International Journal of Innovations in Science & Technology

P ISSN : 2618-1630
E ISSN : 2909-6130
Review Article

Service Oriented Architecture for Agriculture System Integration with Ontology

Muhammad Fahad[1], Tariq Javid[2], Hira Beenish[1]
[1]College of Computing & Information Sciences, Karachi Institute of Economics & Technology, Karachi
[2]Graduate School of Engineering & Technology, Hamdard University, Karachi, Pakistan
Correspondence: Muhammad Fahad (**mfahad@kiet.edu.pk**)

Citation |Fahad. M, Javid. T, Beenish. H, "Service-oriented Architecture for Agriculture system integration with ontology". International Journal of Innovations in Science and Technology. Vol 4, Issue 3, 2022, pp: 880-890

Received | July 01, 2022; **Revised** | July 18, 2022; **Accepted** | July 20, 2022; **Published** | July 21, 2022.

Ontology is becoming a famous technique for converting unstructured data into meaningful data which acts as a key factor for decision-making, planning, and implementation in many areas, and agriculture is one of them. There are a lot of issues in agriculture practices e.g., farming, application of pesticides, and provision/ distribution of water to crops. However, some of the issues are critical and need to be resolved urgently to save cultivation from big hazards. In this paper, we have analyzed a few issues based on available literature. A variety of issues are faced in agriculture constantly and need to be resolved on an urgent basis. We have discussed the various ontology systems to acquire more precise results. Since ontology is based on a relation of data through which a user can get the maximum efficiency. Among all the challenges in agriculture, the lack of context-aware agriculture employs ontology with high concerns. This paper proposes a model to fill the gap in a service-oriented architecture.

Keywords: Semantic Web, Data Integration, Semantics of data and processes, Agriculture, Ontologies.

Acknowledgment. This declaration clarifies that all Authors have seen and approved the paper that has been submitted. We assure that the article is the original work of the Authors. We ensure that the article has not been previously published and is not being considered for publication anywhere

Author's Contribution. All authors contributed significantly to the study.

Conflict of interest: The authors of this paper declare no conflict of interest for publishing this article in IJIST.

Project details. Nil

Introduction

In the agriculture domain, smart irrigation and smart control systems have a huge amount of data generated using adequate devices. These types of data can be analyzed effectively if data is integrated in a scientific manner to get the meaningful extraction of data, specifically in the agriculture industry[1]. Agriculture ontology includes a wide range of factors, as detailed in this article. Water usage in the agriculture industry is the basic exertion, as the water resources are becoming depleted daily, which is the most important and focused topic of this era. On the way round, precision agriculture is essential to measure precise crop estimates that depend upon various crop growth factors, including the availability of water, air quality, humidity, soil monitoring, and weather conditions. Provision of a controlled amount of water is helpful for the plants and fruits that are water sensitive. WFD (Wetting Front Detector) is a tool that measures the soil wetness and the saturation point. IoT-based WFD is now implemented for monitoring and ensuring crop yield. The IoT-based WFD, was implemented in northern Thailand [2] that examines different farming techniques under different environmental conditions.

The management of these types of systems is based on three stages. The first stage is the collection of data on crops from different parts of the land considering the local ecological conditions; since this data is in clustered and we need different sensors to analyze the particular area and to make it homogenous. In the second stage, certain operations have to be done on the data with the help of different analytical models to make this data meaningful. Finally, the last stage is the implementation, which requires the above procedure to be implemented effectively. Gathering data, analyzing, processing, and connecting with the cloud is now being used in the production of the agriculture industry. In this regard, different sensors are installed for data collection and integration with the cloud by using the IoT hub; the visualization of this data and the forecast of different parameters to get actionable information. The soil moisture sensor provides an efficient way to analyze the wetness and homogeneity level, to ensure the quality of crops.

In the 1980s, the concept of precision agriculture was introduced by changing the grid-based soil chemical test to the variable-based fertilizer application. The main purpose of precision agriculture was to get the farming output on time with accuracy. In order to get input on the run time farming for the detection or monitoring of the pesticides, there are multiple sensors used, which are mechanically a part of the wireless sensor networks. The use of the WSNs device not only increases productivity and effectiveness but also is part of the portability concept, which is necessary for smart agriculture. Incorporation of WSNs with IoT has a great impact on the agriculture sector as it is the main concern for the remote accessibility of the field which is not in the part of the digital world. This integration is helpful in the agriculture sector, but it can get an abundance of advantages in other fields like energy and water control, wildlife monitoring, and many more as well [3].

Smart agriculture emerged due to the advancement of technology and the advent of microelectronics. Mobile ubiquitous sensor Network (USN) in collaboration with IoT function to observe the remotely sensed datasets and perform the operations related to crop monitoring systems for farmers [4].

The goal of modern agriculture is to cultivate plants in carefully managed settings, such as greenhouses, that can either improve plant production or replicate the environmental conditions of particular geographic regions in order to domestically produce goods that were previously only available overseas [5][6][7][8][9]. In addition, severe weather and disease fluctuations have an impact on agricultural output and quality may be compromised with the complete deployment of modern monitoring and information technologies such as the Internet of Things (IoT), autonomous robots, and smartphones[10]–[19][20][21]. It is now possible to obtain highly accurate information regarding the status of crops and to make rational decisions regarding the management of irrigation, the modification of climate factors, or the enrichment of soil nutrition in agricultural settings[22]. This optimizes the automation of precise management, which in turn increases crop production and has the potential to reduce negative effects on the environment [23]. Farmers and agronomists have already started making use of various technologies in an efficient way to make their job in greenhouses more productive [24]. They use smartphones to remotely monitor their crops and equipment, understand the whole management system accurately through statistical analysis, and instruct the robots to carry out agricultural tasks[25]. This is made possible by the sensor data obtained and transmitted by the internet of things (IoT) [26]. Although greenhouses are taking advantage of the integration of different technologies with efficient human intervention, the current level of artificial intelligence (AI) in agricultural machines and systems is a long way from achieving automated operations and management requiring minimum supervision to maximize production by taking into account variability and uncertainties within precision agriculture (PA) [27]. This is even though greenhouses are taking advantage of the integration of different technologies with efficient human intervention.

To maximize the economic potential and ecological value of the entire PA, it has been identified as a potential additional enabler as well as an essential technological challenge. To this end, the development of technology based on deep learning has provided an effective method for facilitating intelligent management and decision-making in many aspects of PA, such as visual crop categorization [28], real-time plant disease and pest recognition, picking and harvesting automatic robots, and health and quality monitoring of crop growing. In addition, there is a growing potential for agricultural success in the not-too-distant future because deep learning systems may readily make use of data increases brought about by an increase in the number of sensors, cameras, and available cellphones. Deep learning is a technique that was developed in response to the multi-level visual perception process that occurs in the human brain. It enables computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These representations are obtained by non-linear modules (such as convolutional layers or memory units) that each transforms the representation at one level (beginning with the raw input) into a representation at a higher, slightly more abstract level. The combination of a sufficient number of these transformations allows for the automatic discovery of difficult patterns in high-dimensional data and the learning of very complex functions, both of which are necessary for the completion of agricultural tasks.

Agricultural tasks of crop management such as irrigation, picking, pesticide spraying, and fertilization are not suited for use by deep-learning networks, despite their state-of-the-art performance in other study domains. Because there aren't any public datasets that are used as benchmarks and are developed specifically for different agricultural tasks, it's difficult to use deep learning technology and expand the scope of intelligence research in greenhouses. This is the primary factor contributing to the problem. In light of these circumstances, it is clear that proper crop databases need to be constructed by making full use of a variety of collection devices to achieve deeper and wider networks in order to produce superior outcomes.

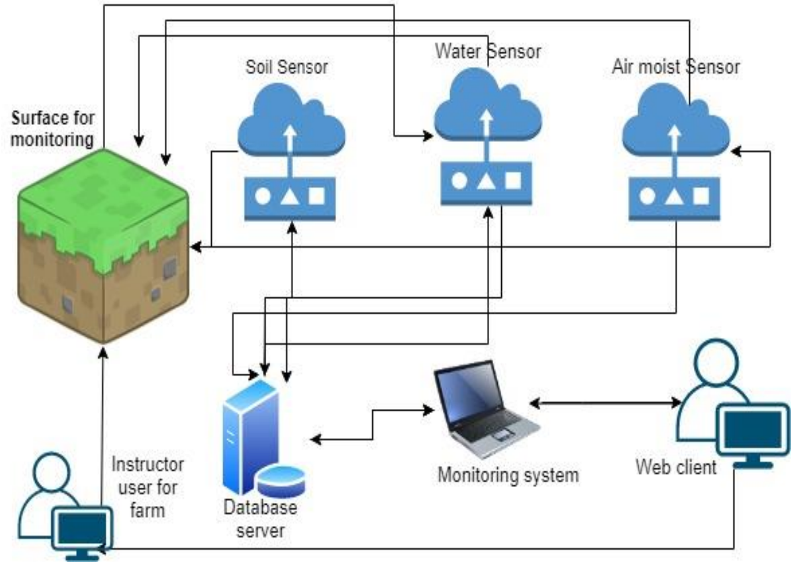

Figure 1. Smart Agriculture Architecture

Figure 1 shows the smart agriculture architecture, with a monitoring and recommendation system. This is a general architectural concept of the agriculture system.

TABLE-1 AGRICULTURE PARAMETERS USED IN DIFFERENT ARTICLES

References	Year	Soil	Water	Fertilizers	Pesticides	Crops
[10]	2016	✓	✓	×	×	✓
[11]	2016	✓	×	✓	×	✓
[11]	2016	✓	✓	✓	✓	✓
[12]	2017	✓	✓	×	✓	✓
[13]	2017	✓	✓	✓	✓	✓
[14]	2019	✓	✓	×	✓	✓
[15]	2019	✓	✓	✓	×	×
[16]	2019	✓	✓	×	×	×
[17]	2019	✓	✓	✓	✓	✓

TABLE-2 SENSORS, DEVICES AND SOFTWARES

Reference	Year	Soil	Water	Fertilizers	Pesticides	Crops
[10]	2016	Soil moisture sensor	Magnetic float sensor	-	-	Software crop profit calculator
[11]	2016	pH level/Nitrogen depletion	-	Application of fertilizers/additives, fertilizer spray	-	Electronic monitoring, plant phonemics

[11]	2016	SMS, WSN's	Smart irrigation	Smart application for fertilizers	Smart application for pesticides	-
[12]	2017	DSS, web services	Fuzzy based, IoT cloud computing	-	Rule based DSS IoT	Big data analytics, Semantic web
[13]	2017	Stem psychomotor sensor	RFID, Evapotranspiration water content	LAI, FPAR and chlorophyll estimations	Forecast models, middle ware	Sap flow meter, dendrometer, V-Track
[14]	2019	Mobile technology	Lora	-	RIFD	Zigbee Technology
[15]	2019	Chemical sensors	Interaction sensor, Hydraulic	Bio sensor	-	-
[16]	2019	SMS, pH sensor	Water level sensor	-	-	-
[17]	2019	SMS, senome sequence, machine learning tool	Efficient techniques	IoT sensors, end to end farm management system	Green house automation, IoT/AI technologies	Crop management
[18]	2019	IoT sensor	Precision irrigation IRRInet	IRRInet	-	Camera equipped Drones

Table 2 contains the description of sensors, devices, and software that are used for different parameters in agriculture practices.

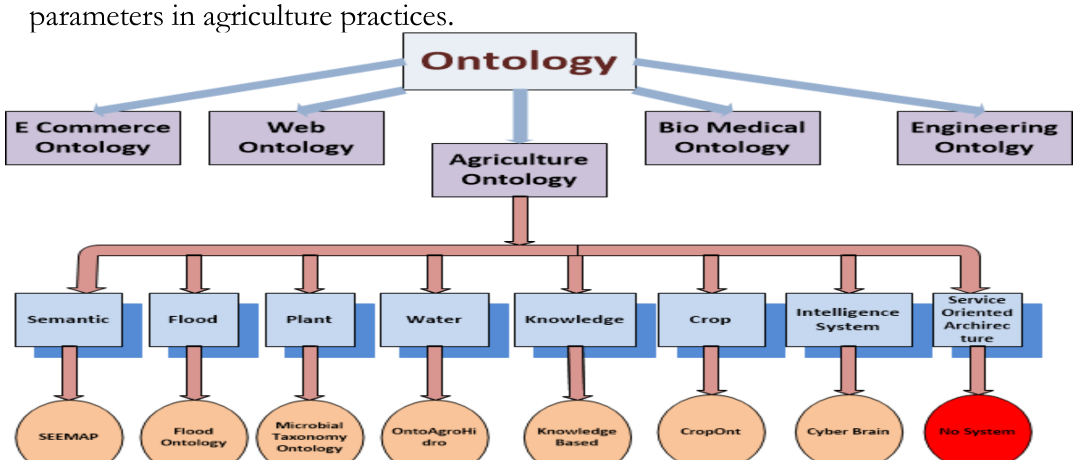

Figure 2. Taxonomy of Ontology used in agriculture with its applications and its gap analysis

As discussed in [30] regarding context awareness and oriented architecture, we need to develop a service-oriented architecture that covers all aspects and parameters essential for crop growth and development e.g. soil moisture monitoring, temperature estimation, application of fertilizer and pesticides etc. This will be used for the service-oriented architecture as these are also a part of smart farming as shown in Figure 3, the architecture of the service-oriented scenario in smart agriculture.

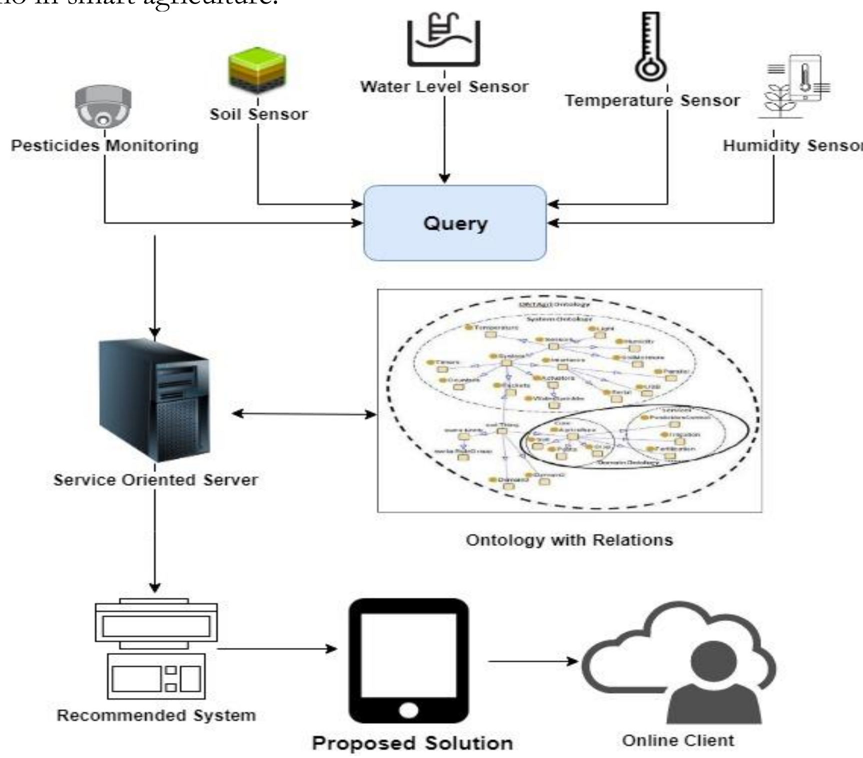

Figure 3. Service oriented Ontology based model

By this, the end user will be able to provide input into this proposed system, which could pertain to catering to any agriculture-related issue. On the other hand, the outcome will provide various solutions based on different ontology-based systems. Figure 3. shows the implementation of the service-oriented ontology-based proposed model for the agriculture system. In service-oriented system agriculture, queries are passed to a service-oriented server, this transfers the queries to the ontology model, to get the result by connecting the relation available in an ontology. However, ontology provides the linkage of the particular query with the required problem. After collecting the information from ontology, the service-oriented recommended system recommends the best possible solution per the user's need. Distribution of agricultural products can become more effective and efficient due to the accessibility with which farmers can distribute various corps and data that can be accessed through a range of devices. The proposed service-oriented ontology (SOO) is the latest concept for this purpose.

Available Tools For Ontology

PROTÉGÉ

Protégé is a tool based on ontology and acquaintance introduced by Stanford University. This tool supports the development of domain ontologies. It also defines the classes, class ranking, variables, value, and boundaries and improves the affairs among classes and properties. Protégé is a free tool that is available at Stanford university website. Along protégé there is a simulation package like OntoViz, EZPal, etc these all simulate ontologies with the assistance of diagrams for the benefit of users. Stanford University is still enhancing this tool, and its recent modified version now contains SWRL (Semantic Web Rule Language), It is on the top of the list of OWL to perform calculations, temporal reasoning, and Prolog rules. Stanford has provided a video tutorial in which they teach protégé from the basics with the plug-in of OWL. The benefit of protégé is that it supports tool builders, and field experts on the same time and it differentiates this tool from others, that these are bound in-field experts and absence of intelligence for meta-modeling. This is why protégé was selected for fluctuations in the model structure. The primary and reasonable reaction to start working on the ontology project is to find appropriate ontology software. This makes it easier to sort and envision the field domain knowledge before and through working on ontology [29].

ISAVIZ

IsaViz is a tool for searching and presenting RDF models in form of graphs. The founder of IsaViz is Emmanuel Pietriga, which is available at W3C Consortium. Xerox Research Center play the role in the construction of IsaViz. They contributed with XVTM, the primary version of ZVTM (Zoomable Visual Transformation Machine) on which IsaViz has been constructed. Since 2004, INRIA is responsible for further developments in future projects. Jena 2 semantic web toolkit is integrated with Isaviz and this toolkit was developed by HP labs. GraphViz library founded by AT&T Research can easily be used in IsaViz. The methodology for building ontology is not included in IsaViz. It takes input in the form of RDF/XML and N-Triples and gives output in the format of RDF/XML, N-Triples, Portable Network Graphics, and protégé/ OilEd [29].

APOLLO

This application is user-friendly where classes, instances, and functions are primitives to run this model. The internal model of Apollo and OKBC protocol is equivalent. Its primitives are perfectly designed according to the OKBC environment. The ontology allows inheritance with other ontologies through which we can access all primitive classes: boolean, integer, float, string, list, etc. There are two types of slots in class:

- Non-Template slots.
- Template Slots.

The non-Template slots are not supported in the primary version of Apollo. We can create many instances for each class and it can inherit all slots of every slot [29].

SWOOP

There are many web-based OWL ontology tools, and SWOOP is one of them that allows various ontology environments. It can compare, edit and merge the ontologies and can compare logical descriptions, definitions, instances, and associated properties. Navigation in SWOOP is simple and easy because of its hyperlinked capabilities. The methodology for building ontology is not supported in SWOOP. Ontological data can be used externally by the user. We can perform it by importing the entire external ontology or linking the external entity, but we cannot partially achieve it by importing OWL. We can get it by using a brute-force syntactic scheme by copy/pasting useful axioms of the external ontology, or by dividing the external ontology into parts while preserving its semantics and using the specific part as required. Searching for a concept across multiple ontologies is allowed. Ontology Searching algorithm SWOOP is used for searching [29].

TOPQUADRANT

TopQuadrant Braid EDG collects the metadata from all data integration environments, creating a Knowledge Graph that provides the visibility, control and intelligence needed to manage change, build connections across metadata silos, reduce errors and ensure data consistency.

Table 3. Tool's Architecture

S.no	Name	Version	Import format	Export format
1	Protégé	5.5.0	XML, RDF (S), XML Schema and OWL	XML, RDF (S), XML Schema, Java, html

2	IsaViz	3.0	XSLT, RDF (S), OIL, DAML+OIL, OWL	XSLT, RDF (S), OIL, DAML+ OIL, OWL
3	Apollo	2.16.2	OCML	OCML
4	Swoop	N/A	RDF (S), OIL, DAML,	RDF (S), OIL, DAML

The table shows the various forms of inputs and outputs, together with the respective ontology versions and their formats in terms of inputs and outputs.

TABLE 4. TOOL'S INFERENCE SERVICES & TOOLS' USABILITY

Feature	Apollo	IsaViz	Protégé	Swoop
Inference Engine	×	✓	With PAL	×
Exception Handling	×	×	×	✓
Consistency Checking	✓	Via type inheritance	Via plugins like FACT and PAL	checks writing mistakes
Collaboration with other Tools	×	×	×	×
Ontology Library	✓	×		×
Visualization	×	Via plug-ins like Graph Viz	×	×
Versioning	×	×	✓	×
Collaboration	×	×	×	×

The above mentioned table shows the features of ontology integrated with the different tools working on the parameters, which are the key factors of query systems.

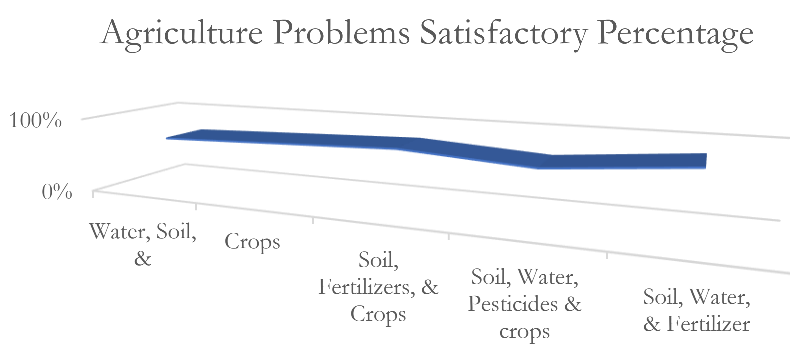

Figure 4. Analysis of agricultural problems with their satisfactory percentage

CONCLUSION AND FUTURE WORK

Agriculture features provide a significant number of semantic resources. These resources are a billboard of hot collection of vocabularies and ontologies. Large and comprehensive resources are integrated through linked data hubs or common vocabularies. Additionally, these resources are free and open, therefore the difference between these technologies within the academic literature is restricted in comparison to complementary domains like biomedicine. Ontologies play an essential role within the Semantic Web, and it needs to enhance existing technologies from machine learning and knowledge retrieval. In this research, we analyzed the traditional agriculture methods available as modern agriculture. Analysis results based on percentages are shown in Figure 4 which shows the agriculture problems and their satisfactory percentages. Within the boundaries of modern technologies like IoT and AI with an ontology that come towards it, we find it beneficial as it reduces human efforts, gives more products, and works efficiently. Service-oriented architecture in agriculture is discussed above, in addition, the issues regarding some parameters are described and we are confronted with many new technologies while researching this topic. Service-oriented architecture makes it easier to handle all the above issues with the proposed model and provides promising results. The future service-oriented model extends to the automatic system controlling the real environment and works accordingly. In an automatic system, the user can evaluate the complete query reports remotely.

REFERENCES

[1] K. Kishore Kumar, "IoT-based smart agriculture," *Handb. Res. Innov. Appl. AI, IoT, Cogn. Technol.*, vol. 5, no. 6, pp. 63–77, 2021, doi: 10.4018/978-1-7998-6870-5.ch004.

[2] P. Sureephong, P. Wiangnak, and S. Wicha, "The comparison of soil sensors for integrated creation of IOT-based Wetting front detector (WFD) with an efficient irrigation system to support precision farming," *2nd Jt. Int. Conf. Digit. Arts, Media Technol. 2017 Digit. Econ. Sustain. Growth, ICDAMT 2017*, pp. 132–135, Apr. 2017, doi: 10.1109/ICDAMT.2017.7904949.

[3] A. Khattab, A. Abdelgawad, and K. Yelmarthi, "Design and implementation of a cloud-based IoT scheme for precision agriculture," *Proc. Int. Conf. Microelectron. ICM*, vol. 0, pp. 201–204, Jul. 2016, doi: 10.1109/ICM.2016.7847850.

[4] F. J. Ferrández-Pastor, J. M. García-Chamizo, M. Nieto-Hidalgo, J. Mora-Pascual, and J. Mora-Martínez, "Developing Ubiquitous Sensor Network Platform Using Internet of Things: Application in Precision Agriculture," *Sensors 2016, Vol. 16, Page 1141*, vol. 16, no. 7, p. 1141, Jul. 2016, doi: 10.3390/S16071141.

[5] M. K. I. Abd Rahman, M. S. Z. Abidin, M. S. A. Mahmud, S. Buyamin, M. H. I. Ishak, and A. A. Emmanuel, "Advancement of a smart fibrous capillary irrigation management system with an internet of things integration," *Bull. Electr. Eng. Informatics*, vol. 8, no. 4, pp. 1402–1410, 2019, doi: 10.11591/eei.v8i4.1606.

[6] T. Cu, C. Lamacchia, and T. Nguyen, "The Internet of Things: Can a Tree Talk to You?," *AMCIS 2017 Proc.*, Aug. 2017, Accessed: Aug. 01, 2022. [Online]. Available: https://aisel.aisnet.org/amcis2017/AdvancesIS/Presentations/31

[7] M. Poveda-villalon *et al.*, "Ontological requirement specification for smart irrigation systems : a SOSA / SSN and SAREF comparison To cite this version : HAL Id : hal-02042584 Ontological Requirement Specification for Smart Irrigation Systems : a SOSA / SSN and SAREF Comparison," 2020.

[8] S. Chaudhary, M. Bhise, A. Banerjee, A. Goyal, and C. Moradiya, "Agro advisory system for cotton crop," *2015 7th Int. Conf. Commun. Syst. Networks, COMSNETS 2015 - Proc.*, no. December 2018, 2015, doi: 10.1109/COMSNETS.2015.7098701.

[9] S. K. Miryala, A. Anbarasu, and S. Ramaiah, *Emerging Technologies for Agriculture and Environment*, no. January. Springer Singapore, 2020. doi: 10.1007/978-981-13-7968-0.

[10] I. Mohanraj, K. Ashokumar, and J. Naren, "Field Monitoring and Automation Using IOT in Agriculture Domain," *Procedia Comput. Sci.*, vol. 93, pp. 931–939, Jan. 2016, doi: 10.1016/J.PROCS.2016.07.275.

[11] P. P. Jayaraman, A. Yavari, D. Georgakopoulos, A. Morshed, and A. Zaslavsky, "Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt," *Sensors 2016, Vol. 16, Page 1884*, vol. 16, no. 11, p. 1884, Nov. 2016, doi: 10.3390/S16111884.

[12] W. Bazán-Vera, O. Bermeo-Almeida, T. Samaniego-Cobo, A. Alarcon-Salvatierra, A. Rodríguez-Méndez, and V. Bazán-Vera, "The current state and effects of agromatic: a systematic literature review," *Commun. Comput. Inf. Sci.*, vol. 749, pp. 269–281, 2017,

doi: 10.1007/978-3-319-67283-0_20/COVER.
[13] C. Brewster, I. Roussaki, N. Kalatzis, K. Doolin, and K. Ellis, "IoT in Agriculture: Designing a Europe-Wide Large-Scale Pilot," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 26–33, 2017, doi: 10.1109/MCOM.2017.1600528.
[14] A. A. R. Madushanki, M. N. Halgamuge, W. A. H. S. Wirasagoda, and A. Syed, "Adoption of the Internet of Things (IoT) in agriculture and smart farming towards urban greening: A review," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 4, pp. 11–28, 2019, doi: 10.14569/ijacsa.2019.0100402.
[15] C. M. d. Morais, D. Sadok, and J. Kelner, "An IoT sensor and scenario survey for data researchers," *J. Brazilian Comput. Soc.*, vol. 25, no. 1, pp. 1–17, Dec. 2019, doi: 10.1186/S13173-019-0085-7/TABLES/14.
[16] A. Chougule and D. Mukhopadhyay, "Developing Ontology for Smart Irrigation of Vineyards," *Adv. Intell. Syst. Comput.*, vol. 882, no. January, pp. 17–24, 2019, doi: 10.1007/978-981-13-5953-8_2.
[17] E. Alreshidi, "Smart Sustainable Agriculture (SSA) solution underpinned by Internet of Things (IoT) and Artificial Intelligence (AI)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 5, pp. 93–102, 2019, doi: 10.14569/ijacsa.2019.0100513.
[18] C. Kamienski *et al.*, "Smart water management platform: IoT-based precision irrigation for agriculture," *Sensors (Switzerland)*, vol. 19, no. 2, 2019, doi: 10.3390/s19020276.
[19] M. Poveda-Villalón, Q. D. Nguyen, C. Roussey, C. De Vaulx, and J. P. Chanet, "Ontological requirement specification for smart irrigation systems: A SOSA/SSN and SAREF comparison," *CEUR Workshop Proc.*, vol. 2213, pp. 1–16, 2018.
[20] A. Goldstein, L. Fink, and G. Ravid, "A Framework for Evaluating Agricultural Ontologies," Jun. 2019, doi: 10.48550/arxiv.1906.10450.
[21] B. Drury, R. Fernandes, M. F. Moura, and A. de Andrade Lopes, "A survey of semantic web technology for agriculture," *Inf. Process. Agric.*, vol. 6, no. 4, pp. 487–501, Dec. 2019, doi: 10.1016/J.INPA.2019.02.001.
[22] J. Lacasta, F. J. Lopez-Pellicer, B. Espejo-García, J. Nogueras-Iso, and F. J. Zarazaga-Soria, "Agricultural recommendation system for crop protection," *Comput. Electron. Agric.*, vol. 152, pp. 82–89, Sep. 2018, doi: 10.1016/J.COMPAG.2018.06.049.
[23] R. Bonacin, O. F. Nabuco, and I. Pierozzi Junior, "Ontology models of the impacts of agriculture and climate changes on water resources: Scenarios on interoperability and information recovery," *Futur. Gener. Comput. Syst.*, vol. 54, pp. 423–434, Jan. 2016, doi: 10.1016/J.FUTURE.2015.04.010.
[24] J. Liao, L. Li, and X. Liu, "An integrated, ontology-based agricultural information system:," *http://dx.doi.org/10.1177/0266666913510716*, vol. 31, no. 2, pp. 150–163, Nov. 2013, doi: 10.1177/0266666913510716.
[25] Aqeel-ur-Rehman and Zubair Ahmed Shaikh, "ONTAgri : Scalable Service Oriented Agriculture Ontology for Precision Farming," *2011 Int. Conf. Agric. Biosyst. Eng.*, no. August 2015, pp. 411–413, 2011.
[26] N. Bansal and S. K. Malik, "A framework for agriculture ontology development in semantic web," *Proc. - 2011 Int. Conf. Commun. Syst. Netw. Technol. CSNT 2011*, pp. 283–286, 2011, doi: 10.1109/CSNT.2011.68.
[27] K. Onkov, "Ontology of Crop Pest Control," *ACM Int. Conf. Proceeding Ser.*, no. July, pp. 8–12, 2020, doi: 10.1145/3388176.3388208.

[28] M. Fahad, T. Javid, H. Beenish, A. A. Siddiqui, and G. Ahmed, "Extending ONTAgri with Service-Oriented Architecture towards Precision Farming Application," *Sustain. 2021, Vol. 13, Page 9801*, vol. 13, no. 17, p. 9801, Aug. 2021, doi: 10.3390/SU13179801.
[29] B. Kapoor and S. Sharma, "A Comparative Study of Ontology building Tools in Semantic Web Applications," *Int. J. Web Semant. Technol.*, vol. 1, no. 3, pp. 1–13, 2010, doi: 10.5121/ijwest.2010.1301.