

Design of Multiple Ontology Based Agro Knowledge Mining Model

Azween Abdullah¹, E.Murali^{*2}, Sreeji S³, Dr.Balamurugan Balusamy⁴, S.Rajashree⁵

¹Professor and Dean, Perdana University, Malaysia

azween@perdanuniversity.edu.my

²Department of computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, India
emurali88@gmail.com

³Department of computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, India
sreeji.cse@gmail.com

⁴Associate Dean-Student Engagement, Shiv Nadar University, balamurugan.balusamy@snu.edu.in

⁵Department of computer science and engineering, Sathyabama institute of science and technology, Chennai, India
rajashree.cse@sathyabama.ac.in

Abstract—Farming is regarded as a major industry in India, accounting for 17% of the country's GDP growth. Agriculture employs 60% of the population hence it is considered an important sector in India. The important factors for agriculture are pest management, disease prevention, irrigation management, soil mineral composition, crop management, location, and the season in which the crop is grown. Hence all this information along with the techniques are well known only by the experienced farmers. Hence it is important to create an agro knowledge management system. As a result, this work makes an attempt to develop a multiple ontology-based agro knowledge management system. The designed system consists of agriculture information related to attributes of soil mineral, moisture, season, location, crop type, and temperature. It consists of multiple ontologies such as soil ontology, crop ontology, location ontology, and crop season ontology to provide agronomy knowledge. Soil ontology is premeditated to classify the soil type in a hierarchical order while crop ontology classifies the crop type, location ontology classifies locations suitable for different crop types and finally, crop season ontology classifies the season that is suitable for different crops. A rule base is built to develop the knowledge base and to validate the truthfulness of the knowledge base. Visualization of a knowledge base is carried out for better understanding and decision-making.

Keywords-ontology; knowledge management system; ontology visualization; data mining; multiple ontology.

I. INTRODUCTION

An ontology[16] is a formal description of knowledge that includes a group of concepts from a certain field and the connections between them. The main objectives of ontology are sharable, reusable, and also add new knowledge about the domain. The classification and discovery of knowledge get much easier when the conceptualization improves the data elements through property characteristics. Natural language processing[21], machine learning, information retrieval, data mining[22], and knowledge representation[23] techniques have all contributed to the evolution of ontology development. The technique also allows for the creation of numerous interpretable patterns that can be used to make future predictions. In the field of agriculture, ontology has proved to have a broad application in a taxonomy of agriculture information, design and building up of information, & knowledge base[17] and development of information search engines.

In this attempt, agro knowledge management using multiple ontologies is created as soil ontology, crop ontology[13], location ontology[14], and crop season

ontology. All these ontologies are integrated to ensure multilevel reusability and scalability of the agro knowledge which serves as an objective of the research attempt. As the representations become more practical for incorporating information at any time, the knowledge level tends to rise, and this may have an impact on the pattern established previously. As a result, incremental mining is proposed to accept and process the rising data set for inferences without omitting previously recognized patterns, and to extract the pattern from various sources.

II. RELATED WORK

Ontology is served different purposes like knowledge management system, knowledge base decision support system, expert system, sharing of conceptual data, reuse of knowledge domain, and other intelligent systems. Hence ontology is becoming a major tool for knowledge representation. The use of ontology in the field of agriculture is used for several purposes such as knowledge sharing to the farmers and supporting farmer decisions. The framework of multiple ontology models is useful in representing knowledge across various domains which are highlighted in this section.

Earlier, A cluster-based multiple ontology parallel merger process was proposed by Sunitha abburu[1] et. al(2013). Same domain ontology was given as input. For experimental purposes, four ontologies are taken. As a result, the recommended technique took just 725 milliseconds, reduced merging costs across different ontologies, and produced a better and more consistent merger ontology.

SwaranLata[2] et al(2013). have proposed a semantic web query on e-governance data and the building of an ontology for the agriculture sector. The ontology development comprises of identifying the concept, establishing the relationship, setting rules, and finally agriculture ontology. As a result, a web query ontology model has been designed. Similarly, Chuan Lei et. al(2018) has designed an architecture that serves a diversity of an application NLQ service, chatbots, and other application that use programming API. Ontology query language represent queries that operate on a set of concepts and relationships to predict used to compare properties, express the join between concepts, use binary operation, and use path expression. Finally, an ontology based back to back NLQ system to explore the database and knowledge base.

A new cybercrime ontology with multiple perspectives for cybercrime classification has been designed by Charlette Donalds[3] et. al(2019). The conceptual model consists of a designed classification of attacks of various events like Email_Hacked, LulzSec associate indicated. As a result, a knowledge-based cyber-attack was designed. Similarly, A framework was designed by Athanasios kiourtis[4] et. al(2019) where a non-communicable system to communication system for transforming healthcare data into ontologies is carried out. A data-driven strategy was designed for automating healthcare-related activities, improving disease diagnosis, more precisely predicting outcomes, and managing patients. As a result, the developed mechanisms created new opportunities in the field of healthcare opportunity.

JinLiu[5] et al(2019). have suggested a deep learning based approach to correlate several ontology rule bases that finds new suggestion rules. To demonstrate the utility of several ontologies, a case study of traffic security application that links the vehicle ontology and the traffic management ontology has been developed.

Similarly, Nikolay Shilov[6] et. al(2019) has created a standard information model that allows for smooth knowledge interchange while maintaining the existing information. As a result, an effective information system for multiple ontologies with terminologies is built.

Human Phenotype ontology was initiated to find abnormalities in human disease was proposed by Sebastian

Kohler[7] et. al(2020). For computationally assessing the phenotypic anomalies identified in human disease, a multiple ontology model for neurology, nephrology, immunology, pulmonology, and newborn screening was created. Likewise, an online collaboration portal was developed for a domain expert to process a new disease. Multiple ontology for decision support based on the human-machine environment which aimed to solve the real-world problem was proposed by Alexander Smirnov[8] et. al(2021). To enable interoperability between system components and coordinate relevant processes, a multi-ontology knowledge decision support system built on human-machine collective intelligence is created. The method reflected the significance of applying multiple ontologies in system development. Having learned about the importance and usage of multiple ontologies, this system for agronomy is envisioned with the idea of incorporating several individual ontologies of a subdomain.

III. AGRO ONTOLOGY FRAMEWORK

The framework consists of agro data collection followed by data pre-processing[12] and then multiple ontology based knowledge models are designed which consist of soil ontology[9], crop ontology, location ontology, and crop season ontology. To validate the designed framework rule evaluation is processed. Agro knowledge visualization[10] is performed to bring out a better understanding to the end-user. The design of the agro multiple ontology agro knowledge model is shown in Fig. 1.

- A. Argo_data acquisition and validation
- B. Multiple Ontology based Knowledge model
- C. Agro_Rule Base and Evaluation
- D. Agro_Knowledge Visualization

A. *Argo_data acquisition and validation*

As per the objective of the research, Argo information are collected from a reputable exterior source. Soil type, crop type, location, crop season, temperature, and humidity are the agriculture data collected. In the agro data pre-processing[11], data cleaning, and data integration is performed. Inappropriate and incomplete data are removed in data cleaning. A data integration task is performed where the attribute irrelevant to the research objective is removed since the data are collected from multiple sources. Pre-processed data are given as input to multiple ontology based knowledge models.

B. *Multiple Ontology based Knowledge model*

Four different sub domains of agronomy such as soil, crop, location, and season are considered in this attempt for creating the knowledge model. Consequently, Soil ontology, crop ontology, location ontology, and crop season ontology are designed in the multiple ontology based knowledge model.

The designed soil ontology consists of soil minerals such as calcium, magnesium, potassium, and phosphorus are given as input and soil type is acquired as result. In crop ontology[18], attribute such as soil classification, temperature, and humidity is given as input and crop type is acquired as result. Similarly, In location ontology attribute such as soil classification, temperature, and crop type are given as input, and crops suitable for a particular location are acquired as result. Finally, in crop season ontology, attribute such as location, crop type,

and temperature are given as input, and crop season is obtained as output. All the above ontology design process starts with conceptualization which is followed by formalization. Collection of germane facts about the conceptualization starts with soil mineral for soil ontology, crop type for crop ontology, location for location ontology, and season for crop season. A semi-structured knowledge base is created in the formalization. The ontology taxonomy is shown in Fig. 2 - 5

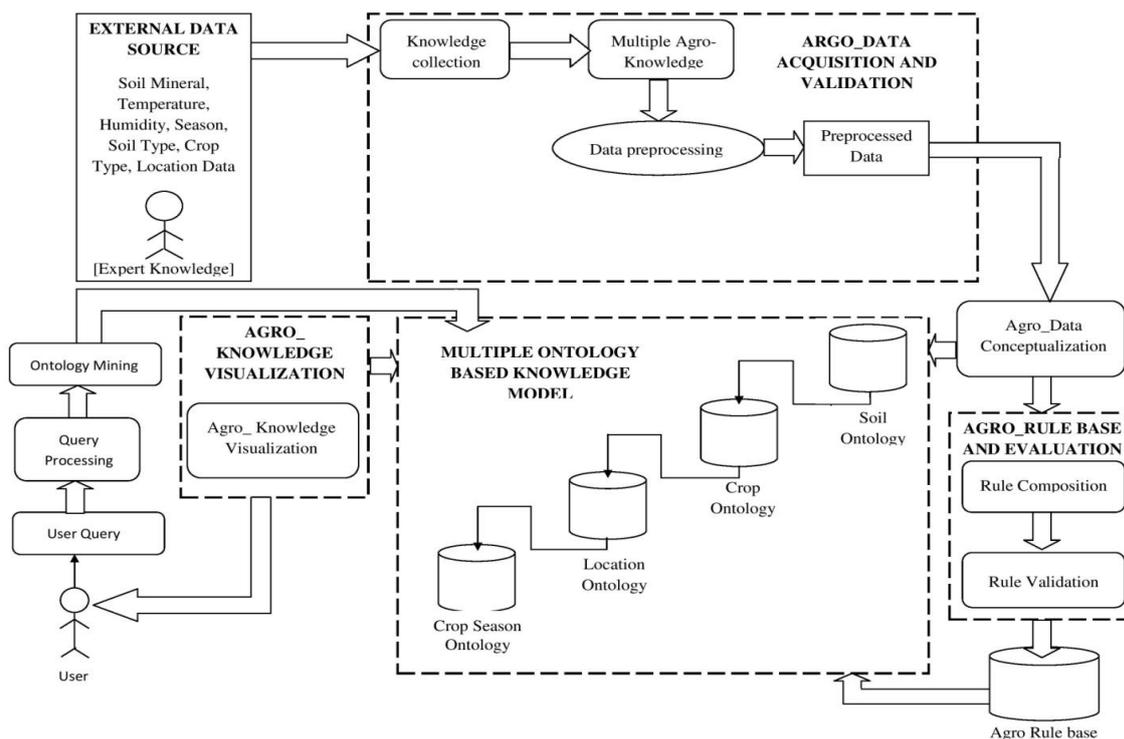


Fig. 1 A framework of multiple ontology agro knowledge mining model

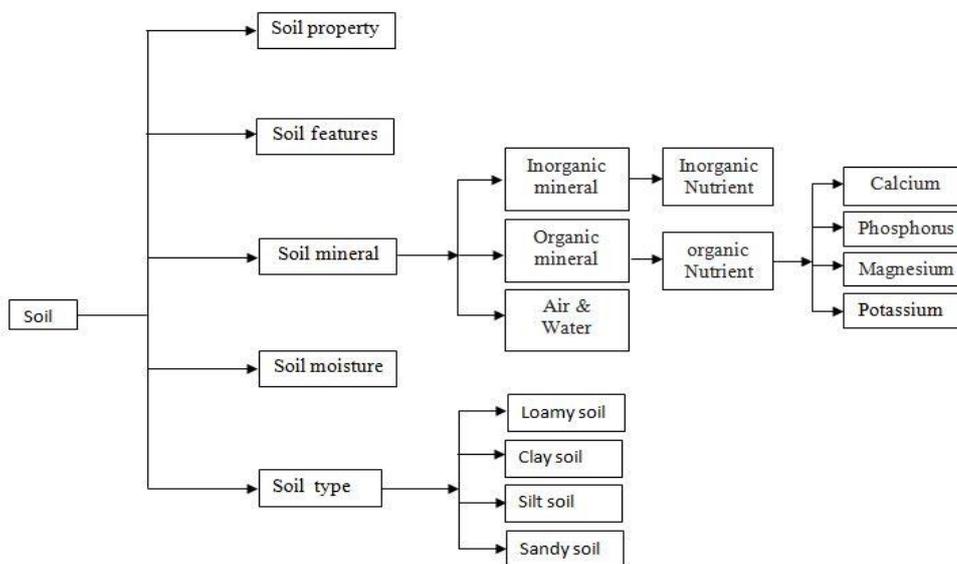


Fig. 2 Soil Ontology Taxonomy

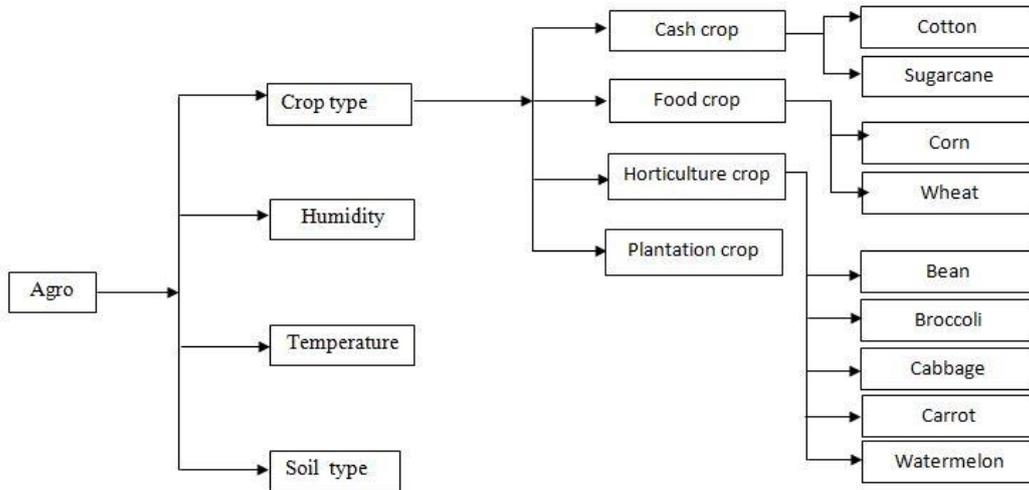


Fig. 3 Crop Ontology Taxonomy

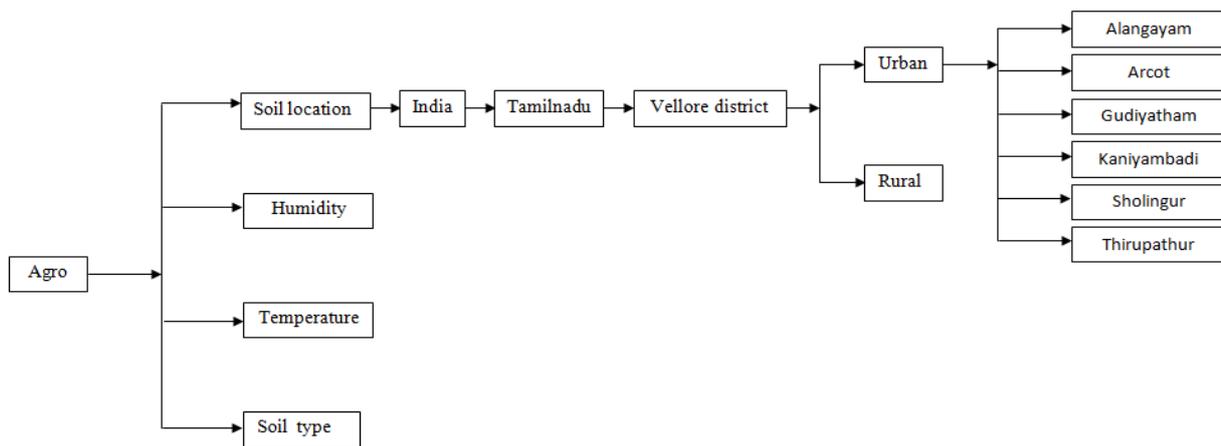


Fig. 4 Location Ontology Taxonomy

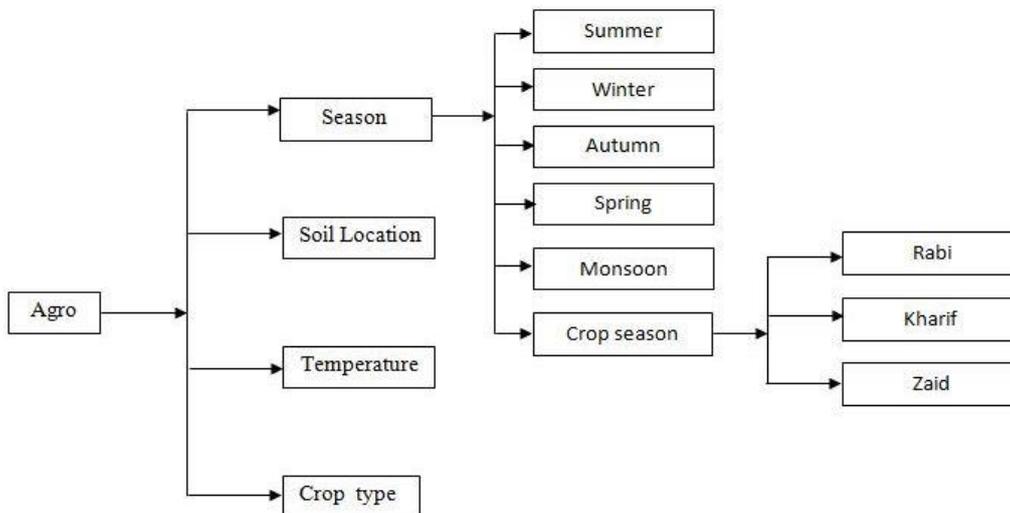


Fig. 5 Crop season Ontology Taxonomy

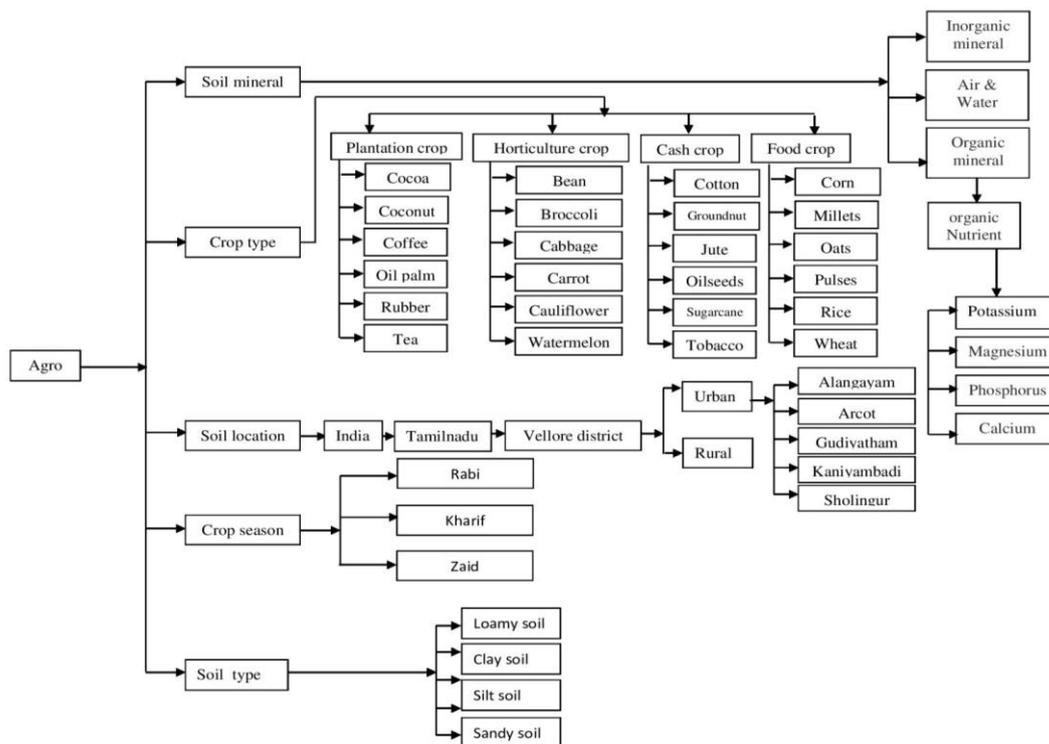


Fig. 6 Integrated Taxonomy of Agro Knowledge

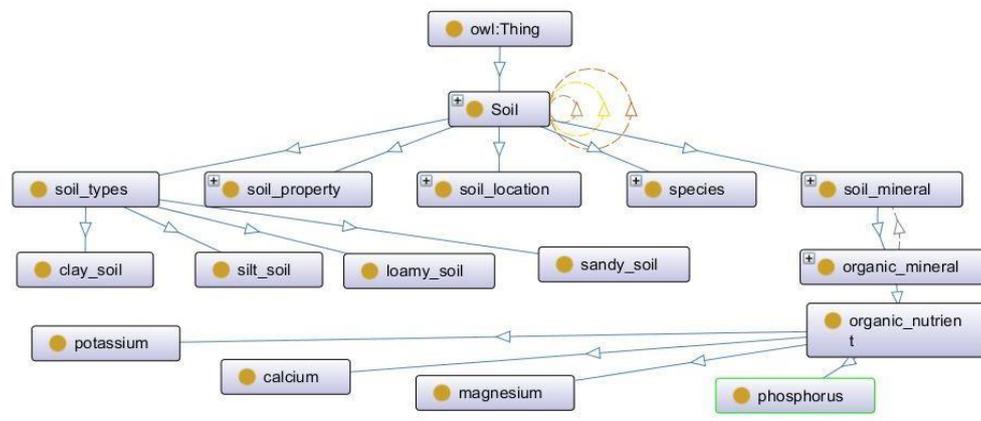


Fig. 7 Hierarchy structure of soil ontology

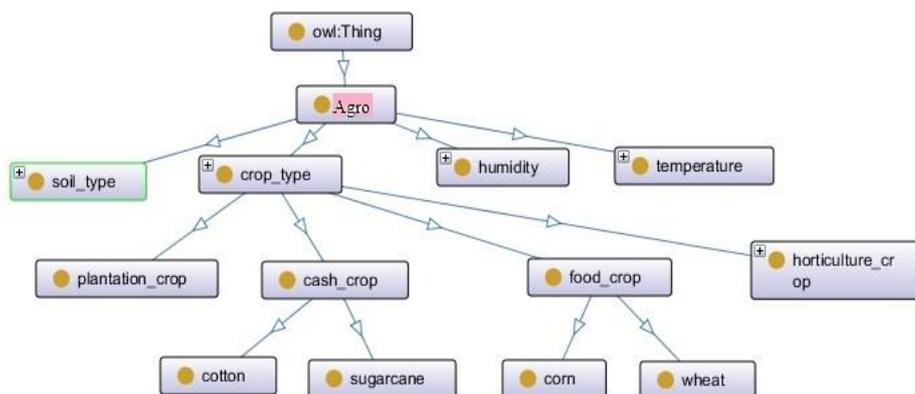


Fig. 8 Hierarchy structure of crop ontology

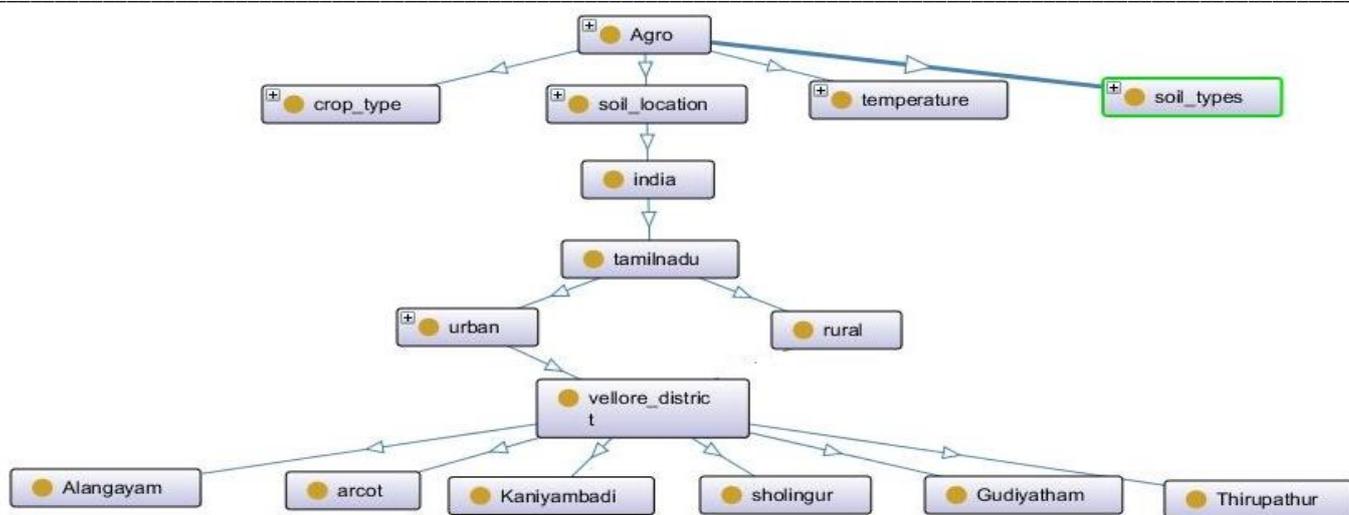


Fig. 9 Hierarchy structure of location ontology

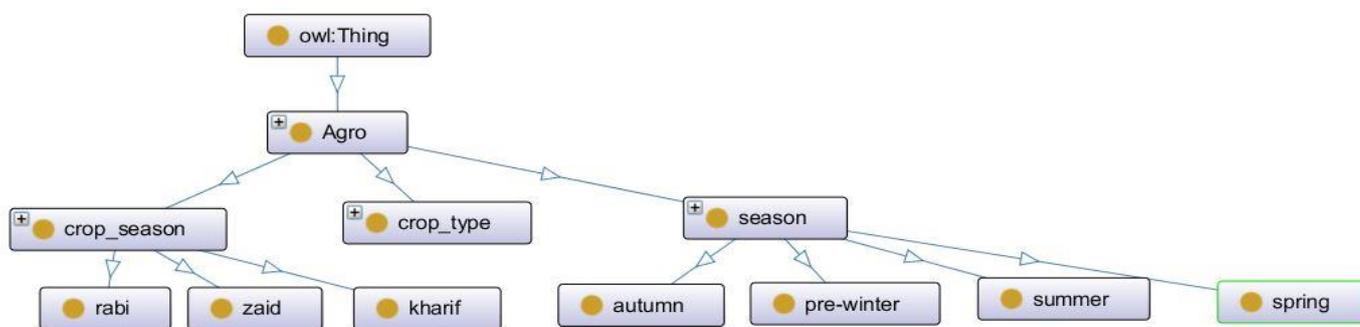


Fig. 10 Hierarchy structure of crop season ontology

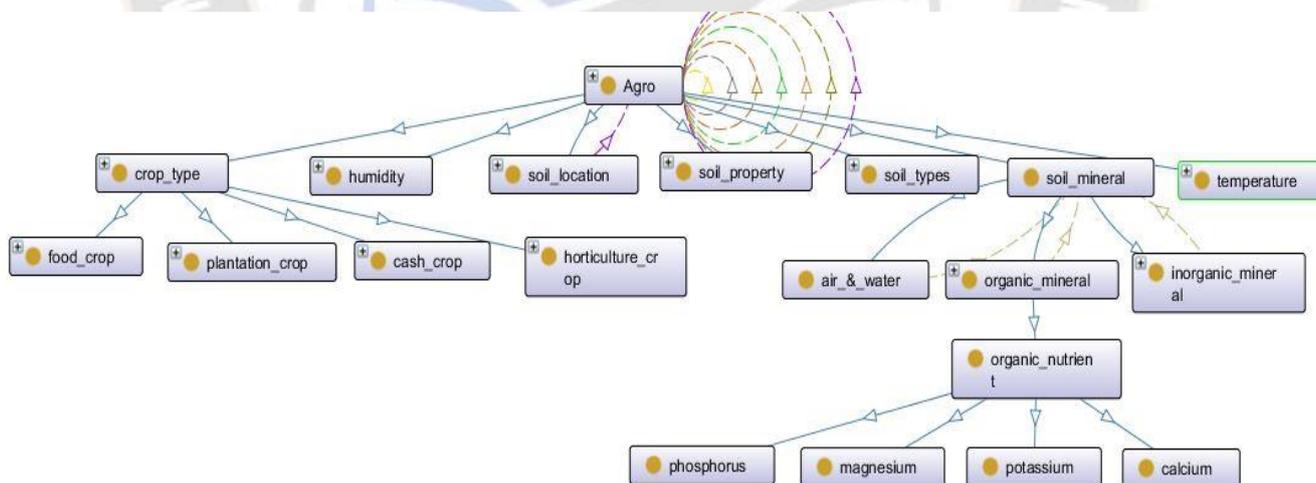


Fig. 11 Class Hierarchy for Agro_Knowledge

The outcome of the preceding ontology model is given as input to the upcoming ontology model in the integrated multiple ontology[20] agro knowledge model. Soil ontology output is fed into crop ontology, while crop ontology output is fed into location ontology. Similarly, crop season ontology receives information from location ontology. The integrated taxonomy of the agro knowledge model is shown in Fig. 6.

After the required data collections and an ontology model is created. The class structure is described using the object properties. The relationship between the classes is described using the object properties. The classification structure is created using protégé which is shown in Fig. 7-10. The class hierarchy of the integrated knowledge base is shown in Fig. 11.

C. Agro_Rule Base and Evaluation

To bring the truthfulness of the agro multiple ontology knowledge model, rule validation is carried out. For the rule evaluation[19], support, confidence, lift, conviction, and leverage are used.

1. Support

Support is defined by,

$$Support(X) = \frac{\text{Number of transactions in X}}{\text{Total number of transaction}} \quad (1)$$

The observed results are as follows

TABLE 1 : SUPPORT

S.No	Ontology	Range
1.	Soil ontology	[0, 0.28]
2.	Crop ontology	[0.08, 0.46]
3.	Location ontology	[0.2, 0.5]
4.	Crop season ontology	[0, 0.28]
5.	Multiple ontology Agro knowledge base	[0, 0.24]

2. Confidence

Confidence is defined by,

$$Confidence(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \quad (2)$$

The observed results are as follows

TABLE 2 CONFIDENCE

S.No	Ontology	Range
1.	Soil ontology	[0, 0.4]
2.	Crop ontology	[0.26, 0.54]
3.	Location ontology	[0.35, 0.56]
4.	Crop season ontology	[0.24, 0.6]
5.	Multiple ontology Agro knowledge base	[0, 0.4]

3. Lift

Lift value is defined by,

$$Lift(X \Rightarrow Y) = \frac{Support(XUY)}{Support(X) \times Support(Y)} \quad (3)$$

The observed results are as follows

TABLE 3 LIFT

S.No	Ontology	Range
1.	Soil ontology	[0, 0.2]
2.	Crop ontology	[0.69, 1.08]
3.	Location ontology	[0.63, 0.99]
4.	Crop season ontology	[0.53, 0.95]
5.	Multiple ontology agro knowledge base	[0, 10]

In soil ontology, twenty one rules out of twenty eight rules are strongly associated. There is no significant association in crop ontology, location ontology, and crop season ontology. In multiple ontology agro knowledge base, seventeen rules have values greater than one and five rules are closer to one. Hence twenty two rules out of thirty four rules are strongly associated.

4. Conviction

Conviction is defined by

$$Conviction(X \Rightarrow Y) = (1 - support(Y)) / ((1 - confidence(X \Rightarrow Y))) \quad (4)$$

TABLE 4 CONVICTON

S.No	Ontology	Range
1.	Soil ontology	[0.88, 1.23]
2.	Crop ontology	[0.76, 1.09]
3.	Location ontology	[0.68, 1]
4.	Crop season ontology	[0.63, 0.93]
5.	Multiple ontology agro knowledge base	[0.78, 1.9]

In soil ontology, fifteen rules out of twenty eight rules are strongly associated. There is no significant association in crop ontology, location ontology, and crop season ontology. In multiple ontology agro knowledge base, seventeen rules have a value larger than one and twelve rules are nearer to one. Hence twenty nine rules out of thirty four rules are strongly associated.

5. Leverage

Leverage is defined by

$$Leverage(X \Rightarrow Y) = Support(XUY) - (Support(X) * Support(Y)) \quad (5)$$

TABLE 5 LEVERAGE

S.No	Ontology	Range
1.	Soil ontology	[-0.02, 0.1]
2.	Crop ontology	[-0.07, 0.04]
3.	Location ontology	[-0.12, 0]
4.	Crop season ontology	[-0.12, -0.01]
5.	Multiple ontology agro knowledge base	[-0.04, 0.05]

The value zero denote independence and a value over zero denote desirability of rules. In the soil ontology and crop ontology, two rules are not preferable. In location ontology & crop season ontology, one rule is not acceptable. In multiple ontology agro knowledge base, two rules out of thirty four rules are not preferable.

6. Normalized support, confidence, lift, conviction, leverage for multiple ontology agro knowledge base

The normalized rule evaluation of support, confidence, lift, conviction, and leverage is given in the chart below in Fig. 12.

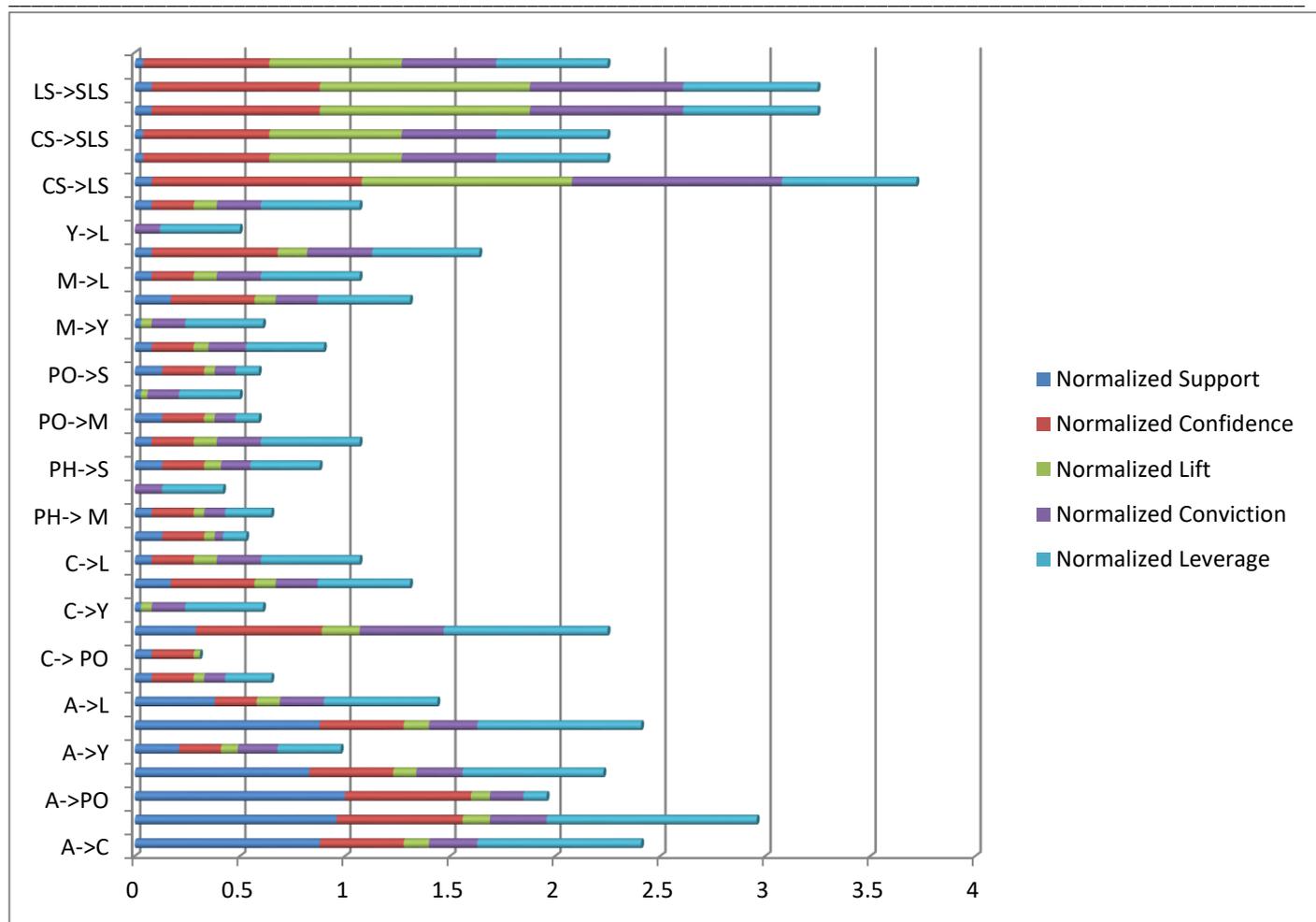


Fig. 12 Chart for Normalized multiple ontology rule evaluation

D. Agro Knowledge Visualization

A graphical representation of ontology is shown using the data visualization[15]. This will bring a better understanding

to the farmers. The hierarchical structure is shown in a visualized model in Fig. 13-14

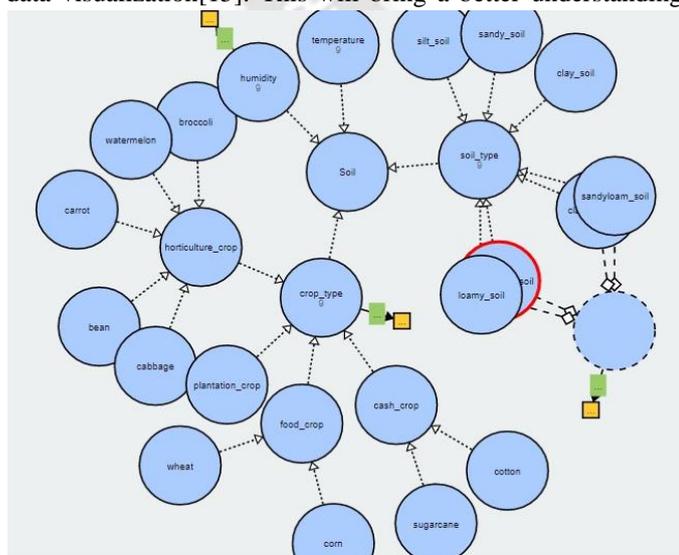


Fig. 13 Visualization of the class hierarchy of crop ontology

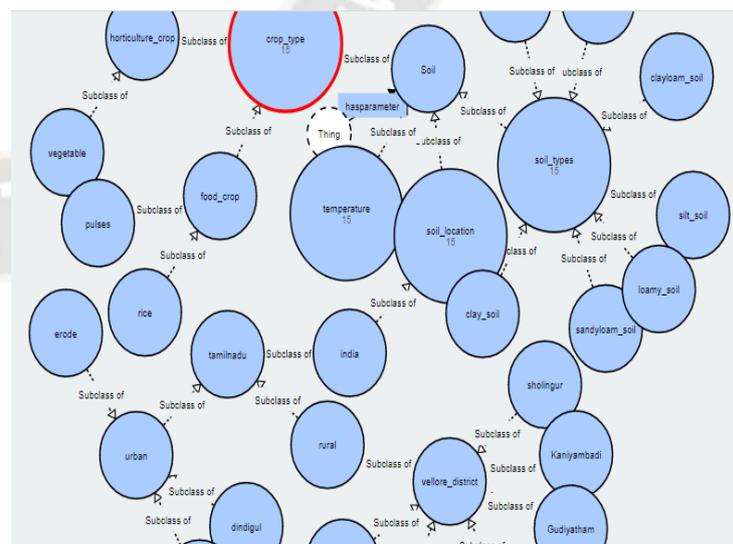


Fig. 14 Visualization of the class hierarchy of location ontology

IV. CONCLUSION

The agriculture domain has been represented with help of an ontology tool. In this framework, multiple ontology of the agro knowledge management system is presented. Hence, soil ontology has given different soil types, crop ontology has given different crop types, location ontology has given different locations suitable for crops, and crop season ontology gives season suitable for different crops. Multiple ontology agro knowledge base gives better results than individual soil, crop, location, and crop season ontology.

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