Taylor & Francis
Taylor & Francis Group

IETE Journal of Research

ISSN: 0377-2063 (Print) 0974-780X (Online) Journal homepage: www.tandfonline.com/journals/tijr20

An Ontology-based Knowledge Mining Model for Effective Exploitation of Agro Information

E. Murali & S. Margret Anouncia

IETE JOURNAL OF RESEARCH
2023, VOL. 69, NO. 11, 7856–7873
https://doi.org/10.1080/03772063.2022.2058629

An Ontology-based Knowledge Mining Model for Effective Exploitation of Agro Information

E. Murali and S. Margret Anouncia

SCOPE, Vellore Institute of Technology, Vellore 632 014, India

ABSTRACT
The quality of agriculture depends on the quality of the yield, which is usually obtained through the well-being of the crop. The quality of any crop depends on the minerals in the soil, the type of soil, the location, and the seasons. The crop yield depends on soil fertility, availability of water, climate, and disease prevention. Although this information is prevailing in plenty among the expert farmers, the means of abducting the information to the future generation has not been much promoted. Hence, the knowledge disseminated regarding agriculture becomes scarce, affecting the entire agricultural process. Given these facts, a single source, strong knowledge management system is proposed to be designed. The system aims to embrace the different kinds of knowledge associated with agriculture and attempt to obtain a single source of agro information that is very much usable and reusable to the users. To ensure the maximum level of reusability, the knowledge of the domain needs to be modeled and represented in a way that is scalable and flexible. One of the knowledge representation techniques that emphasizes on reusability and scalability is ontology. Thus, this paper attempts to design an ontology-based agro knowledge management system. A rule base is constructed to improve the expressiveness of the knowledge. An incremental mining approach is adopted to extract the knowledge from multiple ontology. To understand better to aid decision-making, a visualization task is carried out. A multi ontology-based knowledge mining model is attempted in this research to provide better insight regarding agro knowledge.

KEYWORDS
Crop ontology; Incremental mining approach; Location ontology; Season ontology; Soil ontology; Ontology visualization

1. INTRODUCTION

Ontology Mining is a framework for sharing and reusing knowledge across a particular domain. Ontology, a viable knowledge representation technique, is known for its semantics-based processing. The ontological schema appears to be a useful technique for processing semantic data and its analysis through the service of conceptualization. As the conceptualization enhances the data elements through property characteristics, the classification and discovery of knowledge become very easy. The process further enables generating various interpretable patterns, which would be more helpful for future predictions. To extract useful knowledge patterns from an ontology, several ontology mining techniques, such as web mining technique, natural language processing, machine learning, statistical techniques, data mining, and knowledge representation, are most widely used. These techniques are useful to extract different patterns of data from the represented knowledge.

In this attempt, multiple ontologies, such as soil, location, season, and crop, have been created and integrated. The objective of creating separate multiple ontologies is to ensure the multiple levels of reusability and scalability of the agro knowledge. As the representations are practicable for including data at any instance, the knowledge level tends to increase, and it may have impact the pattern created earlier. Hence, to accept and process the growing dataset for the inferences without omitting the earlier detected patterns and extract the pattern from the different sources, incremental mining is proposed.

2. RELATED WORK

Ontology is a system of knowledge for representing a domain. The ontology model is a framework for representing sharable and reusable knowledge across the domain. To extract information from the reusable source, ontology mining is usually applied. Especially in the dynamic domain like agriculture, where the data take up different dimensions of interpretations, the mining process facilitates the collection, storage, and use of data enabling, easy interpretation, and reusing data. Apart from these, Ontology mining helps increase the quality of entity analysis, improving the use and reuse of information systems, and exploiting the domain knowledge for wide sharing. Yet, many challenges have been associated with the process when dealing with large, dynamic databases. Hence, a feasible solution is expected to obtain by using multiple ontologies. Various studies have been carried out in the past to confirm the effectiveness of ontology and mining. Few notable research studies in this direction are outlined in the following sections.

Ontology development has introduced a lot of reusable knowledge models. It provides better effectiveness in sharing the information of dynamic domains. The mining of the ontology knowledge model generally creates a pattern of facts that might be helpful for different decision-making processes, especially for a dynamic domain like agriculture.

The information flow of agriculture knowledge comes in various domains, such as food, vegetable, fruit, trees, flower, livestock, and aquaculture. Similarly, the information flow of soil mining knowledge comes with soil properties, soil minerals, and soil processes. Crop ontology comes with crop type, plant anatomy, *etc.* Ontology mining helps to increase the quality of entity analysis, increased use and reuse of information systems, and domain knowledge sharing.

A domain ontology cannot be stored in a system with large amounts of data. Various challenges associated with large databases such as searching, analysis, *etc.* A few studies have elaborated on the use of multiple ontologies.

Earlier, Leite and Ricarte [1] proposed a novel framework of fuzzy information retrieval model to multiple ontology. For experimental purposes, Brazilian territorial and climate fuzzy ontology is taken as a sample of input. Finally, knowledge expressed in multiple ontology and relationships as fuzzy relation showed better performance than multi-relationship fuzzy concept. Similarly, aggregate multiple ontology based on the Induced Ordered Weighted Averaging operator (IOWA) was proposed by Lai *et al.* [2]. For similarity aggregation, six operators are used: maximal, minimal, average, at least half, most, as many as possible. To achieve the performance, a combined multiple matching approach is used. As a result, it was found that this method could integrate multiple matching results and improve the performance of the matching system. Abburu and Babu [3] have also proposed a new cluster and parallel-based multiple ontology merge process. The input to the system is multiple ontology, which belongs to the same domain. For experimental purposes, four ontologies are merged, and hence decreased merge cost over multiple ontology is produced. Likewise, the development of Multiple Ontology Workspace Management System (MOWMS) and performance assessment were proposed by Xu *et al.* [4]. The functional requirement of MOWMS consists of user registration, sign-up interface, password encryption, service authorization, verification, ensuring users' work with their own workspace, SPARQL, service endpoints, configuration setting, *etc.* As a result, a private ontology workspace is given to the user, and it enables the user to store and retrieve information on ontology, where performance is reliable, but the response time is more.

Moreover, the recent development of ontology mining has its own path in the agriculture domain. This ontology mining in the agriculture domain is mostly contributed to vegetable supply chain, agriculture e-commerce, plant domain knowledge, agriculture information retrieval, *etc.*

Yue *et al.* [5] proposed a framework for vegetable supply chain ontology construction. In the construction process, the initial stage consists in defining all the concepts and the relationships between them. In the next stage, ontology is formalized, and in the final stage, it is examined and evaluated for ontology construction. As a result, information sharing and exchange among the members of the vegetable supply chain is made. Similarlys, a knowledge searching system was proposed by Fu *et al.* [6]. The system has a metadata model construction for agriculture, e-commerce knowledge, and management, consisting of three layers, personnel agriculture, e-commerce knowledge, and agriculture e-commerce's domain metadata model. The system is formalized by RDF, which solves the matching reasoning of e-commerce knowledge management to realize knowledge sharing.

Analogous to this, an ontology model of plant domain knowledge was proposed by Fan *et al.* [7]. The model was divided into botany and environmental knowledge. The concept and attribute in the plant domain ontology, relationship collection, axiom collection have been identified. Finally, the paper analyzes the plant knowledge model represented using OWL.

Liying *et al.* [8] also proposed an agriculture information retrieval system based on ontology. The classification system of the agriculture information network is made, indexing information is used to classify information. Computer programming is used to classify and index the agriculture information network automatically. The s-matching algorithm of similarity calculating, which includes the structure of shallow, middle, and deep mapping modes is adopted.

An ontology-based knowledge and optimization model to drive the decision support system for intercropping was similarly proposed by Phoksawat and Mahmuddin [9]. Knowledge acquisition and ontology modeling, ontology development and recommender system, and Optimization modeling and DSS implementation are the conceptual frameworks that help in intercropping to get high income with low cost. The appropriate plants that fit the area are also recommended.

IoT techniques will bring out a recent development in visualization.

Kodali *et al.* [10] designed an agriculture soil moisture monitoring system that alerts the farmer on whether the moisture content level is low. Losant platform is an IoT cloud platform that provides data collection, aggregation, visualization, and graph with the help of real-time device and sensor data. Soil moisture sensor data are used as input. To connect with the losant platform, an application is created, which helps to communicate with the sensor and visualize the final output. This method was not satisfactory since the sensor was not placed all over the field.

Similarly, an application on cloud-based IoT has been proposed by Dholu *et al.* [11]. The specialty of this application is the implementation of precision agriculture, where a minimal number of resources are given to crops during the apt time. The inputs to the IoT module are soil moisture sensor, humidity, and temperature sensor. Soil moisture is measured by YL-69 electrodes; DHT 11 device measures the humidity and temperature. IoT platform helps in storing, visualizing, and analyzing the data. A mobile app helps visualize the data, namely temperature, relative humidity, and soil moisture. However, there is no response given by the system to alert the farmer whether some parameters are out of the threshold level.

An IoT platform called VegIoT for smart applications was developed by Codeluppi *et al.* [12]. It deals with the management of vegetable gardens through the collection, monitoring, and analysis of sensor data related to parameters for growing plants. The application consists of a garden wireless sensor network that helps collect data from the field. Home node collects the data and stores it. The mobile app is used for data visualization and vegetable status monitoring. Hence, the tool helps the farmers solve multiple issues and suggests proper action during farming. However, future prediction and disease prevention mechanism was not provided.

Some approaches and models are discussed briefly in the following section.

A system for uniform fertilizer application was developed by Gil *et al.* [13]. The work focuses on the design of new automated assistance tools, and it helps farmers take appropriate actions in the field. The information about fertilizer used in the field is stored using GPS and GIS. The histogram shows the storing of the fertilizer session. Finally, the system helps in substantial savings in the production and the protection of the environment.

Tan *et al.* [14] likewise proposed extensible and integrated software architecture for data analysis and visualization in precision agriculture. The input is collected by a mobile sensor, and it converts them into a uniform internal presentation for data processing. The main purpose of the AgriD software architecture is to provide guidelines for analytical tools that process and visualize the field's collected data. Finally, the results are visualized using Jzy3d, an open-source java library.

Yet another new zoning method that optimally delineates rectangular homogeneous management zones using relative variance to guarantee homogeneity was provided by Cid-Garcia *et al.* [15]. An input of 40 soil samples is taken from an agriculture field. The ILPMZ method delineates the most homogeneous rectangular management zones from a field for soil properties. A classical zoning method is compared with the ILPMZ method. Hence it is found that the ILPMZ method is more efficient.

Similarly, a comparison of four feature sets for the detection of visual features representing non-fruit and coffee fruit was proposed by Carrijo *et al.* [16]. The input used is an Unmanned Aerial Vehicle(UAV), which is used to obtain high-resolution RGB images of a coffee field. The proposed methodology enables the extraction of visual features from image regions and uses supervised Machine Learning (ML) techniques to classify areas as coffee fruits and non-fruits. As a result, the ANN model is more reliable for accurately identifying coffee fruit.

A knowledge base of an agricultural enterprise, a model, and a method was developed by Skobelev *et al.* [17] with the help of a software service. The knowledge base includes information on crop growing conditions, crop production, plant disease, soil type, application of fertilizer, *etc*. In conclusion, the proposed method has a solution for new software tools for managing agricultural production, and it reduces the cost of the end-user.

The 4D reconstruction approach was, analogously, proposed by Dong *et al.* [18] for crop monitoring, which uses a spatio-temporal model of dynamic scenes useful for precision agriculture applications. A sample of 21 rows of peanut plant, where the ground vehicle attached with camera and sensor which collect data, is taken as the input. As a result, the 4D approach is a set of 3D point clouds with a pleasing visual appearance and correct geometric properties. Sehgal *et al.* [19] likewise developed a visual analytical tool using machine learning and optimization-based approach to predict the seed variety chosen by the farmer which helps in decision-making and also provides visualization. Syngenta crop challenge 2016 dataset is used, which is a combination of up to five soybean varieties. In conclusion, a geo-spatial visual analytics tool is used, which explores raw data and helps the farmer get a solution.

A novel vision-based crop-weed classification system was similarly developed by Lottes *et al.* [20]. The experiment was conducted on sugar beet fields with the help of robots. All robots were using RGB + NIR cameras, and the input to the classification system was taken as the sequence of images. As a result, this system classifies crops in different growth stages and spatial arrangements of plants through stimulation. Kuang *et al.* [21] compared the visual classification of kiwifruit images between deep neural network and decision tree classifier with features and classification algorithm to assess the performance and implementation cost. The result recommends that DNN-based object classification gives high accuracy.

Similarly, Michelon *et al.* [22] developed a web application called AgDataBox for the control and management of agriculture fields. The data obtained from different sources, such as soil sample data, georeferenced images, precipitation, field operations, and thematic map, are taken as input. As a result, the thematic map can help toward the correct interpretation to fertilizer application at the right place and in the necessary amount to increase the productive potential in the field. Li *et al.* [23] proposed a novel method for recognizing crop plant in a field with weed. Visual features, such as color, intensity, and orientation, are extracted and combined to generate a saliency map. The experiment results demonstrate that the proposed method accurately segment crop plant from a weedy background in real-time.

A stand-alone crop recommending device that detects the soil quality and provides a list of crops to be cultivated that can be availed from the database was proposed by Martinez-Ojeda *et al.* [24]. The device uses different sensors to measure the PH levels, soil moisture, soil temperature, and soil fertility. Ten samples per day were taken from a testing site for 10 days. The result from the bar chart displayed crops that can be planted in a particular soil type.

A novel map that shows a grid-based multimodal environment with a vegetation index and a digital surface model was similarly developed by Potena *et al.* [25]. The input data are collected from soybeans, sugar beets, and winter wheat fields. Finally, a multimodal environment that uses semantics and geometry of the target field and a data association problem is solved using the LDOF problem.

The following section will highlight the usage of sensors in the field of agriculture.

Flores *et al.* [26] developed a wireless sensor network application to monitor environmental parameters which affect crop development. The recommendation system provides the type and amount of fertilizer to be applied in the field. The main server shows visualized status of the environment and soil around the crop, using which the farmer can take appropriate action for crop yield.

Analogously, a low-cost resistive soil moisture sensors performance was evaluated by Saleh *et al.* [27]. A resistivity-based soil moisture sensor is used to read the amount of moisture present in the soil. Although several errors were identified, such as sensitivity to electrolytic corrosion, sensitivity to soil ion concentration, sensitivity to temperature, and installation error, it is suited only for short application.

A case study of using Soil Moisture Active and Passive (SMAP) soil moisture data products for agriculture land soil assessment was done by Yang *et al.* [28]. Data were collected by measuring surface soil moistureusing a sensor. As a result, the SMAP result is consistent with the NASS survey result. In addition to this, Vegscape-based prototype enhances the user experience for crop condition monitoring and decision support.

A study of barriers to implementing precision agriculture and an automatic decision-making system was likewise proposed by Marios *et al.* [29]. Finally, an overview of the existing agricultural circuit and sensing system used to construct an automated circuit and sensing system was studied.

Similarly, systematic irrigation and soil testing method was proposed by Reddy *et al.* [30]. Here, the moisture sensor, NPK sensor, TCS230 color sensor are used as input. As a result, the NPK sensor was successfully implanted using a control unit. The volumetric percentage of water content is used to control the water pump and decide its water requirement.

El-magrous *et al.* [31] designed, developed, and tested a customizable weather soil sensor station alike, for precision agriculture based on wireless communication, cloud data storage, and computation technology. Finally, statistical and machine learning techniques are integrated into the app for various precision agriculture applications.

The following section will highlight the usage of satellite images, aerial images.

A method for image brightness correction was proposed by Mednieks *et al.* [32]. The image varies due to atmospheric conditions. A multispectral image is analyzed for rural areas related to different vegetation types. Finally, the image of an area is compared before visible light, and correction is proposed.

An assessment of peanut pod maturity by an automated visual analysis was done by Bindlish *et al.* [33]. Visual analysis of the middle layer of the shell is known as mesocarp. As a result, the classification method is based on pod size and mesocarp color. An accuracy of 92.5% was obtained in identifying brown-black peanuts in each sample.

Similarly, a community-based research initiative related to interactive web-based information visualization and GIS decision support system was deployed by Wachowiak *et al.* [34]. As a result, the web service allows for sharing information between the researcher and the producer. The producer allows the researcher to monitor the field and use a decision support system to improve the crop yield.

Later, Xu *et al.* [35] developed an automatic weed mapping and Variable Rate Herbicide Spraying system(VRHS) for row crops. Here, charge-coupled device camera images are used as the input, and image processing technology controls the herbicide application rate. DSP controller helps control the rate of spraying according to real-time weed distribution mapping.

In addition to this, an integrated informatics farming system was proposed by Vijaya Kumar *et al.* [36]. The input to the model is a highly scalable map interface to visualize the data on EROS (Earth Resource Observation Satellites) images. As a result, the farmers have easy access to data regarding their farms which helps them in effective cultivation of crops.

Finally, an automatic vegetation monitoring system was developed by Santos *et al.* [37]. The system analyzes the crop images and divides them into regions using images captured by unmanned aerial vehicles, and are identified by color for easy visualization. As a result, using a portable system allows farmers to identify whether a plant needs special care or not.

The following section will highlight the data visualization and data mining techniques.

Chen and Roeber [38] developed a Nebraska crop surveillance network project. The main objective of this project is automatic field data collection and processing and tracking of soybean disease infection patterns. The system fetches the data from the MYSQL database and feeds them into the ZGDchart computer graph rendering package, which renders the data and displays the result graphically. A chart type, such as a line chart, pie chart, and histogram, is produced in 2D and 3D effects. Later, Zhang *et al.* [39] developed an automatic soil nutrient detection system. The data are collected through an ion-sensitive electrode and displayed on an LCD screen. As a result, it takes only 90seconds to test a soil sample, which helps to improve the test efficiency and accuracy. A labor monitoring system was developed by Tan *et al.* [14]. The system consists of real-time labor monitoring, payroll accrual, and data-based labor analysis. Here, a cloud-based system collects labor information from previously designed labor monitoring devices and visualizes real-time labor productivity data through a mobile-friendly user interface. As a result, the real-time labor monitoring system can be connected to a variety of devices and viewed. Akin to this, Venkata Krishna *et al.* [40] proposed a middleware architecture for precision agriculture to solve agricultural-related problems, such as wastage of water, use of improper fertilizers, choice of wrong crops and seasons, poor yield, *etc*. Finally, a stimulation is developed with a scenario based on the cultivation of paddy, and the results are compared with existing manual cultivation, and a graph is drawn to identify the efficiency.

Analogously, Gandhi *et al.* [41] highlighted a study on applying data visualization techniques to find the correlation between climatic factors and rice crop yield. The dataset is collected from the National Bureau of Soil Survey and Land Use Planning. The experimental results show that J48 and LADTree displayed the highest accuracy, sensitivity, and specificity.

Jedlicka *et al.* [42] also focused on big data visualization for agriculture using 3D visualization. The main objectives are as follows: (i) agriculture and rural development data (ii) predicted crop yield, (iii) linked open data related to agriculture. The main data sources are LANDSAT satellite images. An estimated yield was calculated for a separate scene in relation to each pixel to the mean value of the whole field. The Rostenice application helps visualize the crop yield dataset from satellite imagery.

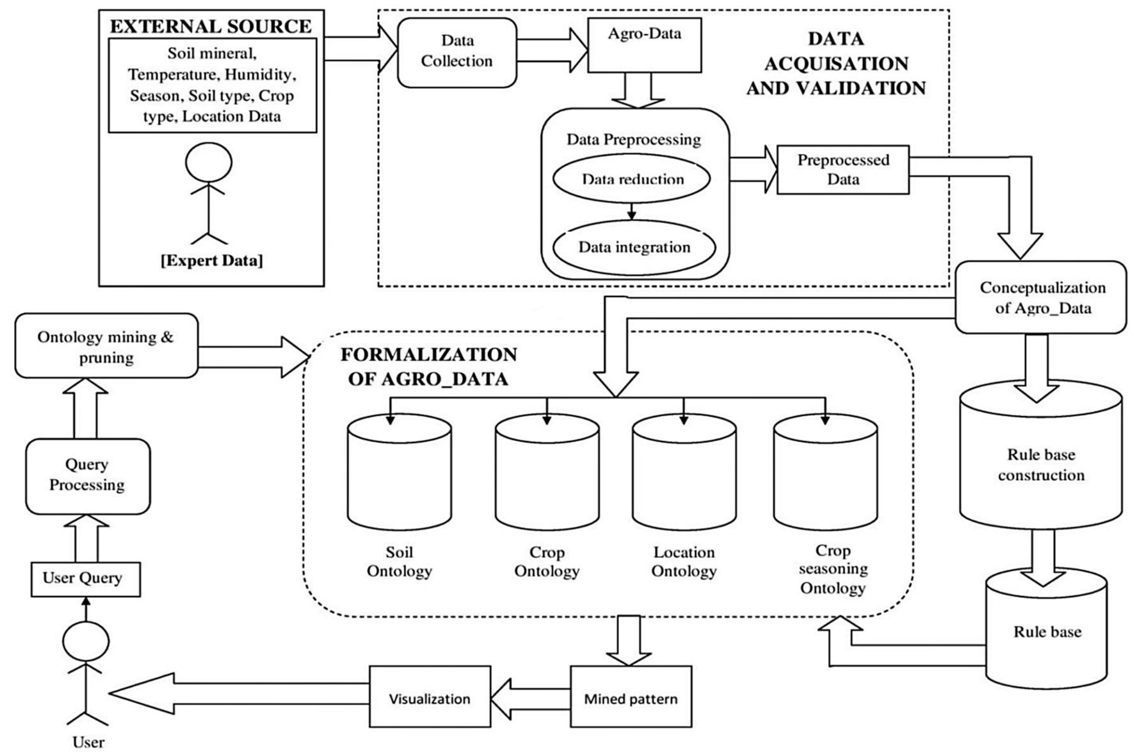

Figure 1: Agro incremental mining model framework for performance evaluation

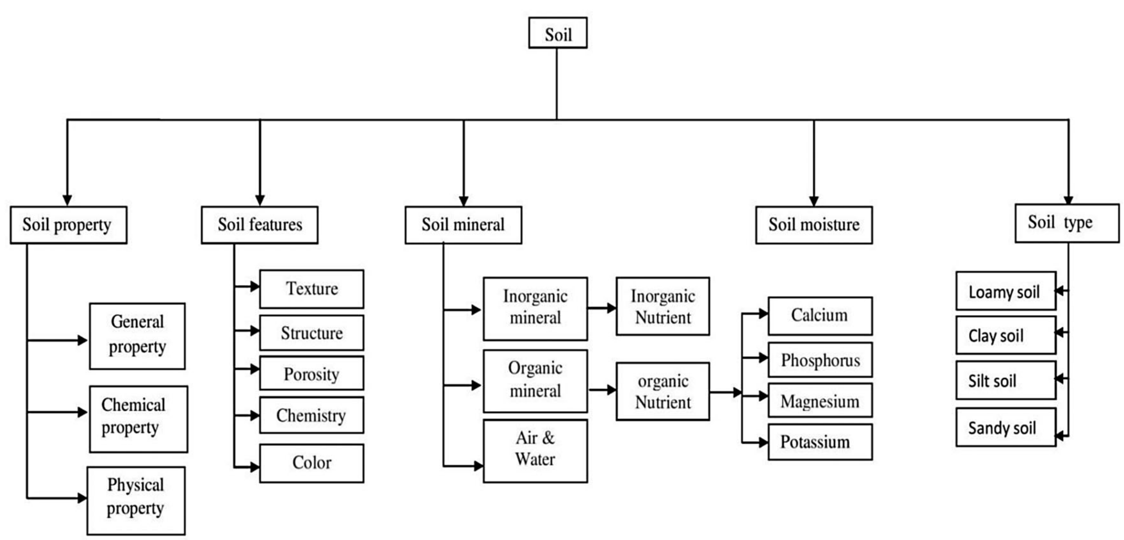

Figure 2: Agro_incremental mining soil ontology concept

Table 1: Object property of soil ontology, crop ontology, location ontology, and crop seasoning ontology

S.No	Model	Object property
1.	Soil ontology	Clay_soilsubclassofsoil_types
2.	Crop ontology	Wheat subclassoffood_crop
3.	Location ontology	Arcotsubclassofvellore_district
4.	Crop seasoning ontology	Rabi subclassofcrop_season

Finally, a visual sensing system for monitoring and controlling purposes in agriculture and forest area was later developed by Pinho *et al.* [43]. Disease control, post-processing, parameter estimation, UAVs, and satellites were addressed in the study. Centralized server and software tools helps in the decision-making process.

Thus, with the study carried out, a comparison agro ontology model will bring out efficiency. In view of this, a framework is proposed, which has been elaborated in the following section.

3. DESIGN OF AGRO ONTOLOGY FRAMEWORK

(i) Argo_data acquisition and validation
(ii) Ontology Agro_incremental mining model
(iii) Multiple ontology Agro_incremental mining model
(iv) Agro_incremental mining model visualization

The system is designed to enclose the agro facts related to attributes of soil mineral, temperature, humidity, season, soil type, crop type, and location as soil ontology. A crop ontology is separately designed to categorize the crops in a hierarchical order, while a Crop season ontology is planned to enclose the facts existing between the climate and the crop. An ontology pruning is performed to omit the irrelevant facts and thereby improving the efficiency of reasoning. The design of agro multiple ontology incremental mining framework was given in Figure 1.

3.1 Agro_Data Acquisition and Validation

The agriculture data are collected from an external source as per the paper's objective. The data collected have facts about soil mineral, temperature, humidity, season, soil type, crop type, and location, which are collected from a reputable resource. The collected data are subjected to agro pre-processing, where data cleaning is performed. In data cleaning, irrelevant and incomplete data are cleaned and normalized for further processing. As the data were from a reliable source, the availability of issues is limited, and hence a manual screening was done to get rid of these issues. The

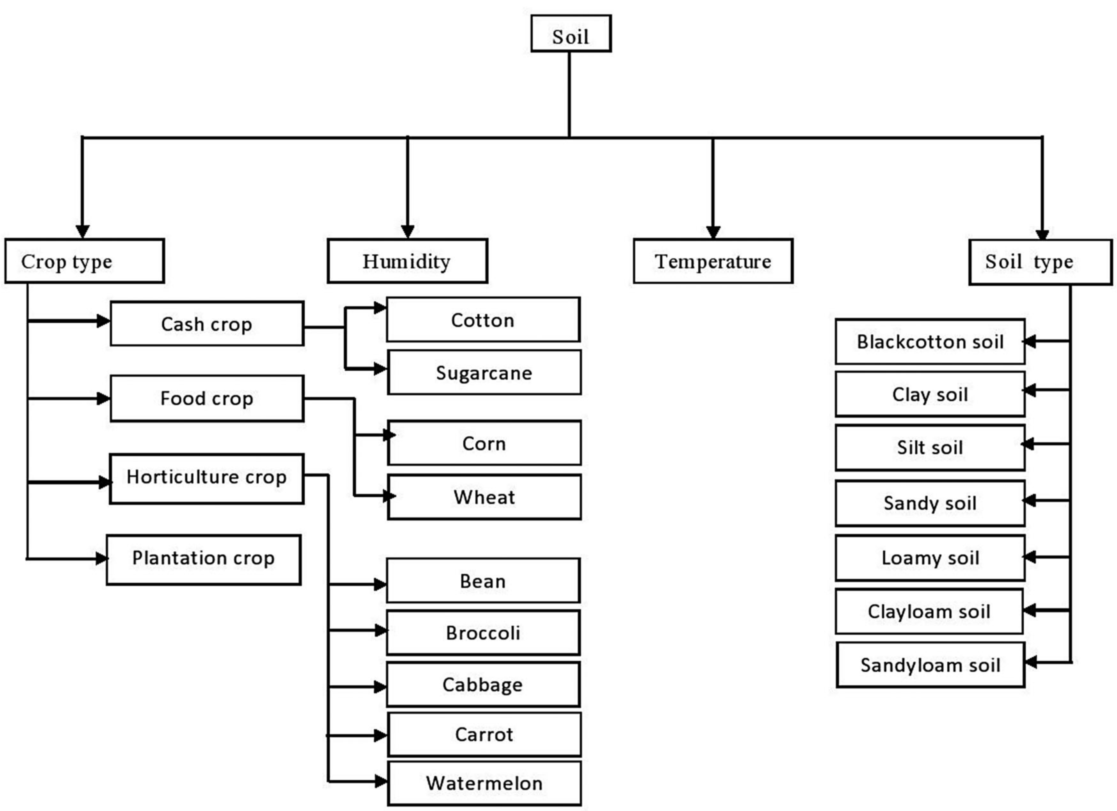

Figure 3: Agro_incremental mining crop ontology concept

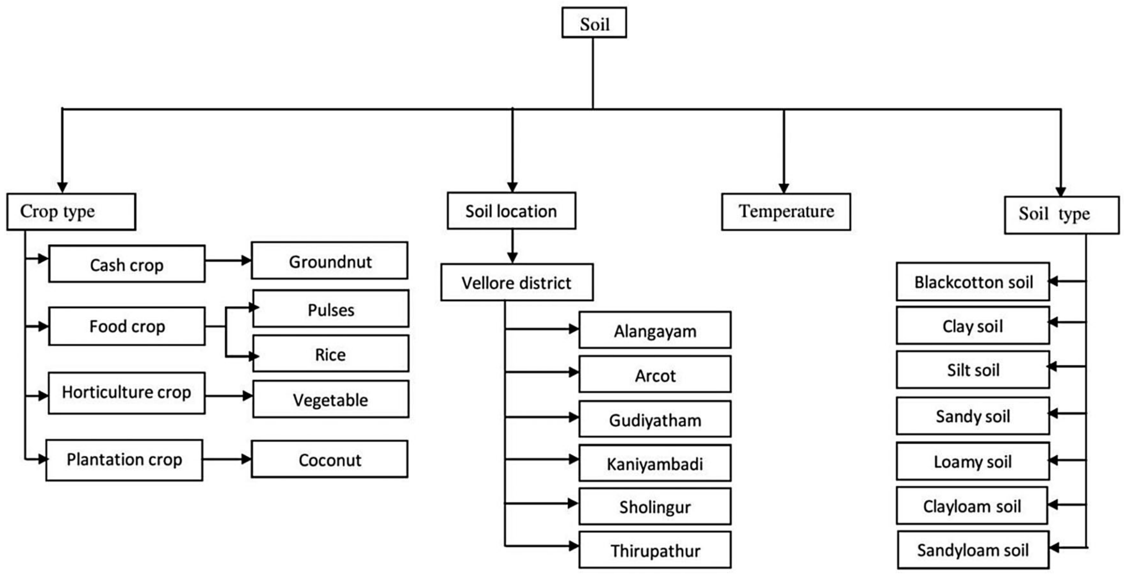

Figure 4: Agro_incremental mining location ontology concept

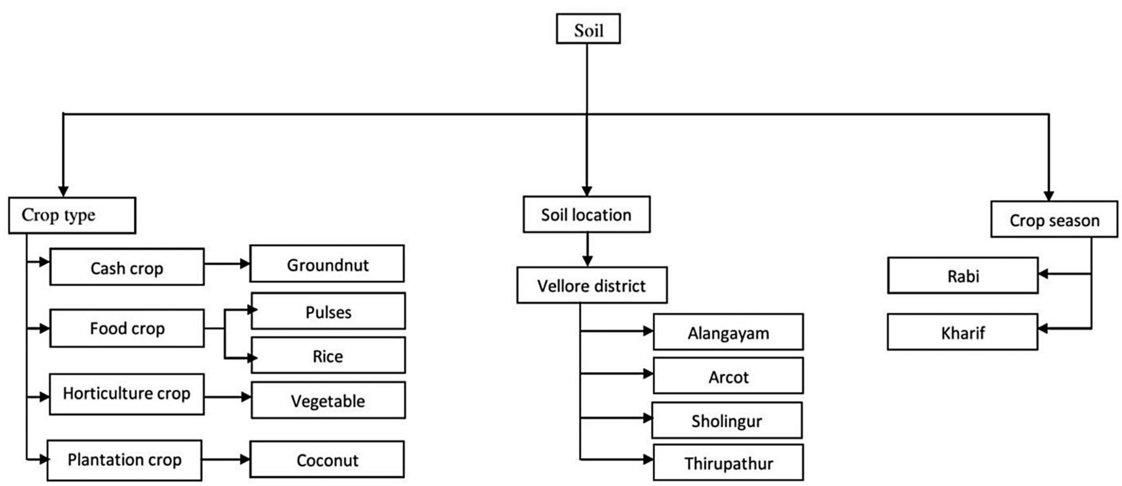

Figure 5: Agro_incremental mining crop seasoning ontology concept

cleaning process was followed by a data reduction in which attributes that are not related to research objectives are removed, and in the data integration task performed since ontology Agro_incremental mining models required data from different sources. Preprocessed data contain information on soil minerals, such as calcium, magnesium, phosphorus, temperature, humidity, season, soil type, crop type, and location. Preprocessed data are given as input to the ontology Agro_incremental mining model and multiple ontology incremental mining models.

3.2 Ontology Agro Mining Model

Soil ontology has an input of soil mineral composition where soil type is based on mineral data. In crop ontology, the input data, such as soil type, temperature, humidity, and crop type, are obtained as output. In location ontology, the data soil type, temperature, and crop type are given as input, and the location is obtained as output. Crop seasoning ontology, crop type, temperature, and location are given as input, and seasoning is obtained as output. All the above ontology agro models commence with conceptualization, and they are followed by formalization. The conceptualization begins with collecting relevant facts such as soil mineral for soil ontology, crop type for crop ontology, location for location ontology, and seasoning for crop seasoning ontology. The formalization is carried out to create a semi-structured knowledge base. From the collected data, an ontology structure is created. The concept for ontology model construction is given in Figures 2–5.

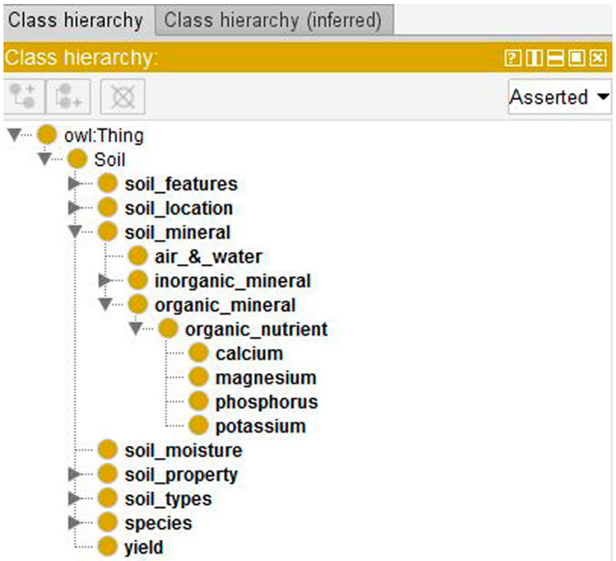

Figure 6: Class hierarchy for ontology soil ontology

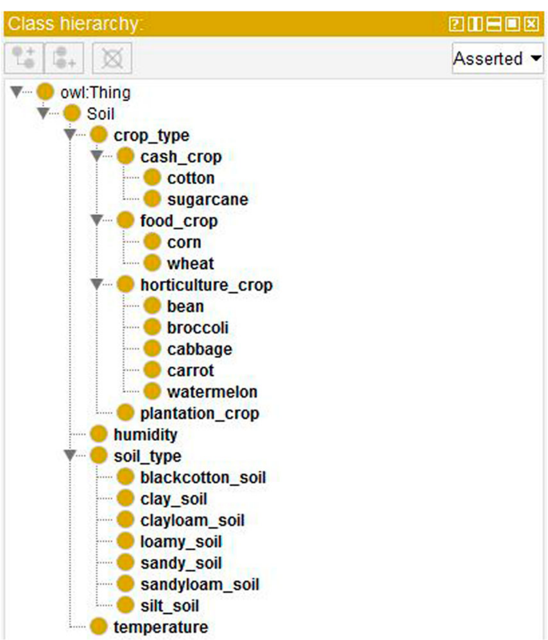

Figure 7: Class hierarchy for ontology crop ontology

Initially, the data needed for the model are collected, and an analysis is made for usability for model creation. The collected data are used for building up an ontology model. The nomenclature structure created in the protégé ontology is given in Figures 6–9.

Having created a class structure, the class is described using the object properties. The object property is used to describe the relationship between the classes. A sample object property is given for illustration purposes (Table 1).

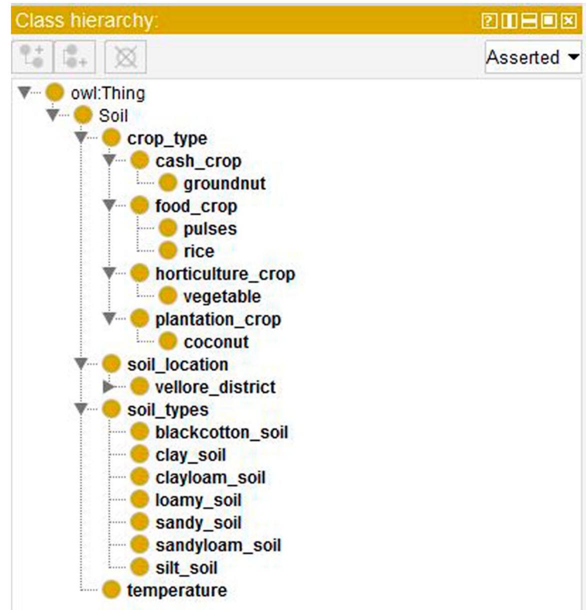

Figure 8: Class hierarchy for ontology location ontology

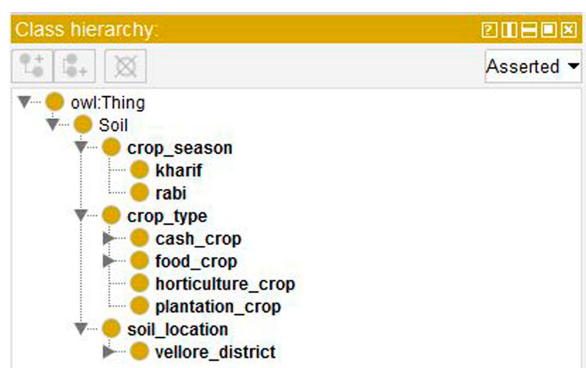

Figure 9: Class hierarchy for ontology crop seasoning ontology

3.3 Multiple Ontology Agro_Incremental Mining Model

Multiple ontology Agro_incremental mining models begin with the process of creating an incremental ontology model where the output of the previous ontology model is given as input to the next ontology model. Soil ontology commences with the conceptualization of ontology agro incremental mining that is relevant to soil type based on mineral composition. This is followed by crop ontology which begins with the output of soil ontology, which is given as input along with temperature and humidity, where crop classification is obtained. In location ontology, which starts with output from the previous model, is given as input to the current model and temperature and soil type. Finally, to obtain crop seasoning as output, the input location is obtained

Algorithm: Soil, crop, and location classification

```
Input: Let ObtainedData {1 … n1+1} and V{1 … n2+1} be a new Vector's
Vn = {V1, V2, V3 … ..until} // get user input as thresholdValue e.g. V1 - > 2000
//1 →
functionobtainSoilType(Vn)
        for i = V1 to until do
                ObtainedData ← Database.getSoilInfo(i)
                // primaryKey = thresholdValue
                // TableName = soilInfo, primaryKey = thresholdValue
                //1st row record→ |thresholdVale = 2000 | soilname = claysoil|
                //2nd row record→ | thresholdVale = 2001 | soilname = claysoil|
                soilType = ObtainedData.soilname
            returnsoilType
        end for
end function
Input: Let ObtainedData {1 … d1+1}and T{1 … d2+1} be a new Vector's
Tn = {T1, T2, T3 … ..until} // get user input temperature Value e.g. T1 - > 100
Hn = {H1, H2, H3 … ..until} // get user input humidity Value e.g. H1 - > low or medium or high
soil_type = S1//obtain data from previous function S1- > claysoil
// 2→
        functionobtainCropType(Sn,Tn,Hn)
                if thesoil_type = S1 AND temperature = T1 AND humidity = H1
                        crop_type ←  ObtainedData.crop
   Type
                        returncropType
                end if
        end function
Input: Let ObtainedData {1 … c1+1}and A{1 … c2+1} be a new Vector's
An = {A1, A2, A3 … ..until} // get user input as Temperature Value e.g. A1 - > 100
soil_type = E1//obtain data from previous function E1- > claysoil
crop_type = F1//obtain data from previous function F1- > soybean
//3→
        functionobtainlocation(En, An,Cn)
                if thesoil_type = E1 AND temperature = A1 AND crop_type = F1
                        location ← ObtainedData.location
                        return location
                end if
        end function
Input: Let ObtainedData {1 … s1+1}and A{1 … s2+1} be a new Vector's
Un = {U1, U2, U3 … ..until} // get user input temperature Value e.g. U1 - > 100
crop_type = R1//obtain data from previous function F1- > soybean
location = L1// obtain data from previous function
//4→
        functionobtainCropSeasoning(Un, Rn,Ln)
                if the cropType = = R1 AND temperature = = U1AND location = = l1
                          cropSeasoning ←  ObtainedData.
   seasoning
                          returncropSeasoning
                end if
        end function
Output:Soil_type, crop_type, location, crop_seasoning
```

Table 2: Object property of multiple ontology

S.No	Object property
1.	Soil_featuressubclassof soil
2.	Soil_locationsubclassof soil
3.	Crop_typesubclassof soil
4.	Humidity subclassof soil

from the previous model along with temperature and crop type.

The concept of the multiple ontology agro incremental mining model is given in Figure 10.

As followed in the individual ontology model, in this multiple agro ontology mining model we are building a class structure. The ontology class construction is given in Figure 11.

A sample object property is tabulated in Table 2.

An algorithm is proposed that takes input as soil mineral details in iteration 1 and provides the output of soil type. In iteration 2, the output of iteration 1 with temperature and humidity is taken as input to produce crop type. Similarly, incremental algorithm fashion is followed up to iteration 4. In iterations 3 and 4, location & crop seasoning is obtained as output.

The above algorithm can be mathematically expressed as follows.

Input details of the algorithm are given by soil minerals, temperature, humidity, soil type, crop type, and location.

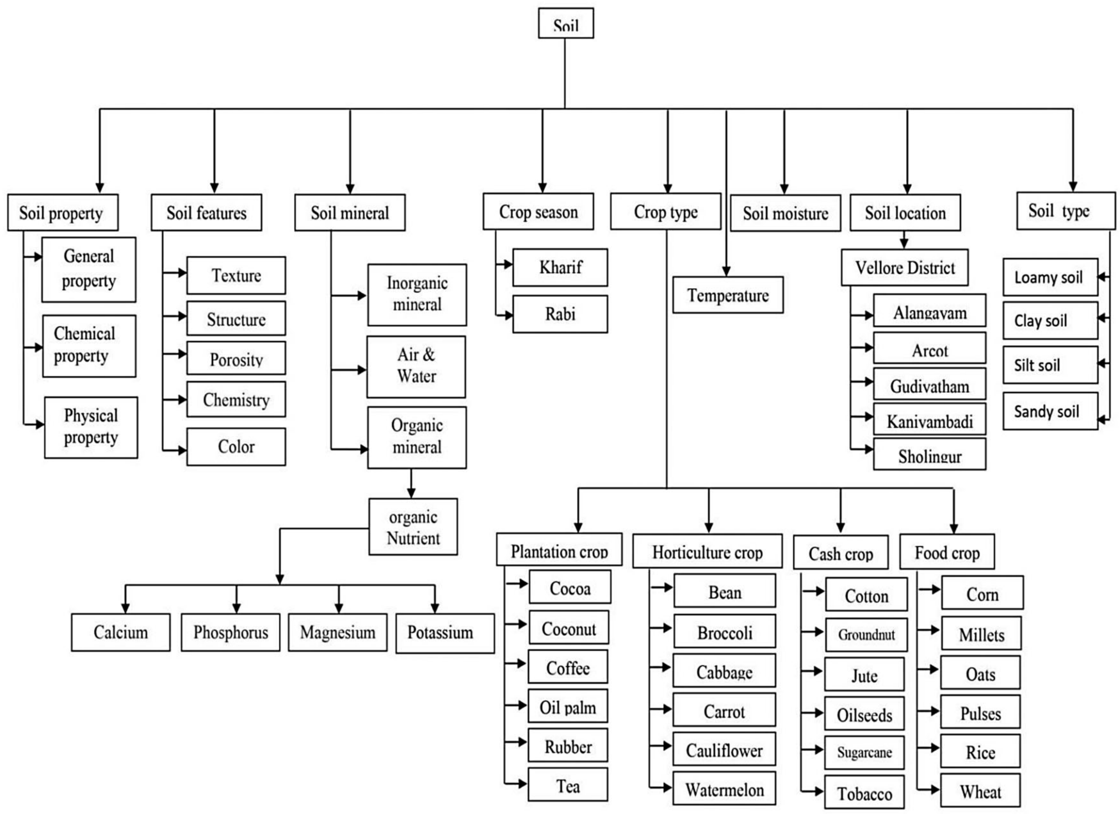

Figure 10: MultipleAgro_incremental mining concept

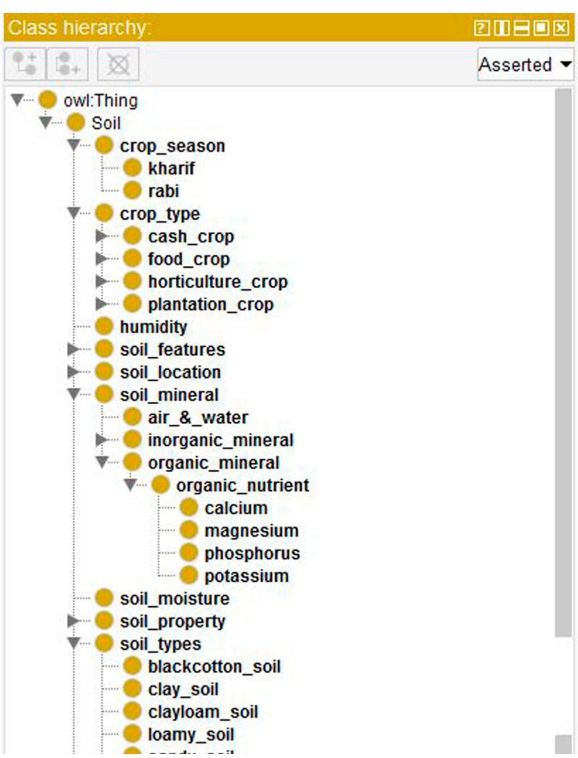

Figure 11: Class hierarchy for Multiple Agro_incremental mining

With each input, a vector S0 is created. The S0 is the vertex weight at one-time point.

At some point of time, the weight of the vertex changes depending on the weight of the factors influencing it. For graph representation, we can use a knowledgeable matrix about the group of objects and the relationships between them.

Let the I state the matrix that the entry of the matrix is the weight between the vertices i and j. We call it the approximate weight of the algorithm matrix.

$$S_1 = XS_0, \tag{1}$$

$$\text{For } n^{th} \text{step, } S_n = X^n S_0 \tag{2}$$

$$\text{For } (n+1) \text{ step, } S_{n+1} = X^{n+1} S_0 \tag{3}$$

If we write S_0as linear combination of eigen values

$$a_{ij}:S_0 = \lambda_i a_i \tag{4}$$

$$\text{Then } n^{th}\ S_n = \sum \lambda_i^n a^i \tag{5}$$

3.3.1 Rule Evaluation for Agro Incremental Mining Model

The performance of the ontology model is evaluated by comparing the rule validation, which will bring out the truthfulness of the model. Support, confidence, lift, conviction, and leverage are carried out for the rule evaluation.

Table 3: Multiple ontology rule evaluations

	Multiple ontology				
Rule	Support (X_c)	Confidence (X_c)	Lift (X_c)	Conviction (X_c)	Leverage (X_c)
A→C	0.21	0.20	1.17	1.04	0.030
A→PH	0.23	0.3	1.28	1.08	0.050
A→PO	0.24	0.3	0.89	0.96	−0.030
A→M	0.20	0.2	1.11	1.03	0.020
A→Y	0.05	0.19	0.79	0.99	−0.013
A→S	0.21	0.2	1.17	1.04	0.030
A→L	0.09	0.19	1.11	1.01	0.009
C→PH	0.02	0.18	0.50	0.89	−0.020
C→PO	0.02	0.19	0.33	0.78	−0.040
C→M	0.07	0.3	1.75	1.23	0.030
C→Y	0.007	0.0	0.50	0.96	−0.007
C→S	0.04	0.2	1.00	1.00	0.000
C→L	0.02	0.18	1.11	1.01	0.002
PH→PO	0.03	0.19	0.50	0.82	−0.030
PH→M	0.02	0.17	0.50	0.89	−0.020
PH→Y	0.00	0.0	0.00	0.93	−0.014
PH→S	0.03	0.18	0.75	0.94	−0.010
PH→L	0.02	0.19	1.11	1.01	0.002
PO→M	0.03	0.17	0.50	0.89	−0.030
PO→Y	0.007	0.0	0.33	0.95	−0.014
PO→S	0.03	0.18	0.50	0.89	−0.030
PO→L	0.02	0.19	0.74	0.98	−0.007
M→Y	0.007	0.0	0.50	0.96	−0.007
M→S	0.04	0.2	1.00	1.00	0.000
M→L	0.02	0.18	1.11	1.01	0.002
Y→S	0.02	0.3	1.43	1.13	0.006
Y→L	0	0.0	0.00	0.91	−0.006
S→L	0.02	0.17	1.11	1.01	0.002
CS→LS	0.02	0.4	10.00	1.90	0.018
CS→SS	0.01	0.3	6.25	1.28	0.008
CS→SLS	0.01	0.3	6.25	1.28	0.008
LS→SS	0.02	0.4	10.00	1.60	0.018
LS→SLS	0.02	0.4	10.00	1.60	0.018
SS→SLS	0.01	0.3	6.25	1.28	0.008

Support:

To bring out the evaluation process, the support is calculated by the number of transactions in database D to the total number of transactions. The support (X) is given by the expression

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

As a result, it is observed that

The range of support for individual ontology 1:[0,0.28]

The range of support for individual ontology 2:[0.08,0.46]

The range of support for individual ontology 3:[0.2,0.5]

The range of support for individual ontology 4:[0,0.28]

The range of support for multiple ontology:[0,0.24]

Confidence:

Confidence is defined as how often each item in Y appears in the transaction item in X.

$$\text{Confidence}(X \Rightarrow Y) = \frac{\text{Supp}(X \cup Y)}{\text{Supp}(X)}$$

As a result, it is observed that

The range of confidence for individual ontology 1: [0,0.4]

The range of confidence for individual ontology 2: [0.26,0.54]

The range of confidence for individual ontology 3: [0.35,0.56]

The range of confidence for individual ontology 4: [0.24,0.6]

The range of confidence for multiple ontology: [0,0.4]

Lift:

The lift value of an association rule is the ratio of the confidence of the rule and the expected confidence of the rule. If the lift value is greater than 1.0, it implies a strong

Table 4: Normalized multiple ontology rule evaluation

Rule	Normalized Support	Normalized Confidence	Normalized Lift	Normalized Conviction	Normalized Leverage
A→C	0.88	0.40	0.12	0.23	0.78
A→PH	0.96	0.60	0.13	0.27	1.00
A→PO	1.00	0.60	0.09	0.16	0.11
A→M	0.83	0.40	0.11	0.22	0.67
A→Y	0.21	0.20	0.08	0.19	0.30
A→S	0.88	0.40	0.12	0.23	0.78
A→L	0.38	0.20	0.11	0.21	0.54
C→PH	0.08	0.20	0.05	0.10	0.22
C→PO	0.08	0.20	0.03	0.00	0.00
C→M	0.29	0.60	0.18	0.40	0.78
C→Y	0.03	0.00	0.05	0.16	0.37
C→S	0.17	0.40	0.10	0.20	0.44
C→L	0.08	0.20	0.11	0.21	0.47
PH→PO	0.13	0.20	0.05	0.04	0.11
PH→M	0.08	0.20	0.05	0.10	0.22
PH→Y	0.00	0.00	0.00	0.13	0.29
PH→S	0.13	0.20	0.08	0.14	0.33
PH→L	0.08	0.20	0.11	0.21	0.47
PO→M	0.13	0.20	0.05	0.10	0.11
PO→Y	0.03	0.00	0.03	0.15	0.29
PO→S	0.13	0.20	0.05	0.10	0.11
PO→L	0.08	0.20	0.07	0.18	0.37
M→Y	0.03	0.00	0.05	0.16	0.37
M→S	0.17	0.40	0.10	0.20	0.44

(*continued*).

Table 4: Continued.

Rule	Normalized Support	Normalized Confidence	Normalized Lift	Normalized Conviction	Normalized Leverage
M→L	0.08	0.20	0.11	0.21	0.47
Y→S	0.08	0.60	0.14	0.31	0.51
Y→L	0.00	0.00	0.00	0.12	0.38
S→L	0.08	0.20	0.11	0.21	0.47
CS→LS	0.08	1.00	1.00	1.00	0.64
CS→SS	0.04	0.60	0.63	0.45	0.53
CS→SLS	0.04	0.60	0.63	0.45	0.53
LS→SS	0.08	0.80	1.00	0.73	0.64
LS→SLS	0.08	0.80	1.00	0.73	0.64
SS→SLS	0.04	0.60	0.63	0.45	0.53

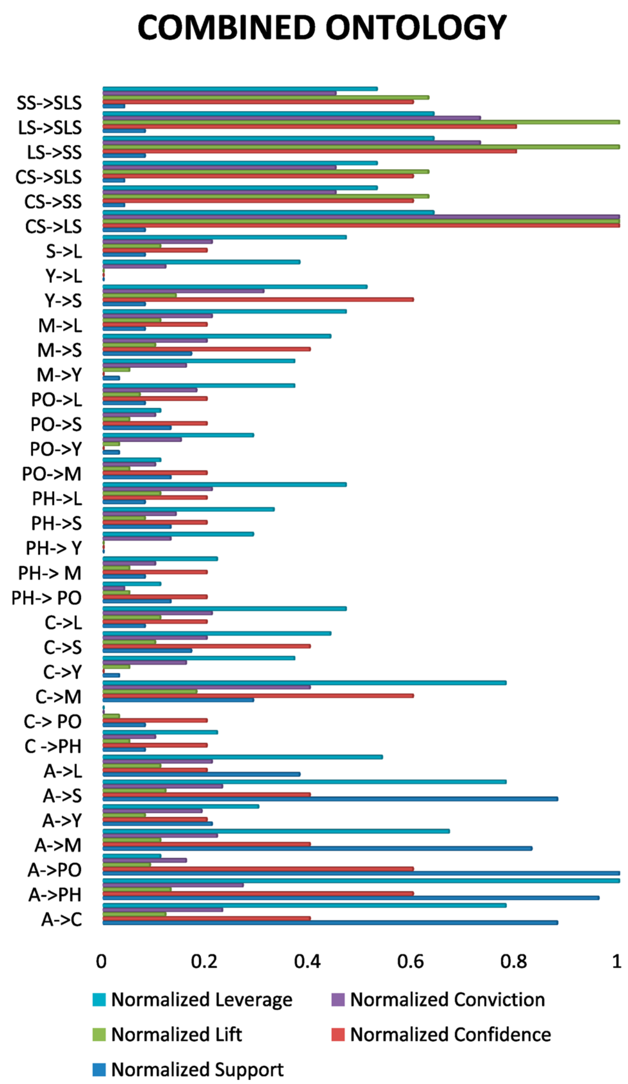

Figure 12: Chart for Normalized multiple ontology rule evaluation

association between X and Y.

$$Lift(X => Y) = \frac{P(X|Y)}{P(Y)} = \frac{Supp(XUY)}{Supp(X)xSupp(Y)}$$

As a result, it is observed that

The range of lift for individual ontology 1: [0,2]

The range of lift for individual ontology 2: [0.69,1.08]

The range of lift for individual ontology 3: [0.63,0.99]

The range of lift for individual ontology 4: [0.53,0.95]

The range of lift for multiple ontology: [0,10]

In ontology 1, 21 rules out of 28 are strongly associated. In ontology 2, 3, and 4, there is no strong association, whereas in multiple ontology 17 rules have a value greater than 1, and5 rules are closer to 1. Therefore, out of 34 rules, 22 rules are very much strongly associated.

Conviction:

Conviction is defined by the following expression

$$\text{Conv}(X \Rightarrow Y) = (1 - \text{supp}(Y))/((1 - \text{conf}(X \Rightarrow Y))$$

As a result, it is observed that

The range of conviction for individual ontology 1: [0.88,1.23]

The range of conviction for individual ontology 2: [0.76,1.09]

The range of conviction for individual ontology 3: [0.68,1]

The range of conviction for individual ontology 4: [0.63,0.93]

The range of conviction for multiple ontology: [0.78,1.9]

In ontology 1, 15 rules out of 28 are strongly associated. In ontology 2, 3, and 4, there is no strong association, whereas in multiple ontology 17 rules have a value greater than 1, and 12 rules are closer to 1. Therefore, out of 34 rules, 29 rules are very much strongly associated.

Leverage:

The leverage is computed using the following expession

$$\text{Leverage}(X \Rightarrow Y) = \text{Supp}(X \cup Y) - \text{Supp}(X) * \text{Supp}(Y)$$

The computed outcome of the leverage is

The range of leverage for individual ontology 1: [−0.02, 0.1]

The range of leverage for individual ontology 2: [−0.07, 0.04]

The range of leverage for individual ontology 3: [−0.12,0]

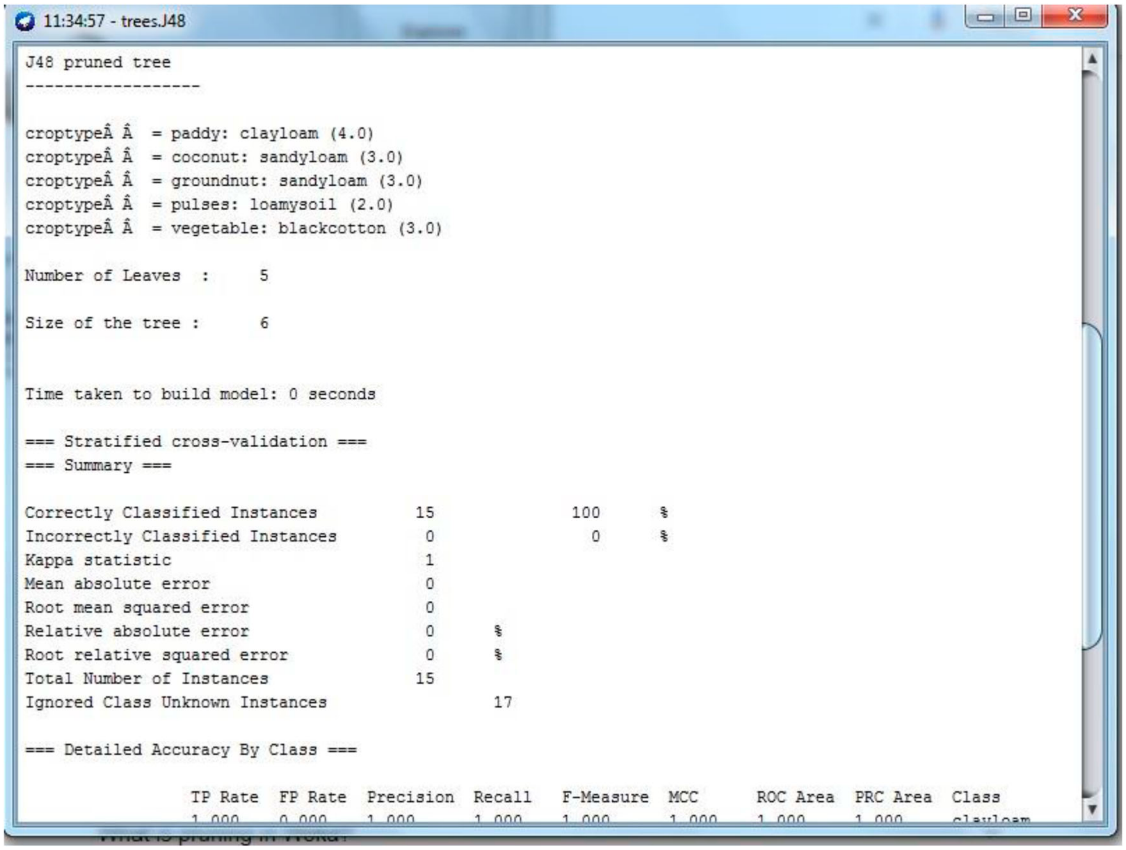

Figure 13: Pruning for selection phase – crop type

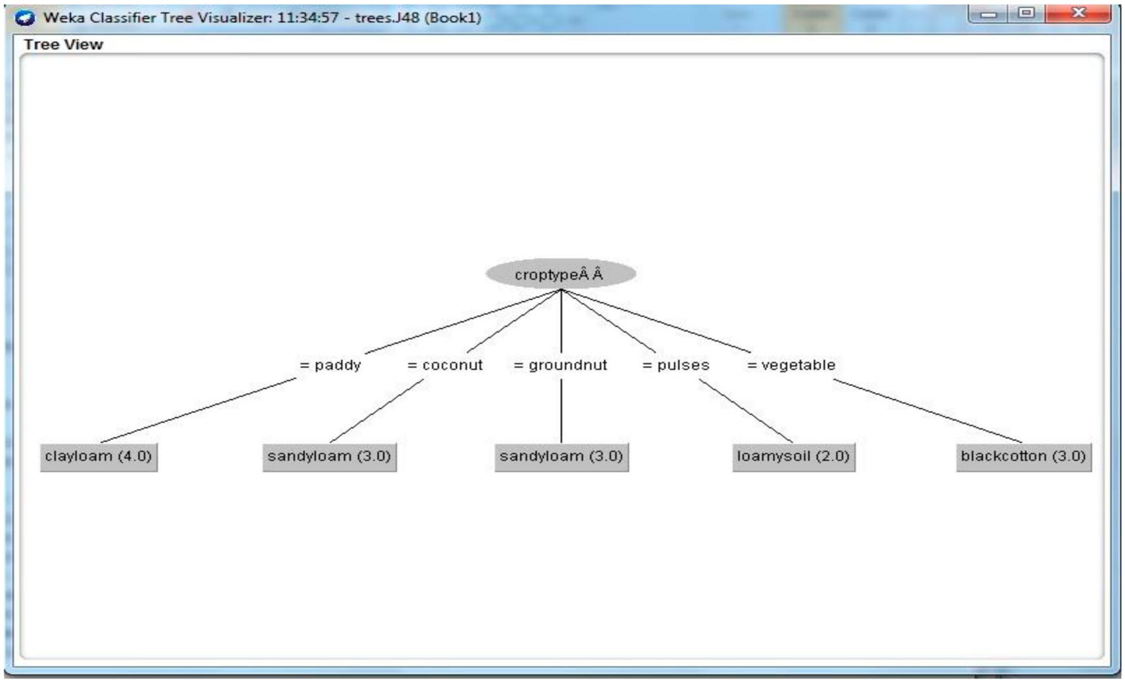

Figure 14: Decision tree Pruning for crop type

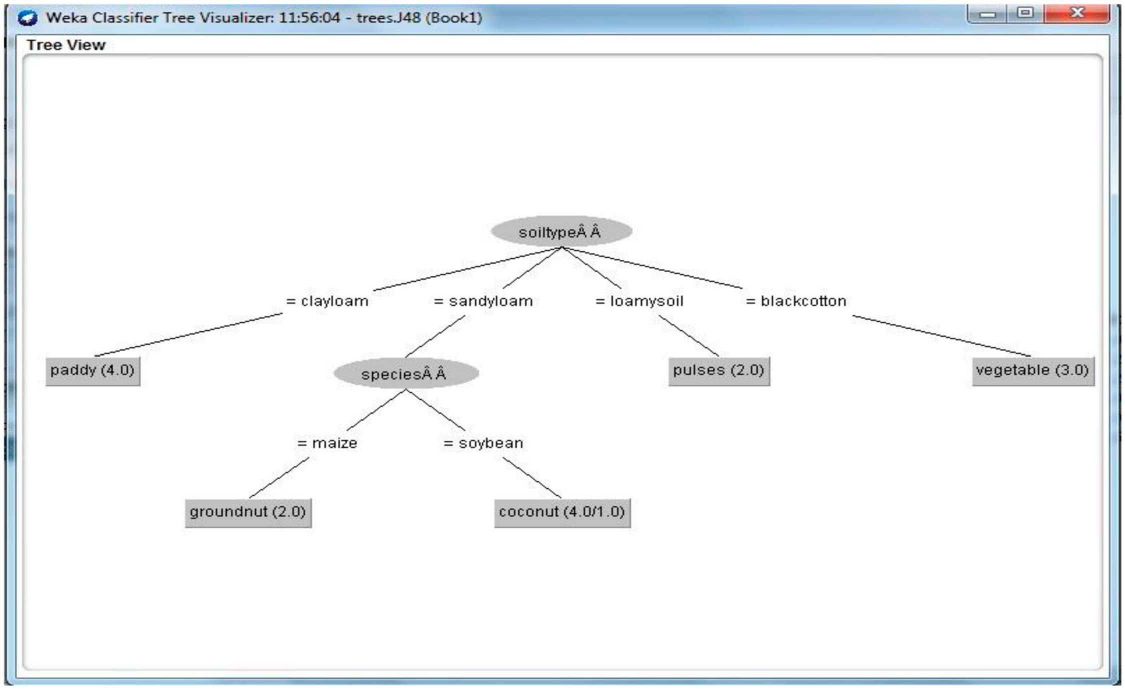

Figure 15: Decision tree Pruning for soil type

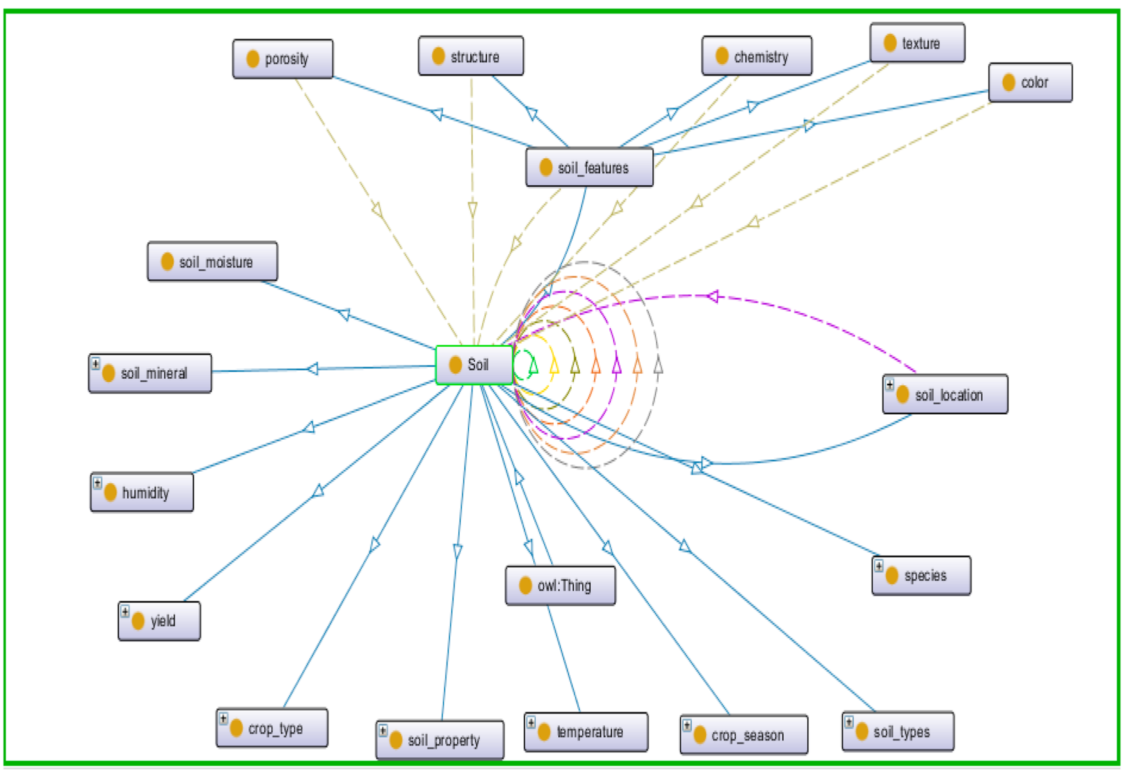

Figure 16: Visualized class hierarchy

The range of leverage for individual ontology 4: [−0.12, −0.01]

The range of leverage for multiple ontology: [−0.04, 0.05]

The value "0" indicates independence, and the value above "0" indicates acceptance of rules. From Table 3, it is noted that, in ontology 1, 2 rules are not desirable, and in ontology 3, 1 rule is not desirable, whereas in multiple ontology 2 rules, out of 34 rules are not desirable.

Normalized Support, Confidence, Lift, Conviction, Leverage for Multiple:

Table 4 and Figure 12. The Normalized support, confidence, lift, conviction, leverage for multiple ontology rule evaluation is given in the Table 4 and normalized chart is given in Figure 1.

3.3.2 Ontology Pruning

The intention of the pruning is to automatically pull out a subset of conceptualization that is appropriate to the ontology domain. In this ontology pruning, irrelevant data for the subset concept are removed, which will increase the processing time of the concept. In the following concept, two stages are involved. The first phase consists of the selection phase, and the second phase consists of the pruning phase. In the selection phase, a subset of crop type is selected. In the pruning phase, decision tree pruning is applied to the subset of the concept, which will increase the execution time. A sample snapshot is applied for illustration purposes (Figures 13–15).

4. AGRO_INCREMENTAL MINING MODEL VISUALIZATION

Data visualization is the technique used to communicate data or information in a graphical form. Data values will be represented visually by a pictorial mark such as size or color will help in determining the value of data. Ontology-based agro incremental mining model is shown in a visualized form in Figure 16.

5. CONCLUSION

Ontology is a tool for representing domain knowledge. A structured method of ontology is important for ontology development and evaluation. This paper presents the performance evaluation of individual ontology agro incremental mining with multiple ontology agro incremental mining models. The results of the comparative study bring out that multiple ontology agro incremental mining models have good performance than the individual ontology agro incremental mining model.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

REFERENCES

1. M. A. d. A. Leite and I. L. M. Ricarte, "Fuzzy information retrieval model based on multiple related ontologies," in *2008 20th IEEE International Conference on Tools with Artificial Intelligence*, 2008, pp. 309–16, DOI:10.1109/ICTAI.2008.72.
2. J. Lai, Y. Wang, R. Zhang, X. Gu, T. Yu, and J. Li, "Aggregating multiple ontology similarity based on IOWA operator," in *2010 2nd International Workshop on Database Technology and Applications*, 2010, pp. 1–4, DOI:10.1109/DBTA.2010.5659030.
3. S. Abburu and G. S. Babu, "A cluster based multiple ontology parallel merge method," in *2013 International Conference on Recent Trends in Information Technology (ICRTIT)*, 2013, pp. 335–40, DOI:10.1109/ICRTIT.2013.6844226.
4. X. Xu, G. M. Luis, A. Lobov, and J. L. Martinez Lastra, "Multiple ontology workspace management and performance assessment," in *2015 IEEE 13th International Conference on Industrial Informatics (INDIN)*, 2015, pp. 1063–8, DOI:10.1109/INDIN.2015.7281882.
5. J. Yue, W. Mu, X. Liu, and Z. Fu, "Using protégé to construct vegetable SCM knowledge ontology," in *2006 6th World Congress on Intelligent Control and Automation*, 2006, pp. 7123–7, DOI:10.1109/WCICA.2006.1714467.
6. Z. Fu, J. Yue, D. Lin and X. Liu, "Ontology-based metadata model for agriculture E-commerce knowledge management," in *Third International Conference on Semantics, Knowledge and Grid (SKG 2007)*, 2007, pp. 616–17, DOI:10.1109/SKG.2007.139.
7. J. Fan, X. Zhang, and T. Dong, "Research of plant domain knowledge model based on ontology," in *2008 3rd International Conference on Innovative Computing Information and Control*, 2008, pp. 108–108, DOI:10.1109/ICICIC.2008.451.
8. D. Liying, L. Hongjuan, H. Dongbin, W. Zhe, and L. Xuning, "Research on intelligent searching of agricultural information based on ontology," in *2012 International Conference on Computer Science and Service System*, 2012, pp. 1026–9, DOI:10.1109/CSSS.2012.260.
9. K. Phoksawat and M. Mahmuddin, "Ontology-based knowledge and optimization model for decision support system to intercropping," in *2016 International Computer Science and Engineering Conference (ICSEC)*, 2016, pp. 1–6, DOI:10.1109/ICSEC.2016.7859927.
10. R. K. Kodali and A. Sahu, "An IoT based soil moisture monitoring on LosantPlatform," in *2016 2nd International Conference on Contemporary Computing and Informatics (IC3I)*, 2016, pp. 764–8, DOI:10.1109/IC3I.2016.7918063.
11. M. Dholu and K. A. Ghodinde, "Internet of Things (IoT) for precision agriculture application," in *2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI)*, IEEE, 2018, pp. 339–42, DOI:10.1109/ICOEI.2018.8553720.
12. G. Codeluppi, A. Cilfone, L. Davoli, and G. Ferrari, "VegIoT garden: A modular IoT management platform for urban vegetable gardens," in *IEEE International Workshop on Metrology for Agriculture and Forestry*

(MetroAgriFor), 2019, pp. 121–6, DOI:10.1109/MetroAgriFor.2019.8909228.

13. J. Gomez Gill, M. Martilnez Zarzuela2, F. J. Diaz Pernas, J. F. Diez Higuera, D. Gonzalez Ortega, and D. Boto-Giralda, "Dynamic generation of fertilizer maps using GPS technology," in *2005 IEEE Conference on Emerging Technologies and Factory Automation*, 2005, pp. 667–72, DOI:10.1109/ETFA.2005.1612739.

14. L. Tan, R. Haley, R. Wortman, Y. Ampatzidis, and M. Whiting, "An integrated cloud-based platform for labor monitoring and data analysis in Precision agriculture," in *2013 IEEE 14th International Conference on Information Reuse & Integration (IRI)*, 2013, pp. 349–56, DOI:10.1109/IRI.2013.6642492.

15. N. M. Cid-Garcia, V. Albornoz, Y. A. Rios-Solis, and R. Ortega, "Rectangular shape management zone delineation using integer linearprogramming," *Comput. Electron. Agri.*, Vol. 93, pp. 1–9, 2013.

16. G. L. A. Carrijo, D. E. Oliveira, G. A. de Assis, M. G. Carneiro, V. C. Guizilini, and J. R. Souza, "Automatic detection of fruits in coffee crops from aerial images," in *2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR)*, 2017, pp. 1–6, DOI:10.1109/SBR-LARS-R.2017.8215283.

17. P. O. Skobelev, D. S. Budaev, G. Y. Voshchuk, A. N. Mochalkin, S. V. Susarev, and N. G. Gubanov, "Planning of production processes for agricultural enterprises using joint competences of university and IT company in development of knowledge bases," in *2017 IEEE VI Forum Strategic Partnership of Universities and Enterprises of Hi-Tech Branches (Science. Education. Innovations) (SPUE)*, 2017, pp. 141–3, DOI:10.1109/IVForum.2017.8246074.

18. J. Dong, J. G. Burnham, B. Boots, G. Rains, and F. Dellaert, "4D crop monitoring: spatio-temporal reconstruction for agriculture," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, 2017, pp. 3878–85, DOI:10.1109/ICRA.2017.7989447.

19. G. Sehgal, B. Gupta, K. Paneri, K. Singh, G. Sharma, and G. Shroff, "Crop Planning using stochastic visual optimization," in *2017 IEEE Visualization in Data Science (VDS)*, 2017, pp. 47–51, DOI:10.1109/VDS.2017.8573443.

20. P. Lottes, J. Behley, A. Milioto, and C. Stachniss, "Fully convolutional networks with sequential information for robust crop and weed detection in precision farming," *IEEE Robotics Automation Lett.*, Vol. 3, no. 4, Oct. 2018.

21. Y. C. Kuang, L. Streeter, and M. J. Cree, "Evaluation of deep neural network and AlternatingDecision tree for kiwifruit detection," in *2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*,2019, pp. 1–6, DOI:10.1109/I2MTC.2019.8826818.

22. G. K. Michelon, *et al.*, "Software AgDataBox-Map to precision agriculture management," *SoftwareX*, Vol. 10, pp. 1–7, 2019, DOI:10.1016/j.softx.2019.100320.

23. N. Li, X. Zhang, C. Zhang, H. Guo, Z. Sun, and A. X. Wu, "Real-time crop recognition in transplanted fields with prominent weed growth: A visual-attention-based approach," *IEEE Access*, Vol. 7, pp. 185310–21, 2019, DOI:10.1109/ACCESS.2019.2942158.

24. C. O. Martinez-Ojeda, T. M. Amado, and J. C. Dela Cruz, "In field proximal soil sensing for real time crop recommendation using fuzzy logic model," in *2019 International Symposium on Multimedia and Communication Technology (ISMAC)*, 2019, pp. 1–5, DOI:10.1109/ISMAC.2019.8836160.

25. C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, and A. Pretto, "Agricolmap: Aerial-ground collaborative 3D mapping for precision farming," *IEEE Robotics Automation Lett.*, Vol. 4, no. 2, pp. 1085–92, 2019.

26. K. O. Flores, L. M. Butaslac, J. E. M. Gonzales, S. M. G. Dumlao, and R. S. J. Reyes, "Precision agriculture monitoring systemusing wireless sensor network and raspberry Pi local server," in *2016 IEEE Region 10 Conference (TENCON)*, 2016, pp. 3018–21, DOI:10.1109/TENCON.2016.7848600.

27. M. Saleh, I. H. Elhajj, D. Asmar, I. Bashour, and S. Kidess, "Experimental evaluation of low-cost resistive soil moisture sensors," in *2016 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET)*, 2016, 179–84, DOI:10.1109/IMCET.2016.7777448.

28. Z. Yang, W. Crow, L. Hu, L. Di, and R. Mueller, "Smap data for cropland soil moisture assessment: A case study," in *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 2017, pp. 1996–9, DOI:10.1109/IGARSS.2017.8127373.

29. S. Marios and J. Georgiou, "Precision agriculture: Challenges in sensors and electronics for real-time soil and plant monitoring," in *2017 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, 2017, pp. 1–4, DOI:10.1109/BIOCAS.2017.8325180.

30. G. Nithin Reddy, M. Danish, Y. SyamBabu, and G. Koperundevi, "Automatic irrigation and soil quality testing," in *2018 International Conference on Recent Innovations in Electrical, Electronics & Communication Engineering (ICRIEECE)*, 2018, pp. 1363–7, DOI:10.1109/ICRIEECE44171.2018.9009114.

31. A. A. El-magrous, J. D. Sternhagen, G. Hatfield, and Q. Qiao, "Internet of things based weather-soil sensor station for precision agriculture," in *2019 IEEE International Conference on Electro Information Technology (EIT)*, 2019, pp. 92–7, DOI:10.1109/EIT.2019.8833811.

32. I. Mednieks, "A method for correction of rural multispectral aerial image mosaics," in *2012 13th Biennial*

Baltic Electronics Conference (BEC2012), October 3–5, 2012.

33. E. Bindlish, A. Lynn Abbott, and M. Balota, "Assessment of peanut Pod maturity"," in *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 2017, pp. 688–96, DOI:10.1109/WACV.2017.82.

34. M. P. Wachowiak, D. F. Walters, J. M. Kovacs, R. Wachowiak-Smolíková, and A. L. James, "Visual analytics and remote sensing imagery to support community-based research for precision agriculture in emerging areas," *Comput. Electron. Agric.*, Vol. 143, pp. 149–64, 2017.

35. Y. Xu, Z. Gao, L. Khot, X. Meng, and Q. Zhang, "A real-time weed mapping and precision herbicide spraying system for row crops," *Sensors*, Vol. 18, p. 4245, 2018, DOI:10.3390/s18124245.

36. B. P. Vijaya Kumar, N. K. Mahadev Mohit, M. S. Pawan Ranjith, N. D. Nadig, and K. P. Nikita Menon, "Augmentation on satellite imagery with information integrated farming," in *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 2019, pp. 1–5, DOI:10.1109/ICECCT.2019.8869021.

37. S. G. Santos, J. C. Melo, R. G. Constantino, and A. V. Brito, "A solution for vegetation analysis, separation and geolocation of management zones using aerial images by UAVs," in *2019 IX Brazilian Symposium on Computing Systems Engineering (SBESC)*, 2020, pp. 1–8, DOI:10.1109/SBESC49506.2019.9046079.

38. X. Chen and R. Roeber, "Monitoring soybean disease and insect infection patterns in Nebraska," in *2005 IEEE International Conference on Granular Computing*, 2005, pp. 128–30, DOI:10.1109/GRC.2005.1547250.

39. M. Zhang, M. Wang, L. Chen, S. S. Ang, C. V. Nguyen, and J. Zhu, "An automatic fluidic system for the rapid Detection of soil nutrients," in *2008 IEEE International Conference on Automation and Logistics*, 2008, pp. 2742–6, DOI:10.1109/ICAL.2008.4636639.

40. P. Venkata Krishna, S. Misra, S. Sivanesan, and M. S. Obaidat, "Learning automaton based context oriented middleware architecture for precision agriculture," in *2015 International Conference on Computer, Information and Telecommunication Systems (CITS)*, 2015, pp. 1–5, DOI:10.1109/CITS.2015.7297720.

41. N. Gandhi and L. J. Armstrong, "Rice crop yield forecasting of tropical wet and dry climatic zone of India using data mining techniques," in *2016 IEEE International Conference on Advances in Computer Applications (ICACA)*, 2016, pp. 357–63, DOI:10.1109/ICACA.2016.7887981.

42. K. Jedlička and K. Charvát, "Visualisation of big data in agriculture and rural development," in *IST-Africa week conference (IST-Africa)*, 2018, pp. 1–8.

43. T. M. Pinho, J. o. Paulo Coelho, J. Oliveira, and J. Boaventura-Cunha, "An overview on visual sensing for automaticcontrol on smart farming and forest management," in *2018 13th APCA International Conference on Automatic Control and Soft Computing (CONTROLO)*, Jun. 4–6, 2018.

AUTHORS

E Murali is a research scholar in the Vellore Institute of Technology , Vellore, India. He received the bachelor's degree in computer science and engineering from Anna University affiliated college and master's in computer science and engineering from Dr MGR Research and Educational Institute. His areas of interest include data mining, ontology mining and knowledge engineering.

Email: emurali88@gmail.com

S Margret Anouncia is professor at the Vellore Institute of Technology, Vellore, India. She received her bachelor's degree in computer science and engineering from Bharathidasan University and master's in software engineering from Anna University. She has been awarded a doctorate in computer science and engineering at VIT University. Her area of specialization includes digital image processing, software engineering, and knowledge engineering.

Corresponding author. Email: smargretanouncia@gmail.com, smargretanouncia@vit.ac.in