A smart ontology based model to optimize crop decision support

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ABSTRACT

Effective crop recommendation systems are crucial for modern agriculture, yet existing models often struggle to adapt to dynamic environmental conditions and incorporate expert knowledge. This paper proposed a novel model that fuses decision tree (DT) algorithms with ontologies, combining robust data analysis with semantic knowledge representation. DT provide transparent, adaptable decision rules that respond to changing environmental factors, while ontologies structure domain expertise to enable deeper reasoning and improve accuracy. This integrated approach achieved a remarkable 99.77% accuracy on an Indian crop recommendation dataset, significantly outperforming previous methods. By merging the strengths of DT and ontologies, this model offers a powerful, adaptable tool for informed decision-making, supporting farmers in today's complex agricultural landscape.

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1. INTRODUCTION

Agriculture is a critical sector worldwide, serving as the foundation of many economies and providing a livelihood for billions. In India, the country's diverse climatic conditions and vast arable land enable the cultivation of a variety of crops, ranging from staples like rice and wheat to cash crops such as cotton, sugarcane, and spices [1]. Despite its potential, Indian agriculture [2] encounters numerous challenges, including fragmented landholdings, traditional farming methods, and susceptibility to climate change. One important remedy that has surfaced is precision agriculture, which focuses on making customized crop recommendations.

In order to determine which crops are most suited for a certain area, these recommendations take into account a number of variables, including soil type, climate, and resource availability [3], [4]. Humidity, precipitation, temperature, nitrogen (N), phosphorus (P), potassium (K), and pH levels are important factors that affect these recommendations. Achieving high accuracy in these predictions is essential, as inaccuracies can result in substantial agricultural losses. Researchers continue to refine these models to ensure reliable and effective crop selection strategies.

Data-driven decision-making and predictive analysis are made possible by machine learning algorithms [5], which improve accuracy and efficiency across a range of fields. Ontology with the semantic web rules language (SWRL) organizes knowledge structurally, facilitating data integration, retrieval, and interoperability, thereby improving information management and decision support systems. Integrating machine learning with ontology enables intelligent systems to leverage both statistical patterns and domain knowledge, resulting in more robust and context-aware applications with enhanced predictive capabilities [6].

Our model, an ontological decision tree (DT), surpasses traditional methods by combining the strengths of DT with the structured domain knowledge provided by ontologies. This integration enhances data interpretation, allowing for more meaningful feature extraction and accurate crop recommendations. High accuracy and interpretability are guaranteed by the hybrid approach, while more context-aware recommendations are made possible by the incorporation of many data sources, such as historical crop performance and real-time meteorological data, within an ontological framework. Optimization algorithms further refine the recommendations to be precise and tailored to specific farming conditions and goals. Additionally, our model is scalable and adaptable to various regions and crop types, making it versatile and applicable across different agricultural scenarios. Our ontological DT model is a major breakthrough in crop recommendation systems that will propel sustainable agriculture in the future by continuously attaining higher accuracy and better predictive performance.

By applying the ontological DT model to decision-making, this study seeks to increase the precision of forecasting the cultivation of 22 crops. The structure of the paper is as follows: section 2 examines relevant previous research, section 3 presents the suggested model, section 4 examines the model's results, and a comparative analysis of various models, and section 5 wraps up with a synopsis of the suggested methodology and suggestions for additional study.

2. RELATED WORK

Using a dataset of weather and soil variables, Pravallika *et al.* [7] created a machine learning model to forecast crops that would be suited for Indian agriculture [8]. They compared support vector machine (SVM), DT, logistic regression (LR), and Gaussian Naïve Bayes (GNB), with DT and GNB achieving 99.3% accuracy. Similar to this, Dahiphale *et al.* [9] divided the same dataset [8] into 70% training and 30% testing using seven machine learning models, including LR, DT, random forest (RF), SVM, Naïve Bayes, K-nearest neighbors (KNN), and neural network (NN). RF achieved the highest accuracy of 99.54%.

Using KNN, SVM, and RF, Musanase *et al.* [10] divided the data into 80% training and 20% testing to investigate how weather variations affect crop recommendation. In order to predict crops, they developed a graphical user interface (GUI) for entering data such as temperature, humidity, pH, rainfall, nitrogen, potassium, and phosphorus. Barvin and Sampradeepraj [3] designed a mobile app for crop recommendation using SVM, KNN, RF, ANN, and MLR, with data split 75% for training and 25% for testing, finding RF to be the most accurate at 95%.

Bandara *et al.* [11] developed an app using SVM and Naïve Bayes with data from Arduino sensors to recommend crops based on weather and soil conditions in Sri Lanka. Their model includes farmer feedback and supports English and Sinhala for improved accuracy. Massari *et al.* [12] used DT analysis for cardiovascular disease prediction, integrating Ontology with SWRL and a Reasoner for enhanced accuracy. In another study, they applied the same approach for breast cancer detection [13], where the model outperformed existing methods. Table 1 summarizes the recent accuracy results of various models on the same dataset [8], demonstrating the effectiveness of different approaches.

Table 1. Summary of latest accuracy results in India

Ref.	Proposed model	Accuracy (%)
[7]	DT	99.3
[7]	GNB	99.3
[9]	DT	99.09
[9]	LR	94.545
[9]	RF	99.545
[9]	KNN	98.636
[9]	Naïve Bayes	99.5
[9]	SVM	99.242

With a remarkable accuracy of 97.4%, a study in [14] presented the integration of a DT model with the SWRL to predict the presence of COVID-19 based on symptoms. Building on insights from these related studies, we have designed an innovative approach called the ontology-DT model. This method combines the advantages of ontological reasoning with DT to significantly increase the accuracy of crop recommendation systems.

3. METHOD

Building on the advantages outlined in our research, we introduce a novel model, the ontological DT, for crop recommendation. This model leverages the DT algorithm, which is highly effective for crop recommendation due to its capability to handle complex decision-making, its interpretability, and its efficiency in processing both numerical and categorical data. The suggested method uses the Pellet reasoner and the SWRL to extract decision-making rules from the DT algorithm and integrate them into an ontology. SWRL plays a key role in enhancing recommendations by enabling dynamic rule application and reasoning over the ontology, resulting in precise and context-aware crop suggestions. The goal of this approach is to increase crop recommendation accuracy. Figure 1 shows the workflow and structure of the suggested model.

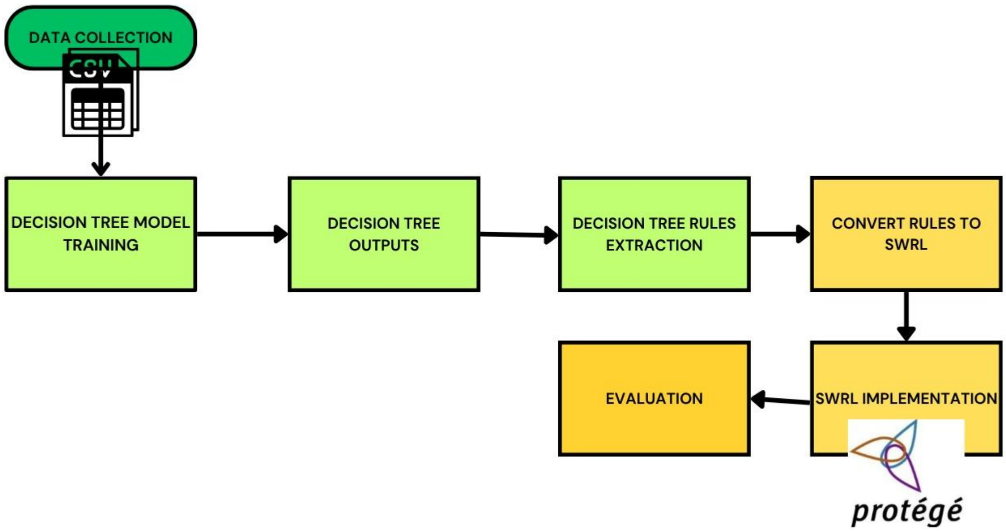

Figure 1. Proposed crop recommendation model

3.1. Data processing

In this study, we employ the Indian crop recommendation dataset [8] to validate the proposed methodology. With 2,200 occurrences and eight unique attributes per instance, the dataset provides a thorough foundation for study. A thorough synopsis of these characteristics is given in Table 2, which highlights their importance in relation to precise crop prescription.

Table 2. Dataset features

Features	Meaning
N	Nitrogen content in the soil.
P	Phosphorous content in the soil.
K	Potassium content in the soil.
Temperature	Ambient temperature in degree Celsius.
Humidity	The moisture level in the air.
PH	Soil pH level.
Rainfall	Amount of precipitation in mm.
Label	The crop type (22 crops): rice, maize, chickpea, kidney beans, pigeon peas, moth beans, mung bean, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, and coffee.

3.2. Decision tree model

In machine learning, the DT algorithm is frequently employed for both regression and classification applications. With each internal node representing a decision based on an attribute, each branch representing the decision's outcome, and each leaf node indicating a class label or regression value, it depicts decisions and their possible outcomes in a tree-like structure [15], [16]. Because of its interpretability, capacity to handle non-linear interactions, and resistance to outliers, this model was selected [17]. It is applicable in a variety of fields, such as fraud detection, medical diagnostics [18], and crop recommendation systems, because it is simple to apply and provides insights into the significance of different variables. The following sections will go into more detail on the DT model's use of Gini impurity as a measure for data splitting.

a. Gini impurity

A DT node's impurity or purity can be measured using the Gini impurity. Based on the distribution of labels in that node, it determines the likelihood that a randomly selected element will be erroneously classified if it is randomly labeled. In (1) is used to determine a node's Gini impurity:

$$Gini(t) = 1 - \sum_{i=1}^{n} pi^2 \tag{1}$$

where n represents the number of classes and pi is the likelihood of choosing an element of class i in node t.

b. Splitting criterion

The Gini impurity of the split serves as the basis for a DT splitting criterion. Utilizing (2), the Gini impurity of a split is determined:

$$Gini\ split = \frac{N_{left}}{N}.Gini(left) + \frac{N_{right}}{N}.Gini(right) \tag{2}$$

where: N is the sum of all the samples. The number of samples in the left and right nodes following the split is denoted by N_left and N_right, respectively. The left and right nodes' respective Gini impurity are Gini(left) and Gini(right).

c. Decision rule

Recursively dividing the data at each node according to the feature that offers the best split—which is identified by minimizing the Gini impurity—is how the DT expands. This process continues until the tree reaches its maximum depth or a stopping condition (such as a minimum number of samples in a node) is met. The decision rule for splitting can be described as (3):

$$\text{Split=arg}\min feature, threshold\ Gini\ split \tag{3}$$

d. Maximum depth

The maximum depth constraint ensures the tree does not grow beyond a certain depth. For a DT with a maximum depth of 12, the depth constraint is:

$$\text{Depth} \leq 12 \tag{4}$$

Our DT model, consisting of 61 nodes and 31 leaves, achieves an impressive accuracy of 99.3%, demonstrating its effectiveness in making accurate predictions. The DT rules extracted from this model are illustrated in Figure 2. These extracted rules are then utilized to generate SWRL rules, which are incorporated into the ontology model to enhance the decision-making process and improve the accuracy of crop recommendations.

```
|--- P <= 107.50
|   |--- K <= 65.00
|   |   |--- humidity <= 27.68
|   |   |   |--- class: kidneybeans
|   |   |--- humidity >  27.68
|   |   |   |--- rainfall <= 30.39
|   |   |   |   |--- class: muskmelon
|   |   |   |--- rainfall >  30.39
|   |   |   |   |--- K <= 25.50
|   |   |   |   |   |--- N <= 59.50
|   |   |   |   |   |   |--- humidity <= 90.00
|   |   |   |   |   |   |   |--- humidity <= 75.03
|   |   |   |   |   |   |   |   |--- rainfall <= 82.48
|   |   |   |   |   |   |   |   |   |--- humidity <= 59.94
|   |   |   |   |   |   |   |   |   |   |--- class: mothbeans
|   |   |   |   |   |   |   |   |   |--- humidity >  59.94
|   |   |   |   |   |   |   |   |   |   |--- rainfall <= 57.68
::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
|--- P >  107.50
|   |--- humidity <= 87.00
|   |   |--- class: grapes
|   |--- humidity >  87.00
|   |   |--- class: apple
|   |   |   |   |   |--- class: apple
```

Figure 2. Extracted DT rules

3.3. Ontology model

Ontologies are formal representations of knowledge within a specific domain, structured as a collection of concepts, categories, and their relationships. They serve as the foundation for semantic web technologies, enabling machines to perceive, process, and reason about information similarly to humans. By organizing knowledge into a hierarchical structure, ontologies enhance communication, interoperability, and integration across various systems and domains. They are especially useful in applications related to artificial intelligence and knowledge management [19], such as decision support systems [20], data integration, information retrieval, and natural language processing [21]. Ontologies facilitate the encoding of domain-specific knowledge in a standardized format, leading to more accurate, consistent representation, retrieval, and application of information [22], [23]. Protégé is a vital tool for creating and managing ontologies, enabling users to design, visualize, and edit complex models of domain knowledge. It supports interoperability and data integration, thereby enhancing semantic web applications and enabling advanced reasoning and decision-making across different domains. In our ontology model:

- "crop_recommendation" is the main class, and it has 22 subclasses: rice, maize, chickpea, kidney beans, pigeon peas, moth beans, mung bean, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, coconut, cotton, jute, and coffee.
- Each crop has a number of instances associated with it, which include data properties imported using the Cellfie plugin in Protégé, as shown in Figure 3.

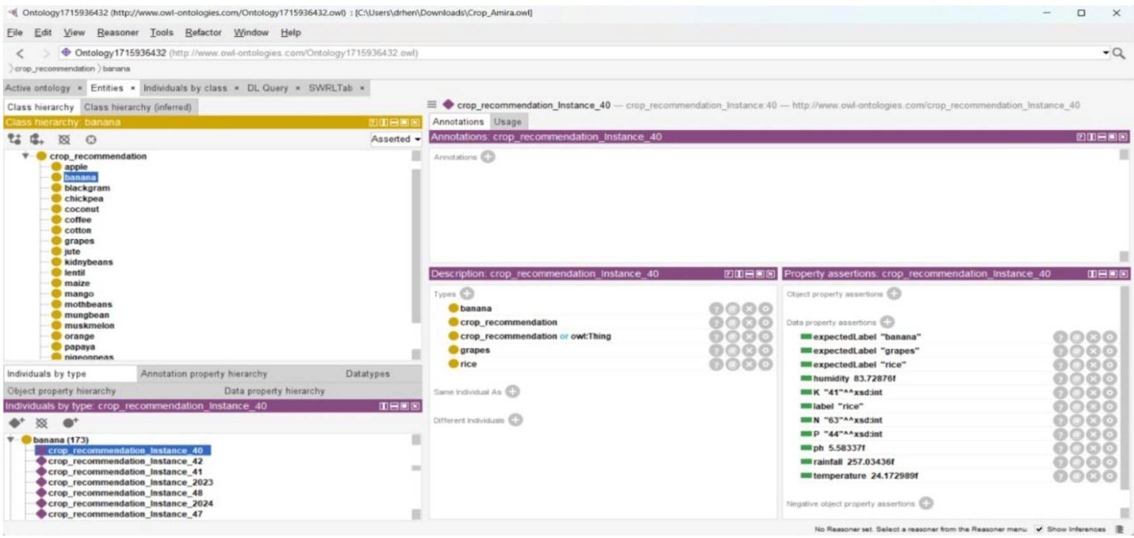

Figure 3. Ontology model with instances and data properties

- One effective language for expressing logic and rules on the Semantic Web is the SWRL [24], [25]. It builds upon web ontology language (OWL) by enabling users to create rules that can infer new knowledge [26] from existing ontologies. SWRL rules can be used to enhance the reasoning capabilities of an ontology, allowing it to derive conclusions beyond the explicitly stored information. Table 3 illustrates how the DT rules are used to derive the SWRL rules in this investigation. The number of leaves that the DT algorithm created was represented by the 31 rules that a Java program produced. The SWRL tab plugin was then used to import these rules into Protégé, enabling automated reasoning and the creation of fresh ontology insights.

Table 3. SWRL opposite the DT rule

Example	
First rule of DT	SWRL rule
If P<= 107.50&&K<=65.00&&humidity<=27.68 then the crop recommendation is kidneybeans	crop_recommendation(?C)^P(?C, ?p) ^ swrlb:lessThanOrEqual(?p, 107.50) ^ K(?C, ?k) ^ swrlb:lessThanOrEqual(?k, 65.00) ^ humidity(?C, ?h) ^ swrlb:lessThanOrEqual(?h, 27.68)-> kidneybeans

– SWRL rules are implemented in the ontology model using the Pellet reasoner [27]. A Java-based open-source OWL 2 reasoner, Pellet was created especially for semantic web applications. It supports various semantic web technologies, including OWL, resource description framework schema (RDFS), and resource description framework (RDF). Pellet can be integrated with libraries such as Jena and the OWL API, providing versatility for applications in ontology management and reasoning.

Key features of Pellet include ontology consistency checking, classification hierarchy computation, and SPARQL query answering [28]. It also provides optimizations for nominal handling, conjunctive query answering, and incremental reasoning. These capabilities make Pellet a robust tool for developers working with complex semantic web projects, enabling advanced reasoning tasks within ontologies. The final judgments in our method are based on the dataset and the inferred rules after Pellet Reasoner processes the SWRL rules inside the ontology model. The outcomes of using the ontology based on the DT model are shown in Table 4.

Table 4. Confusion matrices of crops

Crops	Crops evaluation			
	TP	TN	FP	FN
Rice	17	421	0	2
Maize	21	419	0	0
Chickpea	26	414	0	0
Kidneybeans	20	420	0	0
Pigeonpeas	23	417	0	0
Mothbeans	23	416	0	1
Mungbean	19	421	0	0
Blackgram	20	420	0	0
Lentil	11	428	1	0
Pomegranate	23	417	0	0
Banana	21	419	0	0
Mango	19	421	0	0
Graps	14	426	0	0
Watermelon	19	421	0	0
Muskmelon	17	423	0	0
Apple	23	417	0	0
Orange	14	426	0	0
Papaya	23	417	0	0
Coconut	27	413	0	0
Cotton	17	423	0	0
Jute	23	415	2	0
Coffee	17	423	0	0

4. RESULTS AND DISCUSSION

A confusion matrix, which compares predicted and actual labels to summarize the classification model's performance, can be used to evaluate the ontological DT model. A thorough understanding of the model's efficacy can be obtained by deriving a number of important performance indicators from the confusion matrix. We can efficiently assess the ontological DT model's performance by utilizing the confusion matrix and the resultant performance measures accuracy, precision, recall, and F1 score listed in Table 5.

Table 5. Ontological DT evaluation

		Confusion	Matrix	
	Accuracy	Precision	Recall	F1 score
Ontological DT	0.9977	0.9978	0.9977	0.99778
DT	0.993	0.994	0.993	0.9936

4.1. Comparative analysis of crop recommendation models

To assist farmers in selecting the best crops for their fields while accounting for variables like soil type and climate, crop recommendation systems have employed a variety of models. DT, RF, SVM, and Naïve Bayes are models that are frequently used. Our model outperforms conventional models, attaining higher accuracy rates and better predictive performance, as demonstrated by the comparative tests in Figure 4. This demonstrates the effectiveness of our model in providing actionable crop recommendations that can significantly enhance agricultural productivity and sustainability, especially when considering the challenges posed by changing environmental conditions.

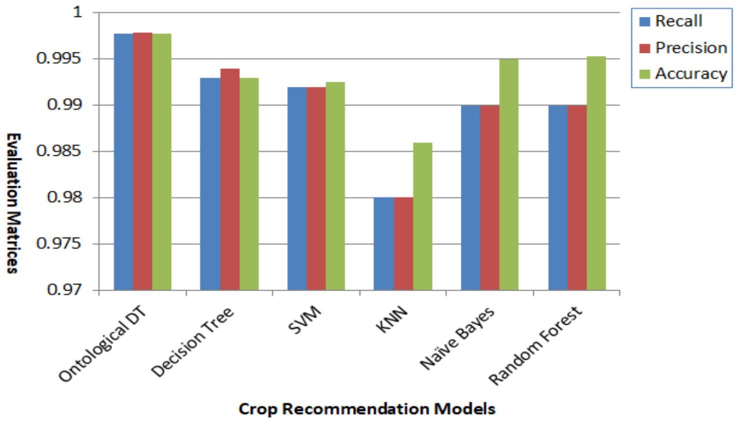

Figure 4. Comparative analysis for predicting crop-recommendation

5. CONCLUSION

Optimizing agricultural output, enhancing food security, and advancing sustainable farming methods all depend on effective crop recommendation. Conventional models with distinct advantages include RF, DT, SVMs, and NN. SVMs are excellent at handling high-dimensional data, RF are robust and manage unpredictability effectively, DT are straightforward and easy to understand, and NN are skilled at identifying intricate, non-linear patterns. But by fusing the advantages of DT with the structured domain knowledge offered by ontologies, our model—which incorporates an ontological DT—outperforms these conventional techniques. The model's interpretability is improved by this integration, which also guarantees that the recommendations are more context-aware and based on domain-specific knowledge, resulting in more precise and useful crop recommendations. By improving data interpretation and enabling more significant feature extraction, ontology integration produces suggestions that are more accurate. High accuracy and interpretability are guaranteed by the hybrid approach, while more context-aware recommendations are made possible by the incorporation of many data sources, such as historical crop performance and real-time meteorological data, within an ontological framework. The recommendations are further refined by optimization algorithms to be accurate and customized to particular farming conditions and objectives. Furthermore, our model is flexible and suitable to a range of agricultural circumstances due to its scalability and adaptability to diverse crop types and geographical areas. Our ontological DT model, which consistently achieves improved accuracy and better predictive performance, is a major breakthrough in crop recommendation systems that will propel sustainable agriculture forward.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [Kaggle] at https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset [8]. (Date accessed: Jun. 08, 2024).

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