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Deep Neural Network System Using Ontology to Recommend Organic Fertilizers for a Sustainable Agriculture

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ABSTRACT

The highest challenge humankind is facing in the current time period is the enormous population growth and the need to meet the food and nutrient to the population. To meet the enormous production, the farmers are more relayed on the usage of chemicals to increase the food production during the cultivation process. Inclination towards chemical fertilizers is because of their popularity and availability, the over usage of these chemicals is a root cause of many major problems like nutrient-less crops, soil quality degradation, and environmental hazards in the long run. The availability of a knowledge base of the soil quality parameters and their related organic fertilizers according to the farmer's region can decrease the inclination towards the utilization of chemical fertilizers and adopt the usage of organic fertilizers. To help in this process of a major change in farming we built an ontology oriented deep learning model which recommends the farmers in choosing the best organic fertilizers based on the soil quality. The domain ontology construction for agriculture is based on semantic language which can be reused in the future. The knowledge base is then utilized by the deep learning model to process the data and recommend the best suitable fertilizers.

1. INTRODUCTION

India is well known for its diversified agricultural crops and their practices. Agriculture is called the backbone occupation of India contributing 70% of the population employed in agriculture. India is the fastest developing country, agriculture plays a very prominent role in development, employment, and source of raw materials which directly affects the economic growth of India helping the growth of GDP predominantly [1]. Indian agriculture is the most diversified field. The cultivation culture varies from geographical regions, historical practices, soil diversity, seasonal changes, the demand for the crop and many more factors [2].

With the rapid growth of population sufficient food production to meet the growth plays a challenge with the minimum amount of cultivation land available with the cause of development. This scenario is not just a part of India it's a challenge faced by the world. To reach the maximum yield unscientific methodologies, inorganic fertilizers and pesticides are used to the maximum extent. The unethical usage of inorganic fertilizers has degraded the nutrient value of soil which makes the cultivation land non-reusable and also inefficient in producing a nutritious yield. It's high time to orient towards saving the limited cultivation land by adopting organic fertilizers in the cultivation practices [3]. Adopting organic fertilization helps maintain the nutrient of soil helping in sustainable agriculture. Soil quality is measured on the basis of chemical properties, soil is tested for PH, Nitrogen, Phosphorus, Nitrogen and Potassium to evaluate the quality and the stage at which the soil needs to be treated to get a good yield [4].

Agriculture practices are widely a diverse field when it comes to India [5]. The agriculture demands, seasons, environment, methodology adopted by each farmer, fertilization technique, culture is widely diverse and has multi dimensions to it. It is also evident that acquiring information related to agriculture is a very tedious task. The farmers have limited access to knowledge related to the type of crop that can be cultivated, fertilization technique, price variation, and policies available to them. As the diversity increases having a default knowledge accumulation technique with a simple database is not an efficient way to retrieve the information.

In this paper, we are trying to address the two main problems in agriculture. Firstly, having a domain knowledge of agriculture which is related to a specific geographical region with all the relevant information needed for cultivation. Secondly, building a recommender system for organic fertilizers using deep learning.

An ontology is a direct approach to managing complex agricultural data and their dimensions effectively. Ontology is nothing but a generalized format for representing knowledge [6]. As we have already observed the dependency present between various domains in agriculture will help the farmers in sustainable agriculture ontologies can actually provide interoperability between the domains and establish a better understanding of the domain [7]. Extensively generalizing an ontology: they define the entities, domains and attributes that are present in the domain and make it accessible to a machine-interpretable format [6].

Deep learning is an extension of machine learning. Deep learning is very popular as it can address complex problems effectively with a minimum amount of time [8]. Deep learning has a promising result with its adopting nature in solving any kind of data like images, sound, and natural languages with good results. Leveraging these advantages of deep learning in a complex domain of agriculture a promising system can be built. When the knowledge base of the domain is present in a machine-interpretable format, utilizing the information related to fertilizers and soil a deep learning model is built to recommend the organic fertilizers to the farmers handily which encourages and helps the farmers in achieving a sustainable agriculture practice benefiting soil to maintain its nutrient value and helping it to rejuvenate.

2. OVERVIEW AND SURVEY

Ontology act as a medium to explain the domain. By acting as a medium, they explain the domain formally, explicitly specifying the sharable information of the domain. This property of ontology solves information sharing between different fields. Ontology also facilitates to access the knowledge base in a machine-readable format. They also act as a backbone for semantic web where the semantic web acts as a retrieval platform for the complex data.

The development of a knowledge base helps in cooperative knowledge sharing among all the dependencies of agriculture by which ontology can also act as a search engine for knowledge retrieval [9]. A study was conducted in Thailand on Rice disease identification and control recommendation to farmers by building a domain ontology and was evaluated with different stakeholders in addressing the queries related to rice crop disease. With this research, they filled the gap that existed between the knowledgebase of ontology and semantic technologies [10]. To fill the gap that exists in searching for the kind of diseases utilizing the capacity of a semantic method with the help of OWL (Web ontology language) was developed and using queries diseases were retrieved [11]. Sri Lankan research found the problem related to agricultural information and utilized ontology by creating SPARQL as an endpoint for retrieval of information, they built a domain ontology that is a user-centric agricultural knowledge repository system. The system they built can be used in different ways like reusing, extending, modifying and pruning [12]. Well-maintained practices in agriculture are maintained or acknowledged and shared for the betterment of agricultural practices [13]. A domain ontology named agricultural online service was developed by keeping knowledge sharing as the main idea of agriculture which supported a multi-linguistic approach [14]. This research showcases the capacity of the relationship property of ontology. A knowledge management system for agriculture particularly for a wheat crop a novel approach that oracle supports RDF (Resource description framework) and OWL to present meaningful knowledge to the usage. The average rating provided by the expert by evaluating the ontology model vs the traditional knowledge management model is very much greater in comparison with the knowledge model [13].

Deep learning is an advance of machine learning. Deep learning algorithms are conceptualized on the basis of the human brain [15]. They have evidently performed and produced outstanding results. Deep learning uses multi-layer, layer-to-layer interconnection to address complex problems by learning the training and target even in an unsupervised and complex dataset. The main aim of deep learning is to understand the data feature from the lower level and then form a higher-level dimensionality abstraction of the feature semantically to rule out the manual effort to make the complex data into a machine-feedable form.

Leveraging machine learning techniques can be extensively seen in building recommender systems. We would like to brief a few of them in the below Table 1 as they form a strong base for improvising the recommendation systems. With this study, we can conclude that the prediction of disease, crop or fertilizer has been reproduced effectively but the efficiency, time, robustness, and adaptability of the system to dynamic changes when it comes to rigorous change of the aspects can be handled with the adoption of building recommender system with deep learning techniques.

Table 1. Machine learning algorithm discussion

Algorithm used for recommender system	Outcome
Random forest	They have made a complete survey of the implementations made by adopting a machine-learning random forest algorithm to predict pesticides and fertilizers by involving the methodology of text processing. They discuss the outcomes produced by them in detail and proofs that the machine learning algorithm is efficient enough to make the recommendations [16].
K-NN, Random Forest, Gradient boosted decision tree, Regularized greedy forest.	An overall effort was made to build a recommendation system that predicts yield and also disease detection. The overall system helped in many ways by predicting the market price, suggesting the best crop to opt for, suggesting the optimum date for cultivation, evaluating demand and supply, weed detection, and fertilizer prediction. The system concentrated the overall picture of agriculture practices [17].
Regression algorithms (Support vector regression, Polynomial regression, Linear regression, Random Forest)	Using majority voting by combining the best algorithms they have built a yield recommendation system based on the crop by considering geographical region, soil chemical properties, and weather data. They have increased the accuracy to 94% than the previous methodologies used [18].
SVM Classification, Decision Tree	They built a system to recommend pest control based on the crop. They have considered almost all crops into consideration to predict the pest. The model shows SVM has outperformed with 89% accuracy than the rest of the algorithms [19].

Recommender Systems work based on defending the over-flooded information against customized information considering the user choice, and personalization [20, 21]. This makes the user experience more meaningful. The advances in deep learning, has made a remarkable change in the architecture of the recommender system by providing stateful results. Deep learning has also helped in improvising the performance measure of the recommender system [22]. Deep learning can capture linear which is user preference and also non-linear which is not a user preference and do the recommendation [23, 24]. It is also able to capture the intricate relationship between all the data sources like text, contextual and visual [22]. There are many who has built a system to recommend features like pest control based on the crop. They have considered almost all crops into consideration to predict the pest. Considering a model built on SVM has outperformed with 89% accuracy than the rest of the algorithms [19].

There are three types of recommender system:

Content-based recommender system: They work based on past reviews, likes or dislikes given by the user by considering the explorative characters of the item and then recommending a new item/user [22, 23].

Collaborative recommender system: They recommend the item by considering the inclination of the current user with other user likes and dislikes [22, 23].

Hybrid recommender system: Hybrids are divided into three types. Monolithic, parallel and pipeline recommender. Monolithic leverages the integration of several recommender systems and then integrates them into one. The other two require two strategies of the recommender to combine and produce the recommendation [22, 23].

Utilization of the above-mentioned recommender architecture has been witnessed in the agriculture field lately. Climatic conditions play a very important role in agriculture. By considering the importance of climate a crop improvisation recommender system based on climate was built with an average accuracy score of ninety percent. A combination of collaborative filtering and case-based reasoning enhances the performance of recommending the best weather condition based on the crop. The recommender system combined collaborative filtering along with case-based reasoning making it a novel approach in a hybrid recommender system [24]. Krishi Mantra is an agriculture recommendation system developed by considering the advantages of ontology and deep learning. They identified the gap that present in the data availability and its reachability, they built a domain ontology which acts as a knowledge base and recommends the required information based on the geographical data, the recommender system inherits the advantages of neural network and resolves the query from the farmers [25].

A collaborative recommender system to answer the questions of the farmer based on the proposed government schemes was built efficiently which supported three languages [26]. SyrAgri is a recommender system that sends recommendations in Mali to the farmer using a collaborative filtering approach. It recommends practices of the crop and type of crop based on parameters like soil type, yield, season, and life cycle of the crop [27].

With the previously mentioned studies, we observe that ontology is an efficient knowledge management system for a multi dimension involving fields like agriculture. To make a decision or predict from the knowledge an application of deep learning which is capable of not just processing the data but also which can learn the features from the data can be applied to recommend organic fertilizers to the farmers based on the soil type. The previous efforts mostly concentrated on recommending crops, pest control and fertilizer recommendation which lacked a domain ontology which eases the knowledge storage, the study also shows organic fertilizer recommender system was not been considered extensively.

3. METHODOLOGY

3.1 Data over-view

The data relating to soil chemical property is gathered from the agricultural soil testing centres near Mysuru, Karnataka, India. The chemical properties which were measured from the soil are PH, EC, Nitrogen, Phosphorus, and Potassium. The soil is mainly identified and classified as black and red soil. The information related to organic fertilizers with respect to the soil quality is gathered from the farmers who have adopted organic cultivation practices and also from the government fertilizer centre experts from the data collected region.

3.2 Domain ontology

A domain ontology is the best solution when we are dealing with agricultural data which is heterogeneous and has difficulty in interoperability [28]. Hence, we built a domain ontology by considering an overall aspect of agriculture activities and the dependent factors required for sustainable growth.

Ontology building is a continuous and iterative process. Complete understanding of the domain from different sources and validation is a key challenge. It must be capable of adapting to future changes without requiring the same amount of rework. Identification of class, sub-class their respective objects, properties, inheritance and hierarchy which are the major skeleton of the ontology is identified according to the domain.

We used protégé as a tool to build the ontology [29, 30]. The tool is capable to handle the structure easily. It also allows querying the ontology effectively.

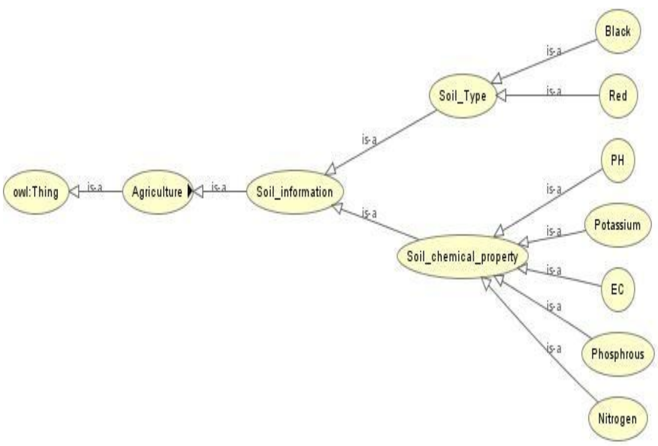

Figure 1. Class and sub class of soil and its chemical properties

In the initial stage, a part of domain ontology was built concerning soil chemical properties. Based on the constructed ontology, we built a deep neural network to classify the soil into healthy or non-healthy depending on the chemical parameter. The system helped to store the knowledge effectively and retrieve the information. As already mentioned, ontology enables data to be in a machine-readable format. By utilizing this we classified the soil into healthy and unhealthy classes with a backpropagation algorithm which produced 93 percent of accuracy [15]. In the later stage, ontology is extended by adding all the required domains which are necessary for agriculture. The extension involved organic fertilizer as a domain with respect to the data collected. Figure 1, represents the domain ontology hierarchy with respect to soil types present in the region and its chemical property and also their sub classes. Figure 2, represents the domain ontology hierarchy of organic fertilizers and their instances.

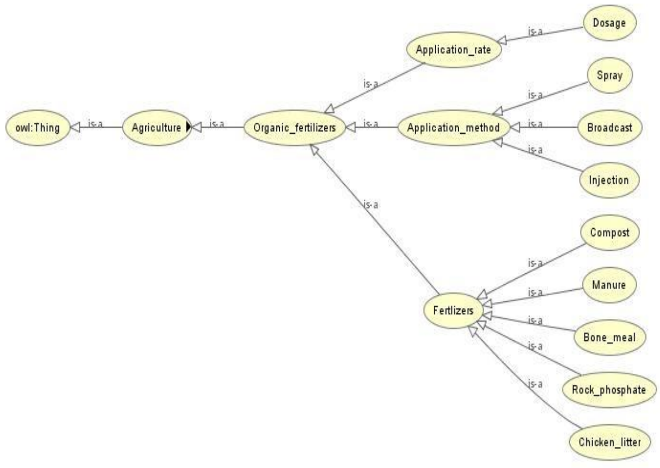

Figure 2. Class and sub class of organic fertilizer domain

3.3 Recommender system

The previous model was built using backpropagation to classify the soil as healthy and unhealthy and is considered as a base model. We built a recommender system to recommend an organic fertilizer based on the lack of nutrient component in the soil when the soil is classified as unhealthy. The pictorial flow of the architecture of the recommender system is explained using Figure 3.

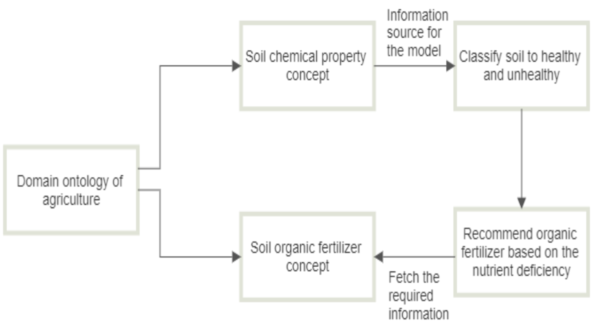

Figure 3. Overview of the architecture of recommender system

3.3.1 Wide and deep neural network for recommendation

Wide components in a generalized linear model which are combined with the neural network are the main idea of wide and deep neural networks.

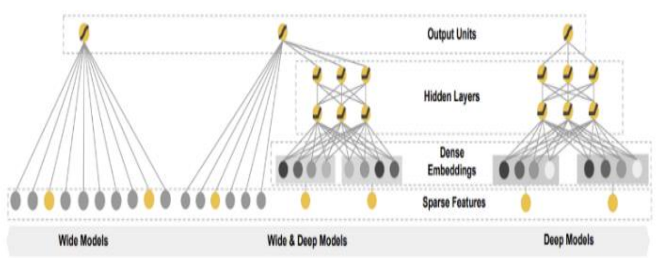

Figure 4. Wide and deep neural network architecture

Memorization is learning the periodic or habitual occurrence of the behavior, item or feature and learning the correlation present in the historical data. Generally memorizing happens in a linear format to predict the output. Generalization is understanding and containing the correlation and generating a new feature which is very new and has not occurred in the past. This solves the cold-start problem by understanding the patterns and generalizing them. The generalization and memorization concept explaining the architecture of the model is represented using Figure 4.

The architecture helps to train wide linear models and deep neural networks to combinedly do the recommendation by adopting generalization and memorization techniques to recommend items [31]. The wide component is nothing but a generalization of the linear model. Y=wTx+b, where Y is the prediction and x=[x_1, x_2, x_3, …., x_d] is a vector of features. w=[w_1, w_2, w_3, …., w_d] is the model features. The feature contains raw input and its features which are then transformed. The cross-product transformation is defined as the below equation. This helps in generalizing the model.

$$\phi_k(\mathrm{x}) = {}_{i=1}^{d}\pi x^{cki}{}_i \tag{1}$$

where, *cki* belongs {0, 1}.

The deep component in the architecture is a feed-forward neural network. This component helps in converting high-dimensional features are converted to lower-level dimensions which are nothing but embedding's. They are first initialized randomly and then values are trained to minimize the final loss. The converted low-dimension embedding's are then fed into hidden layers of the neural network. The computation of hidden layer is shown below.

$$p^{(i+1)} = f(X^{(i)}a^{(i)} + b^{(i)}) \tag{2}$$

Both the components are then combined by the weighted sum of their output logs and then fed to one loss function for training. Joint training happens by back-propagating the gradients from the output end to both model at the same time.

3.3.2 Deep learning and restricted boltzmann machine (RBM) for domain specific ontology

RBM are shallow networks that act as a building block of deep neural networks. The domain-specific ontology of soil and fertilizers are derived based on the ontology-based deep restricted Boltzmann machine model (OB-DRBM). This model helps to build the ontology by guiding the architecture of semantics and also helps in training and the validation of the model [32].

With our domain-oriented ontology which has the semantic level knowledge of soil fertility along with their fertilizers, we use OR-DRBM to guide in building the architecture of the ontology which also helps in training and validation of the deep learning model. Many challenges faced by deep learning in feature learning, predicting, and memory issues can be actively and effectively addressed using domain ontology which is constructed using OR-DRBM. It helps in making our domain ontology learn the representations related to the ontology. The representations are actually composed of the regular type of data with the complex semantic structure of the ontology.

The OR-DRBM are actually an extension of the Restricted Boltzmann Machine (RBM) which uses stochastic binary units, RBM's are made of deep learning neural networks that are fully connected with hidden layers and not within layers [33]. RBM have visible layers as 'v' and invisible layers as 'h', which are structured as a bipartite graph.

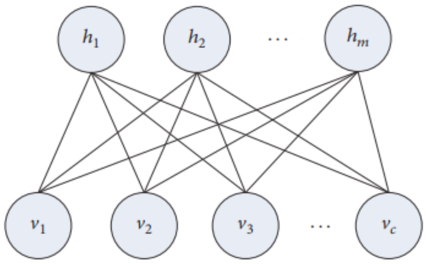

Figure 5. RBM architecture of hidden and visible layers

The probability of connection between hidden and visible are given as $p(v, h)$, X is the partition function. The hidden and visibility of the function in RBM model and interconnection between them are explained in the Figure 5.

$$p(v,h) = \frac{\exp(-E(v,h))}{X} \quad (3)$$

The RBM binary units $A(v, h)$ are defined with the below function, while $\{x_i, y_i\}$ are bias function for hidden and visible layers. This explains the probability of connections between them.

$$A(v,h) = -\sum_i x_i v_i - \sum_j y_j h_j - \sum_{i,j} v_i h_j w_{ij} \quad (4)$$

OB-DRBM architecture follows a hierarchical approach, which starts from top classes and then starts adding up sub-classes. In our domain ontology being *O* and semantic reasoning being *R* becomes the basic building block OB-DRBM model *U*. This follows sub-class relations $\rho(c) \in Q$ for each concept $c \in C$, for C, $Q \in O$. The model building starts by adding the top class of our ontology $c \in C$ for the sequence of subclass *Sc*. For every class of the ontology $c \in Sc$ we build the DRBM model. DRBM takes only its input for the top class of the ontology, the subclass takes input from the higher level and also from its own.

As we already have the DRBM model for every concept in the ontology we adopt a softmax layer Sc which makes learning semantic rich learning in agriculture ontology very easy. The softmax layer contains the target unit at every semantic level. Along with the softmax layer for every concept and DRBM layer, we also add multiple hidden multiple visible restricted Boltzmann machine (MVMH) layer Mc for the subclasses. For every concept *c* in our ontology, we have the DRBM model and each concept is connected to the softmax layer. DRBM decodes the feature from top-level concepts before passing it to the lower sub-classes during this process MVMH layer helps in generating an easy and understandable representation of high features and feeds into the lower sub-classes.

The OB-DRBM model is trained just like any other Boltzmann model. Initially, the model is trained module-wise and layer-wise by applying the greedy method. In the next stage, stochastic gradient descent is used across all the softmax layers to fine-tune the model. This method reduces the error for the layers of softmax output produced. We validate the consistency of output generated from every softmax layer in our model by applying a logistic regression. Let output from softmax be *S* then the output is explained by the below equation.

$$\tilde{z} = argmax_{sCS} \frac{\prod_{c \in s} f_C(n,w)[R(O, x \to s)]}{\sum_{sCS} \prod_{c \in s} \mathrm{fc(n,w)[R(O,x \to s)]}} \quad (5)$$

4. RESULTS

The domain ontology model which emphasizes deep learning recommender systems to predict the organic fertilizers produced a promising result depending on the soil's chemical properties.

The construction of the ontology is the first step in structuring and making the knowledge base for the agriculture domain. We built soil information ontology and organic fertilizers ontology by collecting the information from the farmers and stake holders using the protege tool and validated the ontology by querying the knowledge. In the next step we utilize the ontology by publishing it to sematic world and combine with our deep learning model to extensively use the knowledge to predict the organic fertilizers based on the soil chemical properties.

Our model takes input from farmers which are been tested at soil testing centres based on these values the recommender model recommends the top 'N' number of fertilizers, the farmers can choose the best among the recommendation.

The result in the recommender system is measured based on precision and recall. Both precision and recall take a value between 0 and 1. For every input from the user, the model produces an 'N' recommendation and the value of precession and recall is produced for the recommended items [34]. We also get a prediction rating for the recommended item, if the predicted rating is greater than 3.5 for the item then the item is relevant if lesser than 3.5 then the item is irrelevant.

Precision in the recommender system: Precision measures the amount of correctness the model predicted i.e. it gives the answer for the number of items which are correct from the recommendation system [35]. The top 'N' recommended items are given by calculating the precision. The precession is given based on the below pattern:

$$precession = \frac{(Number\ of\ recommended\ item\ at\ item\ 'N' that\ are\ relevent)}{Number\ of\ recommended\ items\ at\ N} \quad (6)$$

$$precession = \frac{(recommended \cap relavent)}{recommended} \quad (7)$$

Consider an example of how precision is calculated for the recommendation produced by the model for the user whose chemical property is Nitrogen and whose value is 27.9 which is actually a very low value. The system recommends the top three items as fertilizers for the value given. The precision values are mentioned below for the recommended items. The organic fertilizers are numbered with a unique identification number for more convenience in preparing ontology and model training. We have mentioned the name of the fertilizers in the brackets in the below Table 2.

Recall in recommender system: Recall defines the proportion of recommended items that are relevant among the items that are actually recommended [35]. The recall is expressed by the below equation.

$$Recall = \frac{(Number\ of\ recommended\ item\ at\ 'N' that\ are\ relavent)}{Total\ number\ of\ relavent\ items} \quad (8)$$

$$Recall = \frac{(recommended \cap relavent)}{relavent} \quad (9)$$

Table 2. Precession value for nitrogen recommended fertilizers

Precession	Recall	Item Recommended
0.79	0.71	2 (Blood meal)
0.78	0.64	1 (Manure)
0.83	0.77	2 (Blood meal)

With the above-discussed values of precision and recall for the value of Nitrogen entered by the user, the model is about to produce 80% precision in recommending the user organic fertilizers to be used to enrich the soil with Nitrogen components. The model can predict top N fertilizers for all the other chemical values given by the user.

5. CONCLUSIONS

We build a domain ontology by observing and considering most of the important dimensions involved in agriculture. We built and validated the ontology by utilizing OR-DRBM architecture. The model is populated with the data from soil testing centres and built a wide deep neural network architecture to recommend fertilizers to the farmers. Our architecture can be reproduced by adding any more classes or features without involving major changes. Ontology can be reused by adding any other dimensions required by agriculture depending on the socio conditions and regions. We have majorly considered soil properties for recommending fertilizers, the same methodology can be used to recommend the type of crop to be grown under recommended climatic conditions. Wide and deep neural network which is considered to recommend organic fertilizers had given promising performance with accuracy of 80 percent depending on the user soil chemical property. There is still a more place to improvise the accuracy of the recommender model in the future by adoting demographic or more complex hybrid recommender systems.

The model can also be extended to recommend the demand and supply of the crop based on the region, recommend warehouse availability and also the pricing of the crop.

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