_Unit_Sensors	AO:Considered_are	AO:Flow_Sensor
AO:Aquaculture_Unit_Sensors	AO:Considered_are	AO:Nitrite_Sensor
AO:Aquaculture_Unit_Sensors	AO:Considered_are	AO:Total_Ammonia_Nitrogen_Sensor
AO:Hydroponic_Unit	AO:is_Built_with	AO:Drain_Tube
AO:Hydroponic_Unit	AO:is_Built_with	AO:Feed_Line
AO:Hydroponic_Unit	AO:is_Built_with	AO:NFT_Grow_Channel
AO:Hydroponic_Unit	AO:is_Built_with	AO:Return_Pipe
AO:Hydroponic_Unit	AO:is_Built_with	AO:Rockwool_Cubes
AO:Hydroponic_Unit	AO:is_Built_with	AO:Sump_Tank
AO:Aquaculture_Unit	AO:is_Constructed_with	AO:Mechanical_Filter_Tank
AO:Aquaculture_Unit	AO:is_Constructed_with	AO:Biological_Filter_Tank
AO:Aquaculture_Unit	AO:is_Constructed_with	AO:Fish_Tank
AO:Aquaculture_Unit	AO:is_Constructed_with	AO:Delivery_Pipe
AO:Aquaculture_Unit	AO:is_Constructed_with	AO:Fish_Feeder

Fig A. 4. Object properties showing relationships between classes and subclasses

7. Datatype properties of AquaONT (Figure A.5)

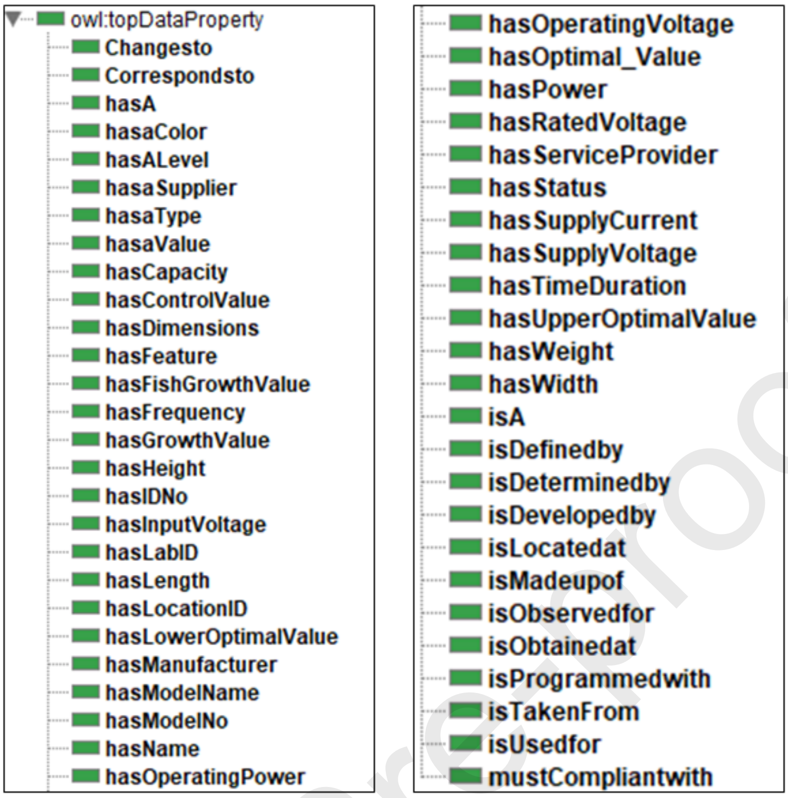

Fig A. 5. Datatype properties of AquaONT

8. Datatype properties showing relationships between instances and attributes (Figure A.6)

Instance	DatatypeProperty	Attribute
AO:Lettuce_Growth_CO2	AO:hasGrowthValue	"1000 ppm"^^
AO:Lettuce_Growth_LightIntensity	AO:hasGrowthValue	"15-17 mols/m^2/day of PAR or PPFD 650-800nm wavelength"^^
AO:Optimal_Relative_Humidity	AO:hasLowerOptimalValue	"60.0"^^xsd:float
AO:Optimal_Relative_Humidity	AO:hasUpperOptimalValue	"80.0"^^xsd:float
AO:Light_Sensor_01	AO:hasModelNo	"SI1147-M01-GM"
AO:Light_Sensor_01	AO:hasaSupplier	"Digi Key"
AO:Light_Sensor_01	AO:hasaType	"Ambient, IR, Ultraviolet (UV)"
AO:Light_Sensor_01	AO:hasManufacturer	"Silicon Labs"
AO:Light_Sensor_01	AO:hasIDNo	"LS01"
AO:Light_Sensor_01	AO:hasSupplyVoltage	"1.71V ~ 3.6V"
AO:NFT_Grow_Channel_01	AO:isMadeupof	"PVC"
AO:NFT_Grow_Channel_01	AO:isUsedfor	"Lettuce Growing"
AO:NFT_Grow_Channel_01	AO:hasaSupplier	"Crop King"
AO:NFT_Grow_Channel_01	AO:hasCapacity	"135 Plants"
AO:NFT_Grow_Channel_01	AO:hasIDNo	"NGC01"
AO:NFT_Grow_Channel_01	AO:hasA	"1 inch Square Holes"

Fig A. 6. Datatype properties showing relationships between instances and attribute

References

[1] Al-Kodmany K. The vertical farm: A review of developments and implications for the vertical city. Buildings, 2018,8(2):24–60.
[2] Wei Y, Li W, An D, Li D, Jiao Y, Wei Q. Equipment and intelligent control system in aquaponics: A review. IEEE Access, 2019,7:169306–169326.
[3] Martinez P, Ahmad R. AllFactory : an aquaponics 4.0 transdisciplinary educational and applied research learning factory at the University of Alberta, In Proceedings of the 2021 Conference on Learning Factories; 2021. p.5–7.
[4] Rhayem A, Mhiri A, Gargouri F. Semantic web technologies for the Internet of Things: systematic literature review. Internet of Things, 2020,11:100206–10027.
[5] Aydin S, Aydin MN. Semantic and syntactic interoperability for agricultural open-data platforms in the context of IoT using crop-specific trait ontologies. Applied Sciences, 2020,10(13):4460–4486.
[6] Drury B, Fernandes R, Moura MF, de Andrade Lopes A. A survey of semantic web technology for agriculture. Information Processing in Agriculture, 2019,6(4):487–501.
[7] Munir K, Sheraz Anjum M. The use of ontologies for effective knowledge modeling and information retrieval. Applied Computing and Informatics, 2018,14(2):116–126.
[8] Martinez-Cruz C, Blanco IJ, Vila MA. Ontologies versus relational databases: Are they so different? A comparison. Artificial Intelligence Review, 2012,38(4):271–290.
[9] Abbasi R, Martinez P, Ahmad R. An ontology model to support the automated design of aquaponic grow beds. Procedia CIRP, 2021,100:55–60.
[10] Yanes AR, Martinez P, Ahmad R. Towards automated aquaponics: A review on monitoring, IoT, and smart systems. Journal of Cleaner Production, 2020,263:121571–121585.
[11] Tyson RV, Danyluk MD, Simonne EH, Treadwell DD. Sustainable aquaponic vegetable and fish co-production. In Proceedings of the Florida State Horticultural Society, 2012,125. p.381–385.
[12] Aceto G, Persico V, Pescapé A. A survey on information and communication technologies for Industry 4.0: State-of-the-art, taxonomies, perspectives, and challenges. IEEE Communications Surveys and Tutorials, 2019,21(4):3467–3501.
[13] Hari Kumar N, Baskaran S, Hariraj S, Krishnan V. An autonomous aquaponics system using 6LoWPAN based WSN. In Proceedings of 4th International Conference on Future Internet of Things and Cloud Workshops, IEEE, 2016. p.125–132.
[14] Hwang J, Yoe H. Study on the context-aware middleware for ubiquitous greenhouses using wireless sensor networks. Sensors, 2011,11(5):4539–4561.
[15] Davenport T, de Long D, Beers M. Successful Knowledge management projects. Sloan Management Review. link: https://sloanreview.mit.edu/article/successful-knowledge-management-projects/. 1998.
[16] Devedzic V. Knowledge modeling - State of the art. Integrated Computer-Aided Engineering, 2001,8(3):257–281.
[17] Bimba AT, Idris N, Al-Hunaiyyan A, Mahmud RB, Abdelaziz A, Khan S, Change V. Towards knowledge modeling and manipulation technologies: A survey. International Journal of Information Management, 2016,36(6):857–871.
[18] Gruber TR. A translation approach to portable ontology specifications. Knowledge Acquisition, 1993,5:1000–1006.
[19] Zhang F, Ma ZM, Li W. Storing OWL ontologies in object-oriented databases. Knowledge-Based Systems, 2015,76:240–255.
[20] Ramos L. Semantic web for manufacturing, trends and open issues: Toward a state of the art. Computers and Industrial Engineering, 2015, 90:444–460.
[21] Maalel A, Mejri L, Mabrouk HH, ben Ghezela H. Towards an ontology of help to the modeling of accident scenario: Application on railroad transport. In the Proceeding of 6th IEEE International Conference on Sciences of Electronics, Technologies of Information and Telecommunications, 2012. p.1–6.
[22] Zhang CX, Cao CG, Gu F, Si JX. Domain-specific formal ontology of archaeology and its application in knowledge acquisition and analysis. Journal of Computer Science and Technology, 2004,19(3): 290-301.
[23] Zhang C, Cao C, Sui Y, Wu X. A Chinese time ontology for the semantic web. Knowledge-Based Systems, 2011, 24(7):1057-1074.
[24] Miller E. An introduction to the Resource Description Framework. Bulletin of the American Society for Information Science and Technology, 1998, 25(1):15–19.
[25] World wide web consortium. W3C organisation. link: https://www.w3.org/OWL/. 2012.
[26] Allemang D, Hendler J. Semantic Web for the Working Ontologist: Effective modeling in RDFS and OWL. Elsevier. Link: http://www.kevenlw.name/downloads/Ontologist.pdf . 2011 /2020 (12:37 PM).
[27] Antoniou G, Groth P, Harmelen F van, Hoekstra R. A Semantic Web Primer (Third Edition). link: https://mitpress.mit.edu/books/semantic-web-primer-third-edition. 2012.
[28] Horrocks I, Patel-Schneider PF, Bechhofer S, Tsarkov D. OWL rules: A proposal and prototype implementation. Journal of Web Semantics, 2005,3(1):23–40.
[29] Musen MA. The protégé project: a look back and a look forward. AI Matters, 2015,1(4):4–12.
[30] Kim M, Kang H, Kwon S, Lee Y, Kim K, Pyo CS. Augmented ontology by handshaking with machine learning. In the Proceedings of International Conference on Advanced Communication Technology, 2017.p.740–743.
[31] Sheth A, Ramakrishnan C. Semantic (Web) technology in action: Ontology-driven information systems for search, integration and analysis. IEEE Data Engineering Bulletin, 2003,26(4):40–50.
[32] Hagedorn T, Bone M, Kruse B, Grosse I, Blackburn M. Knowledge representation with ontologies and semantic web technologies to promote augmented and artificial intelligence in systems engineering. Insight, 2020, 23(1).p.15–20.
[33] Petrenko SA, Makoveichuk KA. Ontology of cybersecurity of self-recovering smart Grid. In Proceedings of CEUR Workshop, 2017. p.98–106.

[34] Sharma N, Mangla M, Mohanty SN, Gupta D, Tiwari P, Shorfuzzaman M, Rawashdeh M. A smart ontology-based IoT framework for remote patient monitoring. Biomedical Signal Processing and Control, 2021,68:102717–102728.
[35] Chukkapalli SSL, Mittal S, Gupta M, Abdelsalam M, Joshi A, Sandhu R, Joshi K. Ontologies and artificial intelligence systems for the cooperative smart farming ecosystem. IEEE Access, 2020,8:45–64.
[36] Dutta S, Chukkapalli SSL, Sulgekar M, Krithivasan S, Das PK, Joshi A. Context-sensitive access control in smart home environments. In the Proceedings of IEEE 6th International Conference on Big Data Security on Cloud, 2020. p.35–41.
[37] AGROVOC, Food and Agriculture Organizations of the United Nations, link: https://agrovoc.uniroma2.it/agrovoc/agrovoc/en/. 2019.
[38] Arnaud E, Cooper L, Shrestha R, Menda N, Nelson RT, Matteis L, Skofic M, Bastow, Ruth, Jaiswal P, Mueller L, McLaren G. Towards a reference plant trait ontology for modeling knowledge of plant traits and phenotypes. In the Proceedings of 4th International Conference on Knowledge Engineering and Ontology Development, KEOD, 2012,2. p. 220–225.
[39] Thunkijjanukij A, Kawtrakul A, Panichsakpatana S, Veesommai U. Ontology development: A case study for thai rice. Agriculture and Natural Resources, 2009,43(3):594–604.
[40] Sodanil M, Phonarin P, Porrawatpreyakorn N. An ontology-based query expansion for an agricultural expert retrieval system. In the Proceedings of ACM International Conference, 2012. p.358–362.
[41] Phonarin P, Nitsuwat S, Haruechaiyasak C. AGRIX: An ontology-based agricultural expertise retrieval framework. Advanced Materials Research, 2012,403:3714–3718.
[42] Pokharel S, Sherif MA, Lehmann J. Ontology-based data access and integration for improving the effectiveness of farming in Nepal. In the Proceedings of IEEE International Joint Conference on Web Intelligence and Intelligent Agent Technology, 2014, 2. p.319–326.
[43] Afzal H, Kasi MK. Ontology-based knowledge modeling for rice crop production. In the Proceedings of International Conference on Future Internet of Things and Cloud, 2019. p.343–350.
[44] Abrahao E, Hirakawa AR. Task ontology modeling for technical knowledge representation in agriculture field operations domain. In the Proceedings of 2nd IEEE International Conference on Information Systems Engineering, 2017. p. 12–16.
[45] Aydin S, Aydin MN. Ontology-based data acquisition model development for agricultural open data platforms and implementation of OWL2MVC tool. Journal of Computers and Electronics in Agriculture, 2020,175:105589–105609.
[46] Sree S, Chukkapalli L. Ontology-driven AI and access control systems for smart fisheries. In the Proceedings of ACM Workshop on Secure and Trustworthy Cyber-Physical Systems, 2021. p.59–68.
[47] Sivamani S, Bae N, Cho Y. A smart service model based on ubiquitous sensor networks using vertical farm ontology. International Journal of Distributed Sensor Networks, 2013,9(12):161495–161502.
[48] Sivamani S, Kim H, Lee M, Park J, Shin C, Cho Y. An Ontology Model for Smart Service in Vertical Farms – An OWL-S Approach. International Journal of U and e-Service, Science and Technology, 2016,9(1):161–170.
[49] Kim T, Bae N, Lee M, Shin C, Cho Yongyun, Park J. A Study of an agricultural ontology model for an intelligent service in a vertical farm. International Journal of Smart Home, 2013,7(4):117–125.
[50] Husna N, Hasbullah M, Zakaria Z. The development of STIF in ontology based on the methontology approach. In the Proceedings of UTM Computing Innovation in Computing Technology and Applications, 2017,2. p.1–7.
[51] Fernandez M, Gómez-Pérez A, Juristo N. Methontology: from ontological art towards ontological engineering. In the Proceedings of the AAAI97 Spring Symposium Series on Ontological Engineering, 1997. p.33–40.
[52] Ahmad R, Masse C, Jituri S, Doucette J, Mertiny P. Alberta Learning Factory for training reconfigurable assembly process value stream mapping. Procedia Manufacturing, 2018,23:237–242.
[53] Scattini N, Maj SP. Aquaponics – A process control approach. Modern Applied Science, 2017,11(11):43–48.
[54] Somerville C, Cohen M, Pantanella E, Stankus A, Lovatelli A. Small-scale aquaponic food production. Integrated fish and plant farming. Link: http://www.fao.org/3/i4021e/i4021e.pdf . 2014 /2021 (1:17 PM).
[55] Zambri MKM, Aras MSM, Khamis A, Shah HNM, Harun MH, Yusof AA. Design and development of intelligent aquaponics system. International Journal of Engineering and Technology (UAE), 2018,7:410–424.
[56] Gu T, Wang XH, Pung HK, Zhang DQ. An ontology-based context model in intelligent environments. ArXiv. link: https://arxiv.org/abs/2003.05055/. 2020.
[57] Abbasi R, Reyes A, Martinez E, Ahmad R. Real-time implementation of a digital twin for robot-based production line. In Proceedings of the 2021 Conference on Learning Factories; 2021. p.1–2.
[58] Brosnan T, Sun DW. Improving quality inspection of food products by computer vision - A review. Journal of Food Engineering, 2004, 61(1):3–16.
[59] Kyaw TY, Ng AK. Smart Aquaponics System for Urban Farming. Energy Procedia, 2017, 143:342–347.
[60] Estellés A, Alcina A. A model for formalizing characteristics in Protégé-OWL. In the Proceedings of CEUR Workshop, 2009. p.1–6.
[61] Health Canada. Nutrient value of some common foods. Canadian nutrient file. Link: http://www.diabetesclinic.ca/en/diab/4nutrition/Nutrient_Content.pdf. 2005 /2021 (2:09 PM)
[62] Abburu S. A Survey on Ontology reasoners and comparison. International Journal of Computer Applications, 2012, 57(17):33–39.
[63] Noy NF, Fergerson RW, Musen MA. The knowledge model of protégé-2000: Combining interoperability and flexibility. In Proceedings of International Conference on Knowledge Engineering and Knowledge Management, Berlin, 2000. p.17–32.
[64] Zhang C, Zhou G, Lu Q. Decision support-oriented ontological modeling of product knowledge. In the Proceedings of IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference, 2017. p.39–43.
[65] Maboko MM, du Plooy CP. Effect of plant spacing on growth and yield of lettuce in a soilless production system. South African Journal of Plant and Soil, 2009,26(3):195–198.

[66] Sharma N, Acharya S, Kumar K, Singh N, Chaurasia OP. Hydroponics as an advanced technique for vegetable production: An overview. Journal of Soil and Water Conservation, 2018,17(4):364–371.
[67] Goddek S, Joyce A, Kotzen B, Burnell GM. Aquaponics food production systems: combined aquaculture and hydroponic production technologies for the future. Cham: Springer Nature, 2019. p.1–619.
[68] Varga M, Csukas B, Kucska B. Implementation of an easily reconfigurable dynamic simulator for recirculating aquaculture systems. Aquacultural Engineering, 2020, 90:102073–102085.
[69] Karimanzira D, Keesman KJ, Kloas W, Baganz D, Rauschenbach T. Dynamic modeling of the INAPRO aquaponic system. Aquacultural Engineering, 2016,75:29–45.
[70] Amin MT, Kissock JK. Dynamic modeling and verification of an energy-efficient greenhouse with aquaponics. In Proceedings of ASME 2016 10th International Conference on Energy Sustainability collocated with the ASME 2016 Power Conference and the ASME 2016 14th International Conference on Fuel Cell Science, Engineering and Technology, 2016,1. p.1–9.
[72] Survey A, Kushala VM, Supriya MC. Deep learning ontology : Dimensions in the field of agriculture, A survey. International Journal of Latest Technology in Engineering, Management & Applied Science, 2018,7(1):17–21.
[73] Naja I, Markovic M, Edwards P, Cottrill C. A semantic framework to support AI system accountability and audit. In Proceedings of European Semantic Web Conference, 2021. p.160–176.
[74] Ayadi A, Samet A, de Beuvron FDB, Zanni-Merk C. Ontology population with deep learning-based NLP: a case study on the Biomolecular Network Ontology. Procedia Computer Science, 2019,159:572–581.
[75] Raaijmakers S, Brewster C. Exploiting ontologies for deep learning: A case for sentiment mining. In the Proceedings of CEUR Workshop, 2018. p.1–4.
[76] Rahman H, Hussain MI. A lightweight dynamic ontology for the Internet of Things using machine learning technique. ICT Express, 2020,7(3):355-360.
[77] Umbrico A, Orlandini A, Cesta A. An Ontology for Human-Robot Collaboration. Procedia CIRP, 2020,93:1097–1102.
[78] Zheng H, Wang Y, Han C, Le F, He R, Lu J. Learning and applying ontology for machine learning in cyber-attack detection. In the Proceedings of 17th IEEE International Conference on Trust, Security and Privacy in Computing and Communications/12th IEEE International Conference on Big Data Science and Engineering, 2018. p.1309–1315.
[79] Swathi Lakshmi V, Nithya V, Sripriya K, Preethi C, Logeshwari K. Prediction of diabetes patient stage using ontology-based machine learning system. In the Proceedings of IEEE International Conference on System, Computation, Automation and Networking, 2019. p.2019–2022.
[80] Steinmetz C, Rettberg A, Ribeiro FGC, Schroeder G, Pereira CE. Internet of things ontology for digital twin in cyber-physical systems. In 8th IEEE Brazilian Symposium on Computing System Engineering, 2018. p.154–159.
[81] Rogushina J, Gladun A, Pryima S. Use of ontologies for metadata records analysis in big data. In the Proceeding of CEUR Workshop, 2018. p.46–63.
[82] Alkahtani M, Choudhary A, De A, Harding JA. A decision support system based on ontology and data mining to improve design using warranty data. Journal of Computers and Industrial Engineering, 2019,128:1027–1039.
[83] Santodomingo R, Rohjans S, Uslar M, Rodríguez-Mondéjar JA, Sanz-Bobi MA. Ontology matching system for future energy smart grids. Journal of Engineering Applications of Artificial Intelligence, 2014,32:242–257.
[84] Huang X, Zanni-Merk C, Crémilleux B. Enhancing deep learning with semantics: An application to manufacturing time series analysis. Procedia Computer Science, 2019,159:437–446.
[85] Moran N, Nieland S, Tintrup gen. Suntrup G, Kleinschmit B. Combining machine learning and ontological data handling for multi-source classification of nature conservation areas. International Journal of Applied Earth Observation and Geoinformation, 2017,54:124–133.
[86] Delgoshaei P, Heidarinejad M, Austin MA. Combined ontology-driven and machine learning approaches to monitoring of building energy consumption. In the Proceeding of Building Performance Modeling Conference and SimBuild, 2018. p. 667-674.

Highlights

- A semantic knowledge model, AquaONT, is proposed to represent the essential knowledge of an aquaponics system.
- An ontological approach is considered to model aquaponics practice in an Industry 4.0 context to facilitate access of data and interoperability.
- The ontology model is validated through experimental test cases related to control parameters, design configuration, and product quality.