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An ontology-based agriculture decision-support system with an evidence-based explanation model

Amani Falah Alharbi [a,*], Muhammad Ahtisham Aslam [b], Khalid Ali Asiry [c], Naif Radi Aljohani [a], Yury Glikman [b]

[a] Department of Information Systems, King Abdulaziz University, Jeddah, 23443, Saudi Arabia
[b] Fraunhofer FOKUS, Kaiserin-Augusta-Allee 31, Berlin, 10589, Germany
[c] Department of Agriculture, King Abdulaziz University, Jeddah, 23443, Saudi Arabia

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ABSTRACT

Effective management of plant diseases and pests requires knowledge that covers multiple domains. At the same time, retrieving the relevant information in a timely manner is always challenging, due to the unstructured nature of agricultural data. Over the years, efforts have been made to develop an ontology-based Decision-Support System (DSS) to facilitate the diagnosis and control of plant diseases. Some major issues with these systems are that: (1) they do not adopt the full extent of the ontological constructs to represent domain entities, which, in turn, reduces reasoning capabilities and prevents systems from being more intelligent, (2) they do not adequately provide the desired level of knowledge to support complex decisions, which requires many factors to be considered, (3) they do not adequately explain or provide evidence to demonstrate the validity of the system's outputs. To address these limitations, we present a novel system termed Agriculture Ontology Based Decision Support System (AgrODSS), which aims to assist in plant disease and pest identification and control. AgrODSS architecture consists of two semantic-based models. First, we developed Plant Diseases and Pests Ontology (PDP-O) to capture, model, and represent diseases and pest knowledge in a machine-understandable format. Second, we designed and developed an Evidence-Based Explanation Model (EBEM) that points to related evidence from the literature to demonstrate the validity of the system outputs. We demonstrate the effectiveness of AgrODSS by executing various queries via AgrODSS SPARQL Endpoint and obtaining valuable information to support decision-making. Finally, we evaluated AgrODSS practically with domain experts (including entomologists and pathologists) and it produced similar answers to those given by the experts, with an overall accuracy of 80.66%. These results demonstrate AgrODSS's ability to assist agricultural stakeholders in making proper disease or pest diagnoses and choosing the appropriate control methods.

1. Introduction

Agricultural production is constantly threatened by various diseases and pests that affect crops, leading to significant economic losses and raising concerns about food security [1–4]. In 2021, it was estimated that up to 40% of global crop yield is lost annually due to pests [5]. Protecting crops is challenging, as a wide range of pests, including insects, plant pathogens, and weeds, can cause damage [6]. Additionally, agricultural operations rely on interconnected knowledge from various domains, requiring the consideration of multiple factors to make informed decisions [7]. However, knowledge about plant diseases and pests is often published in heterogeneous, human-oriented formats, making the retrieval of relevant information difficult and time-consuming. In this context, transforming such knowledge into semantically computable resources has become a pressing need, as it ensures seamless accessibility for decision-makers and facilitates efficient processing by computers.

Ontology-based knowledge representation emerged as an outstanding approach that can revolutionize agriculture, allowing the integration and coordination of large amounts of agricultural information from various sources and enabling semantic interoperability between different information systems [8,9]. Many ontology-based systems and applications have been developed in agriculture to manage and control plant pests and diseases effectively [10–13]. Ontologies are the pillars of Semantic Web Technologies (SWTs). They provide an explicit specification

* Corresponding author.
E-mail address: amalharbi0002@stu.kau.edu.sa (A.F. Alharbi).

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of concepts within a given domain [14]. An ontology is an approach for representing real-world objects or concepts as symbols within a structured semantic model. In SWTs, concepts are referred to as classes, while relationships between these concepts are defined as properties. The logical formalisms behind the ontological models give machines a human-like commonsense in problem-solving and allow the inference of new knowledge from existing knowledge. The flexibility and reasoning capabilities make ontologies a powerful alternative to relational databases, which demand manual creation of every link, making them more difficult to manage as knowledge expands.

This article delves into how ontology-based decision support systems can assist in plant disease and pest identification and control. However, the identification of plant diseases and pests is a complex decision and knowledge-handling problem. Multiple factors affect this decision, ranging from environmental conditions to biological causes [6]. The sheer volume of information available on these factors is overwhelming and is usually scattered among several heterogeneous data sources [15]. This is where an ontology-based system comes into play due to its ability to integrate and coordinate large amounts of agricultural information emerging from various sources and in different formats. However, for those systems to function effectively, they need to provide the desired level of knowledge to support complex decisions. In addition, decision-makers need to trust and understand the rationale behind a system's outputs so that they can use them in a particular situation [16]. This can be achieved by providing an explanation or evidence to demonstrate the validity of system outputs. Evidence is any information item or data related to some matter that must be proven or refuted, it is data used to support statements [17]. This article presents an Agriculture Ontology-Based Decision Support System (AgrODSS) to assist in plant disease and pest identification and control. It works to extract, process, and produce machine-understandable information to enable knowledge-driven decision-making in agriculture. The main contributions of this work can be summarized as follows:

- Design and develop a novel system called the Agriculture Ontology-Based Decision Support System (AgrODSS) to support agricultural decision-making, particularly in plant disease and pest identification and control. *(The novelty of this system lies in its architecture, which consists of two semantic-based models that support the generation of inferences and recommendations.)*
- Design and development of Plant Disease and Pest Ontology (PDP-O) that captures key concepts and relationships within the domain of plant pests and diseases. *(In contrast to other ontologies, the PDP-O adapts a range of ontological constructs to represent domain entities, which, in turn, increases the quality of its structured measures and maximizes reasoning capabilities.)*
- Design and development of the Evidence-Based Explanation Model (EBEM) to demonstrate the validity of the outputs of AgrODSS by pointing to related evidence from the literature. *(This addresses the dearth of evidence to demonstrate the validity of system outputs and makes scientific knowledge easily accessible.)*
- Establishing the SPARQL endpoint as a web-based interface of AgrODSS and executing various queries. The results of these queries were analyzed and reported to demonstrate the system's effectiveness as a use case in identifying diseases and pests and recommending appropriate control methods.
- The results of applying AgrODSS to the domain of date palm pests and diseases were evaluated by domain experts, including entomologists and pathologists.

2. Related work

SWTs and ontologies have much potential for data modeling and machine reasoning in various domains, including agriculture. Several well-known ontologies and controlled vocabularies have been developed by international organizations and working groups to represent agriculture knowledge. AGROVOC[1] is the most comprehensive controlled vocabulary in this domain [18]. It contains more than 40,600 concepts and 963,000 terms in 41 languages. Similarly, the National Agricultural Library Thesaurus (NALT)[2] was developed to improve agricultural information indexing and retrieval and contains more than 135,000 terms divided into 17 subject categories, such as food science, animal care, genetics, enzymes, chemistry, plant diseases, environmental sciences, and biological sciences [19]. However, AGROVOC and NALT lack a precise classification for plant diseases and pests. For instance, hierarchical relationships are informally expressed with two properties (i.e., skos:broader and skos:narrower) which, unlike rdfs:SubClassOf, lack explicit semantic inference rules. This informal structure causes confusion in semantic interpretation and reduces the computational power of reasoning engines. Plant Ontology (PO)[3] is the most popular controlled vocabulary to describe plant anatomy and development stages [20]. However, it lacks vocabulary for diseases and pests.

Considerable research efforts have been made to develop ontology-based systems to identify and control plant diseases and pests. For example, in [21,22] the authors present CropPestO,[4] an ontology developed as the cornerstone of an expert system to support farmers' identification of pests and to recommend the appropriate control measures, with a focus on organic agriculture practices. However, some pests are associated with a sole symptom, which is insufficient to identify diseases accurately. The Plant Disease Ontology (PDO)[5] classifies plant disease based on the causal agents and host plant, focusing on three plants: maize, wheat, and rice [23]. However, this work does not consider the relationship between plant disease and its symptoms or host plants, and this is essential to disease identification. Similarly, Plant-Pathogen Interactions Ontology (PPIO)[6] was created to describe the interaction between a host plant and pathogens [24,25]. PPIO focused on modeling relationships between plants and their pathogens; however, it did not consider other aspects related to plant diseases, such as control methods. In [26] the authors present a Crop-Pest Ontology developed to facilitate image retrieval in the domain of crops and their pests to address the limitation of the keyword-based image retrieval approach. This ontology lacks crucial relationships between key concepts, which are essential for effectively identifying plant diseases or pests. In [27] a Plant Protection Ontology (PPOntology) was developed to capture and model agricultural knowledge related to cereal plant protection, especially barley disorders. Although this work presents a useful modeling approach to represent domain knowledge, it lacks sufficient information about control methods, which are limited to a single category, 'pesticide', and there is no clear link between this category and the plant disorder or organism. In [28] an ontology was created to model knowledge related to the domain of plant-pathology, focusing on diseases of short-cycle and perennial crops. For disease identification this ontology relies on a set of Semantic Web Rule Language (SWRL) rules to describe plant diseases by their associated symptoms; however, these rules specify the inferred disease only when the provided symptoms match the set of symptoms that describe that disease.

In [29] the authors present RiceMan, an expert system developed based on Rice Disease Ontology (RiceDO) and Treatment Ontology (TreatO) [30,31]. These ontologies model knowledge of plant diseases, focusing on rice diseases in Thailand. In this work each rice disease is described on the basis of a class expression using the rdfs:SubClassOf relationship (in other words, the class has no individuals or instances). Although this modeling approach can represent domain knowledge successfully, it limits the inference process to subsumption reasoning

[1] https://agrovoc.fao.org/browse/agrovoc/en/.
[2] https://agclass.nal.usda.gov.
[3] https://ontobee.org/ontology/PO.
[4] http://agrisemantics.inf.um.es/ontologies/CropPestOv2.owl.
[5] https://github.com/Planteome/plant-disease-ontology.
[6] https://code.google.com/archive/p/plant-pathogen-interacions-ontology/.

and reduces the usability of SPARQL queries. Similarly, in [2] the authors present a knowledge-based decision support system that relies on AgriEnt-Ontology to represent agricultural entomology knowledge to support farmers in identifying and managing insect pests. This system relies on ontology and rule-based inference to diagnose insect pests. However, the dependency on the predefined rules to identify a given pest makes it necessary to provide all the symptoms involved in these rules for the system to correctly diagnose this insect pest. This reduces the matching process between entered and stored data, since maybe not every single symptom is noticed and provided by users. In [32] the authors present PCT-O ontology that is leveraged to build a recommendation system to facilitate plant pests' identification and recommendations of suitable treatments. However, symptoms produced by pests are described textually, which causes difficulties in reasoning over this data. In addition, no relationships were considered between the symptoms and the affected parts, or between pests and the most susceptible varieties.

In summary, most of the works discussed above use ontologies to capture and represent agricultural knowledge to support decision-making. However, they do not model all important aspects of the domain (e.g., disease and pest identification and control), resulting in insufficient knowledge models for intelligent decision-support systems. Although they implemented ontologies in OWL, they did not fully utilize its expressiveness to adequately represent domain entities, which, in turn, impacts the quality of structural measures and limits the reasoning capabilities. Furthermore, the lack of explainability or evidence to demonstrate the validity of system outputs ultimately negatively affects stakeholders' acceptance and trust of system recommendations. Tables 1 and 2 summarize and compare existing ontologies and vocabularies in agriculture. Table 1 compares existing ontologies with respect to the structural measures used to represent domain knowledge. It shows that most of the developed ontologies have not fully utilized the range of ontological constructs (such as achieving an adequate level of granularity to represent key classes, using owl:restrictions to describe key classes, defining domains and ranges for properties, specifying property characteristics, defining an adequate number of object or data properties to model complex relationships between concepts, and populating classes with sufficient instances) to effectively describe domain entities. These constructs represent the most significant advantage of semantic-based modeling, playing a crucial role in enhancing the semantic reasoning capabilities of ontological models. Table 2 compares existing ontologies with respect to the knowledge aspects covered by the developed ontologies and the extent to which they represent important aspects and relationships between domain concepts.

3. AgrODSS: agriculture ontology-based decision support system

AgrODSS is an ontology-based DSS system that aims to support decision-making in identifying and controlling plant diseases and pests. The decision-support aspects of this system are to assist stakeholders (e.g., farmers, policymakers, and advisors) in properly diagnosing diseases and pests, and helping them make informed decisions on appropriate control methods. In addition, it provides explanations and evidence to increase users' knowledge and trust of the system recommendations. The architecture of AgrODSS and the workflow of system development are described in the following subsections.

3.1. AgrODSS: architecture

It is recognized that, to effectively manage and analyze information for decision-making, decision support systems should include at least three core components: (1) a database, (2) a model processing component, and (3) a user interface [33]. From this perspective, AgrODSS is built on a layered functional architecture with three layers (see Fig. 1): (1) the semantic layer, (2) the processing layer, and (3) the web interface layer. The layers and components of AgrODSS are described below.

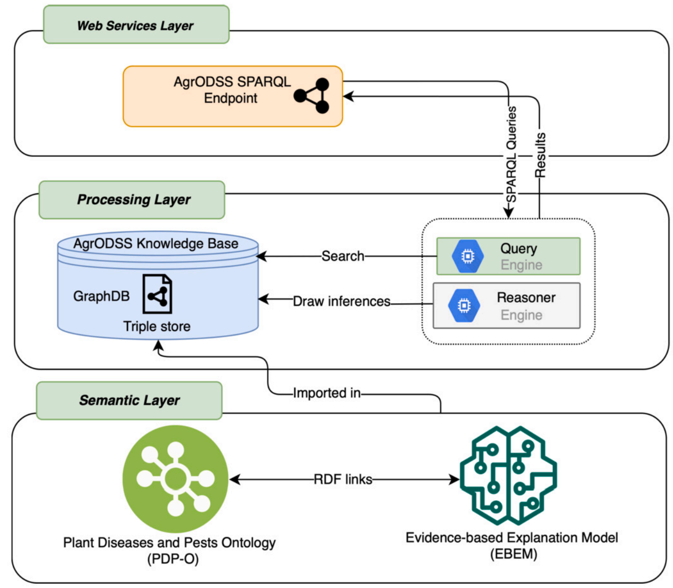


Fig. 1. General architecture of AgrODSS.

3.1.1. Semantic layer

The semantic layer of AgrODSS consists of two semantic-based models: PDP-O and EBEM. On the one hand, the role of PDP-O is to capture key concepts, terms, and relationships related to plant diseases and pests, representing them in a machine-understandable format. On the other hand, the role of the EBEM is to semantically annotate knowledge sources related to plant diseases and pests to demonstrate the validity of AgrODSS recommendations by pointing to related evidence from the literature. Both PDP-O and EBEM form the knowledge base of our system; they consist of a T-Box (or ontology schema) and an A-Box, which contains RDF data (or instances) of classes defined by the T-Box. Detailed descriptions of the design and development of PDP-O and EBEM are presented in Sections 3.2.3 and 3.2.4, respectively.

3.1.2. Processing layer

This layer comprises three core components responsible for managing, analyzing, and inferring information for the decision-making process: a graph database (for storing RDF data in the form of a knowledge graph), a query engine (to access the graph database and retrieve information based on structured queries), and a reasoner engine (for computing inference rules embedded in the semantic layer and generating inferred RDF triples). We implemented AgrODSS using GraphDB,[7] a semantic repository that supports storing, manipulating, reasoning, retrieving, and visualizing RDF data.

This layer serves as an intermediary between the semantic layer and the web interface layer. The query engine processes SPARQL queries involving input data (such as symptoms, environmental conditions, and crop type) and searches the system knowledge base for potential matches related to this input. Meanwhile, the reasoning engine computes implicit relationships among data elements defined in the semantic layer, inferring possible matches (e.g., diseases or pests) relevant to user queries.

3.1.3. Web services layer

Currently, the web-based SPARQL endpoint serves as a means of accessing AgrODSS ***(Access to this SPARQL endpoint can be provided on demand)***.[8] A SPARQL endpoint is a front-end interface that allows users (humans or applications) to access, browse, and query the system's

[7] https://graphdb.ontotext.com.
[8] https://agrodss.fokus.fraunhofer.de/graphdb/.

Table 1
Comparative analysis of existing agricultural ontologies (with respect to the quality of structural measures).

Ontology Name	Ontology's Language	Structural Measures						
		Key classes* are described using OWL:Restrictions	Adequate level of granularity to represent key classes using rdfs:subClassOf	Properties domain and range defined	Property characteristics defined	Object property count	Data property count	Individual count
AGROVOC [18]	SKOS/ RDF/XML	No	No	No	No	0	0	0
National Agricultural Library Thesaurus (NALT) [19]	SKOS/RDF-XML	No	No	No	No	0	0	0
Plant Disease Ontology (PDO) [23]	OWL	Partial	Partial	No	No	4	0	0
CropPestO [21]	OWL	No	No	Yes	No	8	0	11754
Crop-Pest Ontology [26]	OWL	No	Partial	Yes	No	36	4	14
PPOntology [27]	OWL	Yes	Partial	Yes	Partial	15	8	548
RiceDO and TreatO [30,31]	OWL	Yes	Partial	Yes	No	23	0	0
PPIO [24,25]	OWL	Partial	Partial	No	No	13	1	26
AgriEnt-Ontology [2]	OWL	No	Partial	Yes	Partial	8†	0†	19†
PCT-O [32]	OWL	No	Partial	No	No	7†	14†	49,773†
Proposed PDP-O	OWL	Yes	Yes	Yes	Yes	88	32	555

* Key classes (i.e., plant diseases or pest damage, causal agents, symptoms, control methods) because these classes play an essential role in disease or pest identification and control.
† An estimated count is derived from an excerpt of the ontology, as the complete ontology file is unavailable. A selection of representative classes and properties has been provided to illustrate the ontology's style and coverage aspects.

Table 2
Comparative analysis of existing agricultural ontologies (with respect to the knowledge aspects covered by the ontology).

Ontology Name	Domain of interest	Relation between disease or damage and causal agents	Relation between disease or pest and symptoms	Relation between symptom and affected plant parts	Relation between disease or pest and susceptible varieties	Relation between disease or pest and outbreak time	Relation between disease or pest and control methods	Relation between disease or pest and host plant	Provide evidence or link to knowledge source
AGROVOC [18]	Areas of interest to FAO such as animals, plant, fisheries, food, nutrition, forestry, environment…stc.	✓	✓	✗	✗	✗		✓	✓
National Agricultural Library Thesaurus (NALT) [19]	Food science, animal care, genetics, enzymes, chemistry, plant diseases, environmental sciences, and biological sciences.	✗	✗	✗	✗	✗	✗	✗	❍
Plant Disease Ontology (PDO) [23]	Describing plant diseases based on the causal agents and host plant, mainly: maize, wheat and rice.	✓	✗	✗	✗	✗	✗	✗	✗
CropPestO [21]	Plant pests and diseases identification and control methods focusing on organic farming.	✗	✓	✗	✗	✗	✓	✓	✗
Crop-Pest Ontology [26]	Modeling of concepts in crops and related pests domain to facilitate image retrieval.	✗	✗	✓	✗	✗	✗	✓	✗
PPOntology [27]	Plant protection, in particular provide diagnosis and treatment of barley disorders.	✓	✓	✓	✗	✗	✗	✗	✗
RiceDO and TreatO [30,31]	Plant diseases identification and control with a focus on rice diseases.	✓	✓	✓	✗	✗	✓	✗	✗
PPIO [24,25]	Modeling the host-pathogen interaction and the resulting phenotype.	✗	✓	✗	✓	✗	✗	✓	✗
AgriEnt-Ontology [2]	Modeling entomology knowledge to facilitate identifying and managing insect pests.	✓	✓	✗	✗	✗	✓	✓	✓
PCT-O [32]	Modeling of the interactions between pests, crops, and treatments to facilitate pests identification and the selection of appropriate treatments.	✗	✓	✗	✗	✓	✓	❍	✓
Proposed PDP-O	Modeling of agriculture knowledge to assist in decision making regarding plant disease identification and control, emphasizing of date palm disease and insect pests.	✓	✓	✓	✓	✓	✓	✓	✓

'✓' = means coverage; '❍' = means partial coverage; '✗' = means no coverage.

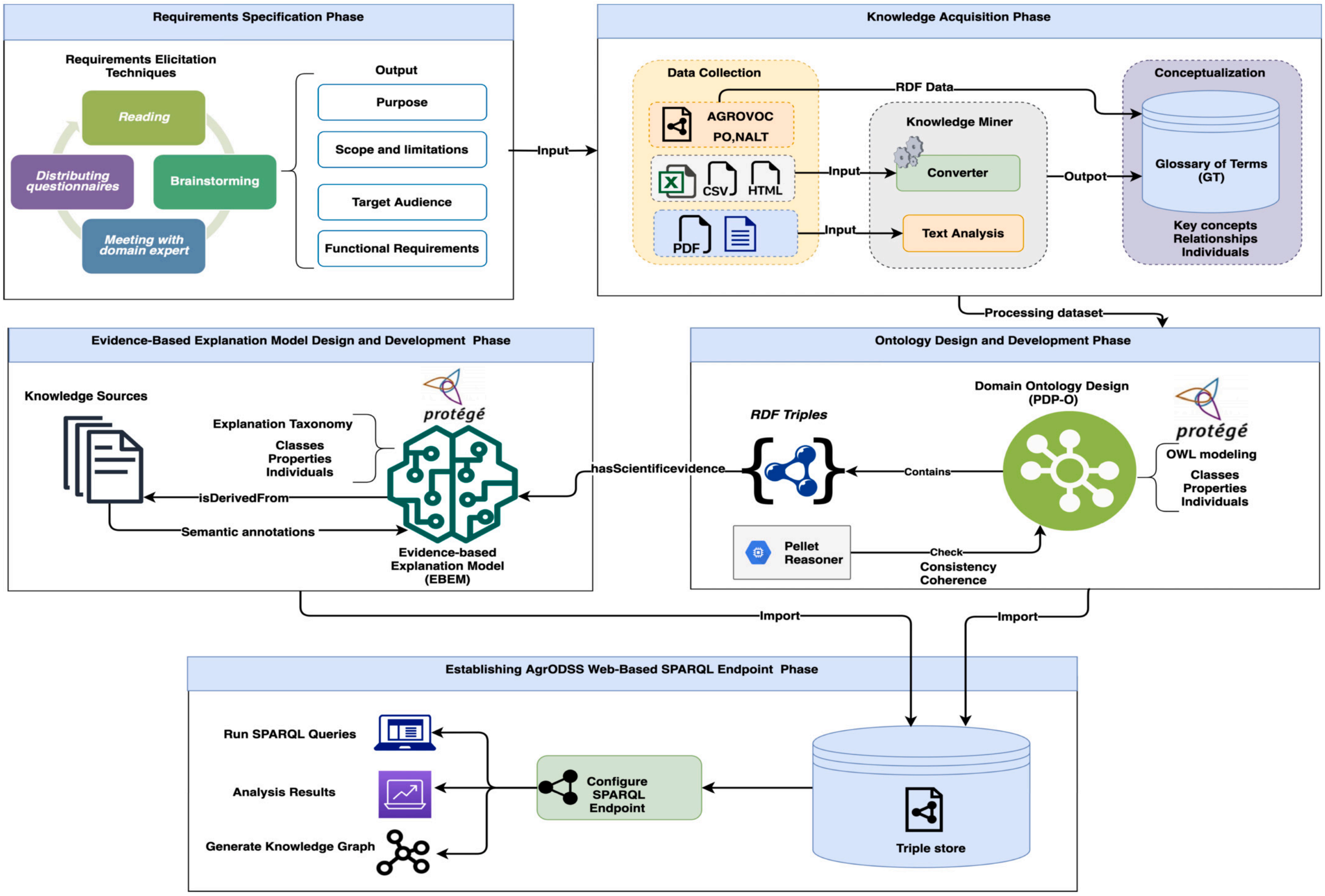


Fig. 2. Workflow within the AgrODSS System.

knowledge base to retrieve specific information. The results of semantic query analysis and reasoning are displayed in this layer in either tabular format or as a knowledge graph. We present use cases for executing various SPARQL queries via the AgrODSS SPARQL endpoint in Section 3.2.4.

3.2. *The workflow of AgrODSS development*

To develop AgrODSS, we designed a research roadmap consisting of five phases (see Fig. 2): (1) requirements specification, (2) knowledge acquisition, (3) ontology design and development, (4) evidence-based explanation model design and development, and (5) establishment of the AgrODSS web-based SPARQL endpoint. The following subsections provide a detailed description of each phase.

3.2.1. *Requirements specification*

This phase aims to assess the feasibility of developing AgrODSS as a practical solution for supporting decision-making in the agricultural domain. Additionally, it focuses on gathering information about user needs to identify system requirements. Our approach to specifying AgrODSS requirements incorporates three requirements elicitation techniques:

1. *Literature review and analysis*: This involved reading and analyzing related work, browsing official institutions' websites, and reviewing publications from authoritative sources (e.g., statistical reports,[9] guidelines,[10] and expert opinions).
2. *Consultations with domain experts*: We conducted this task by holding regular online meetings with two domain experts (one entomologist and one pathologist), each with over 10 years of experience in plant diseases and pests, particularly those affecting date palm crops. They provided us with essential knowledge that our ontology should cover to perform proper diagnosis and recommend suitable control methods. For example, they emphasized focusing on the major diseases and economically significant insect pests impacting date palms. In addition, they shared an Excel datasheet containing names of diseases and insect pests, associated symptoms, affected plant parts, favorable environmental conditions, and suggested control methods. Furthermore, they recommended including images that illustrate the symptoms associated with each disease or pest. Finally, they provided us with knowledge sources for further information extraction to expand the system's knowledge base.
3. *Cross-sectional survey*: A cross-sectional survey was shared with 217 people in the agricultural sector (farmers, researchers, advisors, guidance offices, government agencies, professionals, and scientists) in Saudi Arabia to identify: (1) the need for information technologies in supporting agricultural decisions, (2) the difficulties in the management of diseases and pests of date palms, and (3) stakeholders' attitudes towards the use of technology to facilitate making their decisions. An example of the important findings revealed by the survey is that current practice is traditional, as 33.6% of stakeholders rely on previous experience to manage disease and pests. In addition, there is a lack of technological solutions, as only 8.3% of stakeholders use technology to support their decisions *(More information about the survey and its findings can be found in Supplementary data A)*.

[9] https://ncpd.gov.sa/statistics.
[10] https://ncpd.gov.sa/services/page/farm1/palm-care-guide.

Table 3
AgrODSS main functional requirements and corresponding CQs.

Requirements Category	Functional Requirements	Competency Questions (CQ)
Diagnosis of diseases and pests	**FR1**: System shall correctly identify the nature or identity of a problem present in a plant based on external symptoms expressed by a plant or a particular part.	**CQ1:** What are the abnormal symptoms observed on a plant, or its parts, indicate? **CQ2:** What kind of problem do these symptoms indicate? **CQ3:** What are plant parts affected by this disease or pest? **CQ4:** What are the factors that contribute to the emergence of this disease or damage? **CQ5:** What is the nature of these factors that caused this disease or damage? **CQ6:** What are the varieties or cultivar susceptible to this disease/pest?
	FR2: System shall display all possible symptoms associated with a particular disease or pest.	**CQ7:** What are all possible symptoms associated with a particular disease?
	FR3: System shall provide information to describe characteristics associated with symptoms exhibited by a plant (i.e., the progression and distribution of symptoms).	**CQ8:** How symptoms associated with a particular disease or damage look like? **CQ9:** Are there symptoms on the roots, leaves, stems, flowers, or fruit? **CQ10:** Is the entire plant involved or side of a plant involved?
Identify causal agents	**FR4**: System shall identify all possible (abiotic or biotic) factors that contribute to the emergence of a particular disease/past.	**CQ11:** What are the environmental factors that contribute to the emergence of a particular disease/past? **CQ12:** What are the cultural practices that contribute to the emergence of a particular disease/past? **CQ13:** What are the biotic factors that contribute to the emergence of a particular disease/past?
Recommend the appropriate control method	**FR5**: System shall provide users with the recommendations to control a particular disease/past based on observed symptoms and plant affected part.	**CQ15:** What is the suitable chemical control of a particular disease/past? **CQ16:** What is the suitable culture control of a particular disease/past? **CQ17:** What is the suitable biological control of a particular disease/past?
	FR6: System shall provide users with instruction on how to apply the recommended control method.	**CQ18:** How is the recommended control method can be applied?
Provide evidence to support recommendations	**FR6**: System shall provide users with evidence to show the validity of its recommendations.	**CQ19:** What evidence supports the recommended control method?

Therefore, based on the results obtained by carrying out the three elicitation tasks, we specified the AgrODSS requirements, including its purpose, scope and limitations, intended end-users, and functional requirements, as follows:

- *AgrODSS purpose*: is to provide various stakeholders in the agriculture field with computerized-based decision support to assist in plant diseases and pest identification and control.
- *AgrODSS scope and limitations*: AgrODSS' scope is plant disease and pest identification and control. The identification of diseases and pests is based on external symptoms visible to the human eye, such as leaf spots, mildew, wilting, discoloration, and similar, therefore internal symptoms are not included. For the use case purposes, we populated the knowledge base with data related to date palm diseases and pests. This is because the date palm is an important food crop and plays a significant role in the economy of countries. It is prone to attack by many pests and diseases, causing roughly a 30% loss in yield [34]. Furthermore, like other knowledge areas in agriculture, retrieving the information relevant to date palms poses a challenge as most of the domain knowledge is in a human-oriented format and there is a deficiency of semantic-based representation. Considering the abovementioned importance and deficiencies, the rationale for our choice is justified.
- *AgrODSS target audience*: the targeted end users of AgrODSS are: (1) *Farmers* who are looking to identify diseases and pests early to prevent their spread and to obtain suitable treatments to reduce the impact of pests and diseases on their crops, (2) *Advisors* who need support to recognize the relationship between symptoms and diseases, and between diseases and their causes. Without intelligent systems, they rely on experience and need to memorize all the complex relationships to make proper diagnoses or suggest the appropriate control measures, (3) *Researchers and Students* who can use AgrODSS to investigate the relationships between entities (e.g., symptoms and pathogens) and simulate specific scenarios for their research, and (4) *Government Agencies*, AgrODSS provides a standard data model that can facilitate data integration from various data sources in these organizations to assist managers in making decisions based on data and evidence rather than pure intuition.
- *AgrODSS functional requirements*: Table 3 illustrates AgrODSS' main functional requirements, classified into four categories with corresponding Competency Questions (CQs). CQs are user-oriented questions; in other words, questions that users would like to answer by exploring and querying AgrODSS. Furthermore, CQs outline the scope of the ontology and play an essential role in its development and evaluation, ensuring it meets user requirements.

3.2.2. Knowledge acquisition

Based on the requirements identified in the previous phase (i.e., Section 3.2.1), we conducted knowledge acquisition activities. Knowledge acquisition is a continuous and independent activity throughout the ontology development process, aiming to capture the most important concepts and relationships within the domain of interest. In this work, we relied on several knowledge sources for knowledge acquisition, categorizing them as structured (e.g., ontologies) and unstructured sources (e.g., research articles, books, guideline documents, and Excel spreadsheets).

- *Knowledge acquisition from analyzing structured sources*: this activity aimed to extract the relevant concepts and relationships from existing ontologies for reuse in our ontology, and helped to speed up the ontology construction process. Our survey of available ontologies included searching in search engines and ontology repositories such as AgroPortal [35] (which can be navigated online[11]) and Crop Ontology [36], which provides an open-source web interface known

[11] https://agroportal.lirmm.fr.

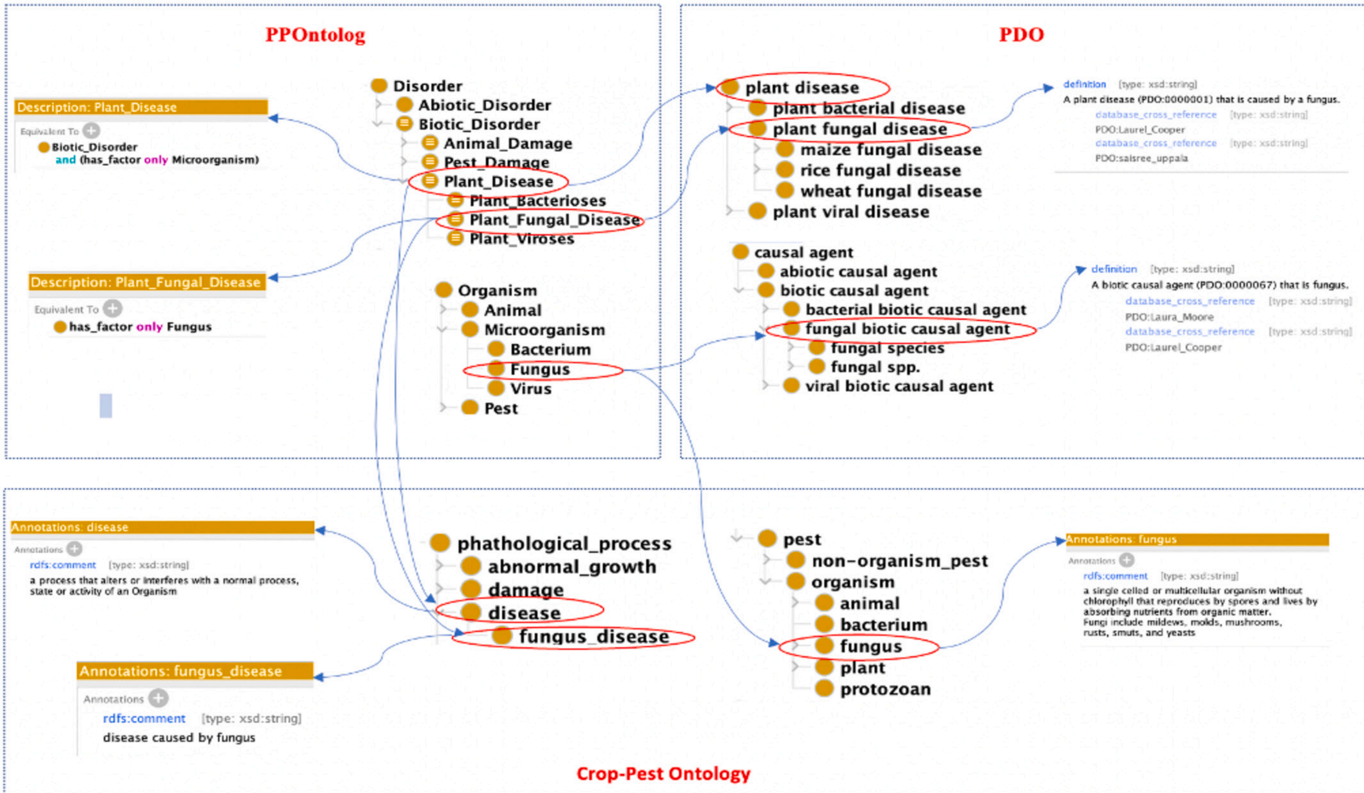


Fig. 3. Knowledge acquisition by analyzing of three of existing ontologies.

as (Crop Ontology Curation Tool)[12] for ontology sharing. We investigated and analyzed a set of ontologies in the agriculture domain, particularly concerning pests and plant diseases. The most relevant ontologies are the Plant Disease Ontology (PDO), Plant Protection Ontology (PPOntology), Crop-Pest Ontology, Plant-Pathogen Interactions Ontology (PPIO), RiceDO and TreatO, and CropPestO. A list of classes and properties extracted from each of these ontologies to construct our ontology can be found in Supplementary data A). By comparing these ontologies, we found similar concepts to represent plant diseases and pests. These concepts may overlap, and some may have the same meaning, but our goal is to speed up the construction of PDP-O by reusing terms or concepts from existing well-defined ontologies. Fig. 3 illustrates the process of analyzing and comparing three existing ontologies, PPOntology, PDO, and Crop-Pest Ontology, showing some class hierarchies of these ontologies and the similarity between classes.

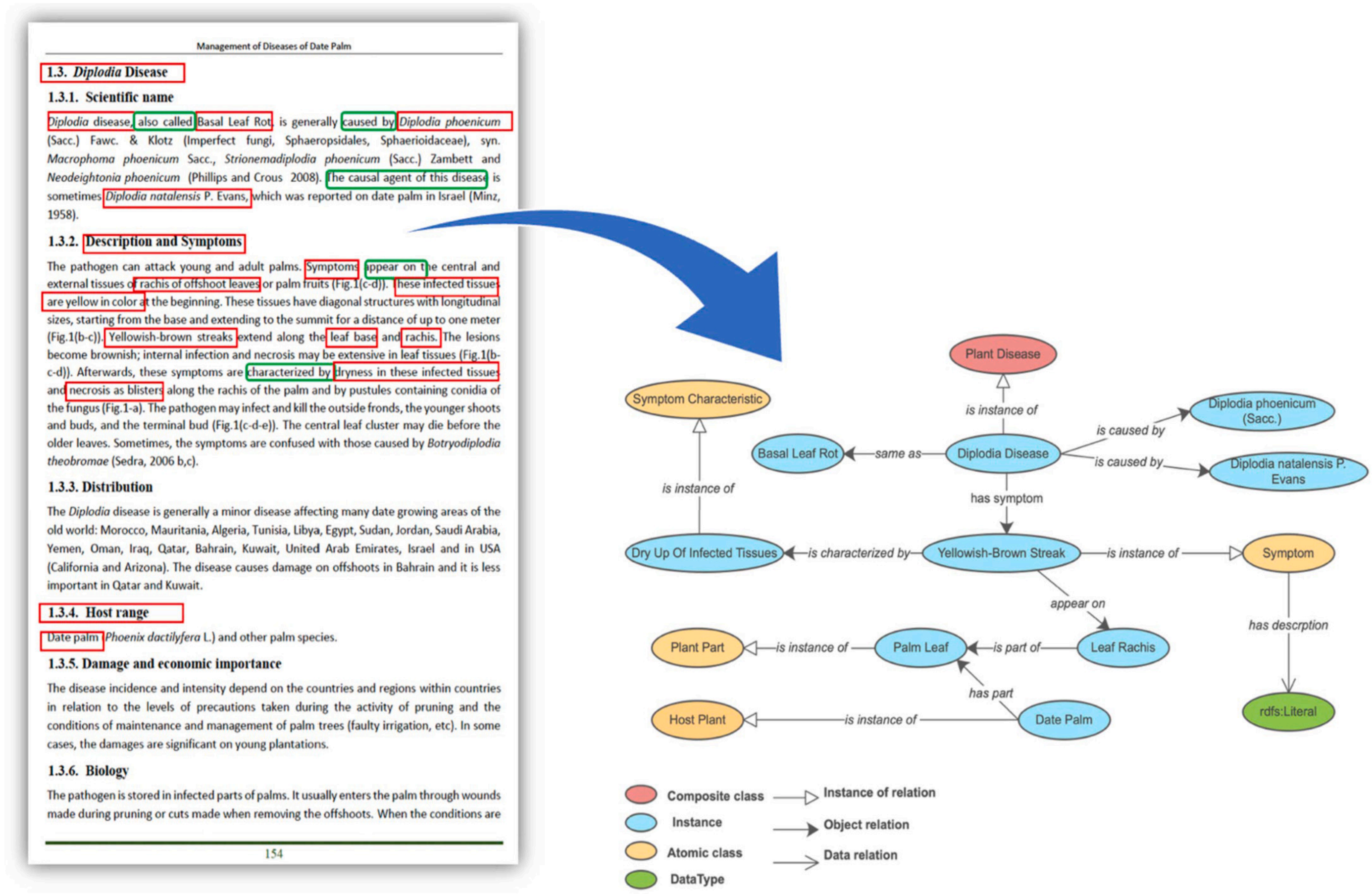
- *Knowledge acquisition by analyzing unstructured sources*: this activity aimed to expand the knowledge base by analyzing non-ontological knowledge sources and adding further terms that were not included in previous ontologies, in addition extracting axioms and individuals for ontology population and enrichment. This activity was carried out manually to extract information from text documents. The rationale behind the manual approach is that the complexity of domain knowledge and overlapping between terms make adapting fully automatic text analysis techniques ineffective. Besides, accurately extracting ontology entities and mapping them to the corresponding class with appropriate relations requires designating complex natural language processing (NLP) algorithms, which have been proven inaccurate [37] or not encouraging [32]. Our corpus is knowledge resources related to plant disease in general, but we gave special attention to sources related to the cultivation of the date palm. These knowledge sources provide reliable information on date palm pests and diseases, and describe the signs and symptoms of each disease and the causal agent (such as fungus and insect pests). The first step in the extraction process was to parse the textual content to extract related entities and available images from the source files. Then, the textual content was transformed into instances according to the PDP-O model and used to fill the various properties to describe ontology instances, while images of pests and symptoms are stored as a graphical description of related instances. After that, each item of textual content was stored with the corresponding knowledge source to identify the scientific evidence of the facts stored in the ontology. The main issue of these data sources is their heterogeneity since none is completely structured and uniform. Some provide the information in tables, but most information is described in plain text. Fig. 4 illustrates the knowledge acquisition process by analyzing the textual content of one such knowledge source. Acquisition of extensive knowledge about date palm pests and diseases allowed us to achieve good coverage of the axioms required to model various relationships between ontology entities, to represent them as OWL axioms, and thus increase the computational power of our ontology.

3.2.3. *Plant Diseases and Pests Ontology (PDP-O) design and development*

This phase is one of the most important in the development of the AgrODSS. It focuses on knowledge modeling by adding semantics to the processed data from the previous phase (i.e., Section 3.2.2) to create PDP-O. PDP-O was implemented using the Web Ontology Language (OWL),[13] allowing us to describe domain concepts and express far more complex relationships that are bound to exist between these concepts. As a suitable ontology development environment, we chose Java-based Protégé [38]. Protégé is an open-sourced ontology editor designed to

[12] https://cropontology.org.

[13] http://www.w3.org/TR/2012/REC-owl2-overview-20121211/.


Management of Diseases of Date Palm

1.3. *Diplodia* Disease

1.3.1. Scientific name

Diplodia disease, also called Basal Leaf Rot, is generally caused by *Diplodia phoenicum* (Sacc.) Fawc. & Klotz (Imperfect fungi, Sphaeropsidales, Sphaerioidaceae), syn. *Macrophoma phoenicum* Sacc., *Strionemadiplodia phoenicum* (Sacc.) Zambett and *Neodeightonia phoenicum* (Phillips and Crous 2008). The causal agent of this disease is sometimes *Diplodia natalensis* P. Evans, which was reported on date palm in Israel (Minz, 1958).

1.3.2. Description and Symptoms

The pathogen can attack young and adult palms. Symptoms appear on the central and external tissues of rachis of offshoot leaves or palm fruits (Fig.1(c-d)). These infected tissues are yellow in color at the beginning. These tissues have diagonal structures with longitudinal sizes, starting from the base and extending to the summit for a distance of up to one meter (Fig.1(b-c)). Yellowish-brown streaks extend along the leaf base and rachis. The lesions become brownish; internal infection and necrosis may be extensive in leaf tissues (Fig.1(b-c-d)). Afterwards, these symptoms are characterized by dryness in these infected tissues and necrosis as blisters along the rachis of the palm and by pustules containing conidia of the fungus (Fig.1-a). The pathogen may infect and kill the outside fronds, the younger shoots and buds, and the terminal bud (Fig.1(c-d-e)). The central leaf cluster may die before the older leaves. Sometimes, the symptoms are confused with those caused by *Botryodiplodia theobromae* (Sedra, 2006 b,c).

1.3.3. Distribution

The *Diplodia* disease is generally a minor disease affecting many date growing areas of the old world: Morocco, Mauritania, Algeria, Tunisia, Libya, Egypt, Sudan, Jordan, Saudi Arabia, Yemen, Oman, Iraq, Qatar, Bahrain, Kuwait, United Arab Emirates, Israel and in USA (California and Arizona). The disease causes damage on offshoots in Bahrain and it is less important in Qatar and Kuwait.

1.3.4. Host range

Date palm (*Phoenix dactilyfera* L.) and other palm species.

1.3.5. Damage and economic importance

The disease incidence and intensity depend on the countries and regions within countries in relation to the levels of precautions taken during the activity of pruning and the conditions of maintenance and management of palm trees (faulty irrigation, etc). In some cases, the damages are significant on young plantations.

1.3.6. Biology

The pathogen is stored in infected parts of palms. It usually enters the palm through wounds made during pruning or cuts made when removing the offshoots. When the conditions are

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Fig. 4. A representative view of the conversion process for knowledge published in traditional PDF format as non-machine-understandable data (on the left) into machine-understandable data in RDF format (on the right).

facilitate the creation of OWL ontologies, and it is supported by a set of plugins such as Pellet Reasoner, to verify automatically the ontology consistency.

Ontology development is an iterative engineering process of several fundamental steps to ensure the correct achievement of deliverables. In this work, three popular ontology engineering methodologies [39–41] were considered as the baseline for building PDP-O. Each methodology has its unique features, but in general, the overall approach involves ontology development steps that do not vary widely. While these methodologies define the necessary steps or workflows for developing the ontology, we continuously collaborated with domain experts through online workshops to establish a commonly agreed knowledge framework. They verified that each class was relevant to our domain of interest, that all classes were arranged within the correct taxonomy and suitable level of granularity, and that all classes, properties, and their definitions (both formal and informal) communicate the intended meaning and accurately represented the characteristics of the domain.

The implementation of PDP-O started with the automatic import of relevant classes and properties from existing ontologies (as mentioned in Section 3.2.2). This import was achieved through soft reuse [42], which involves directly copying selected ontology classes and properties from the source ontology into our ontology using the 'Refactor' tab in Protégé. Original axioms defining entities were removed to maintain consistency of our ontology. For instance, classes such as *Microorganism, Pest, Pest_Insect, Pest_Mite, Cultural_Practice*, as well as properties like *has_cultural_practice and scientific_name*, were imported from PPOntology. Once entities are imported, the next task was to extend the ontology by adding additional classes, properties, and axioms, organizing them, and creating semantic links between various ontology entities. Currently, PDP-O consists of eleven top-level classes (i.e., *Plant_Disease*, *Pest_Damage*, *Symptom*, *Causal_Agent*, *Host_Plant*, *Plant_Part*, *Plant_Variety*, *Symptom_Characteristic*, *Time*, *Control_Method*, and *Causal_Agent_Trait*), which are the root of their own sub-trees. These classes and their own subclasses represent basic concepts within the subject of plant diseases and pests. An excerpt from the PDP-O is illustrated in Fig. 5.

We aimed to address the limitations of previous works by developing a domain ontology with far stronger reasoning ability and providing sufficient knowledge to support complex decisions. Our approach to achieve these goals consists of five main strategies: (1) building PDP-O class hierarchy with a finer level of granularity, (2) enhancing PDP-O classes description using OWL axioms, (3) relationship modeling for enhanced reasoning, (4) enriching the meaning of PDP-O properties by attaching property characteristics, (5) populating PDP-O classes with sufficient instances (or individuals). The following points provide a detailed description of each one of these strategies.

- ***Building PDP-O class hierarchy with a finer level of granularity*** Class hierarchies define a specific type of binary relation that captures inheritance between classes. In OWL ontologies, the standard construct for representing this relationship is rdfs:subClassOf. We paid special attention to classify each key class in PDP-O to a finer level of granularity. For instance, the *Causal_Agent* class tree provides an extended taxonomy that semantically describes disease-causing agents, including both biotic and abiotic agents (see Fig. 5). To represent biotic agents we started with the *Microorganism* class and listed its subclasses (that include *Fungi, Bacteria, Nematodes, Viruses, Phytoplasmas, Protozoa,* and *Viroid*). However, after carefully studying domain knowledge, we concluded that other organisms affect plant health but are not considered to be pathogens, such as insects and mites, so we created a class called *Pest* to represent

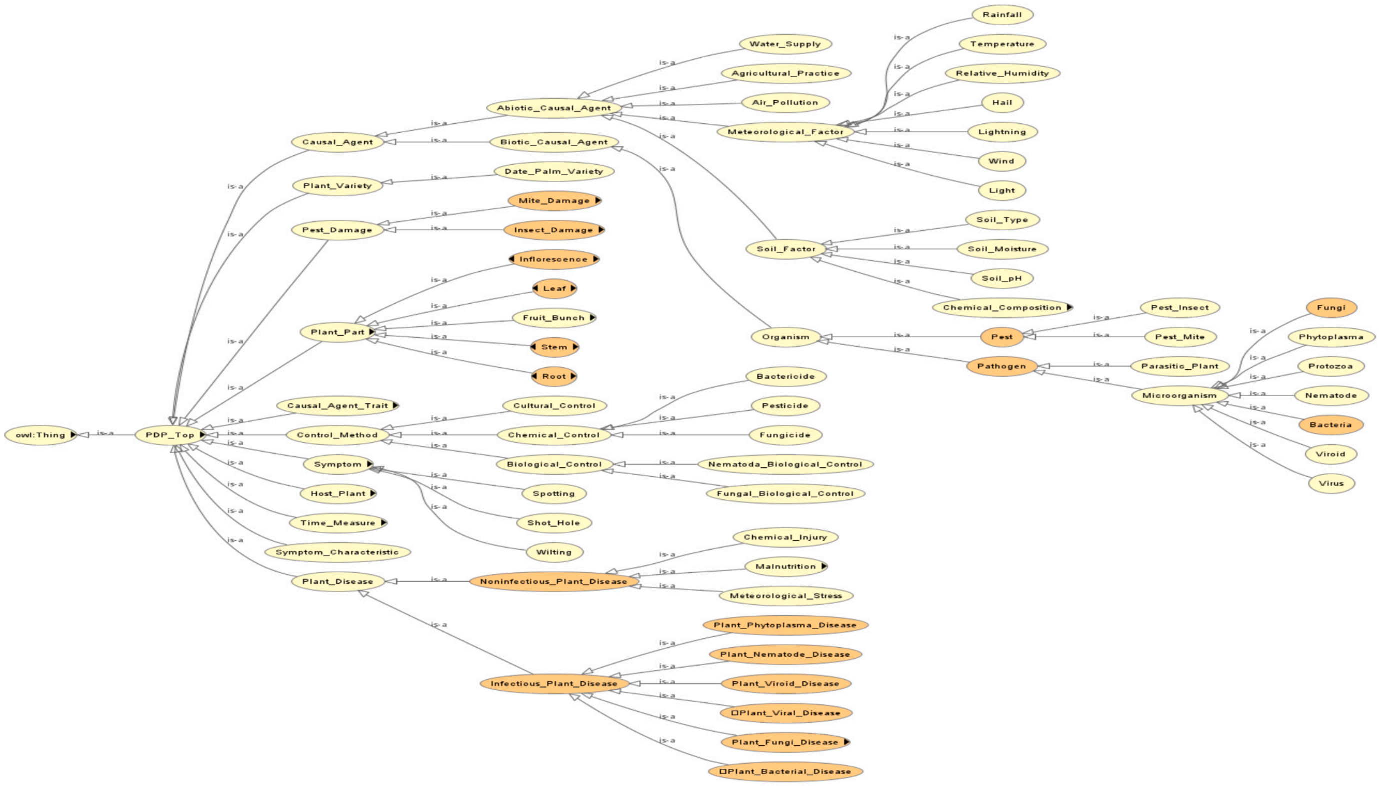

Fig. 5. An excerpt from the PDP-O.

those organisms. Then, to organize these classes into a hierarchal relationship, we created a more general class that includes all previous classes called *Organism*, which is a subset of the more general class called *Biotic_Casual_Agent*. The same approach was taken to other superclasses (e.g., *Symptom, Plant_Disease, Pest_Damege*, and *Plant_Part*). When we built the class hierarchy with a finer level of granularity using rdfs:subClassOf, we enhanced the subsumption reasoning to infer automatically that members of the subclass are included as members of the superclass. This simple inference mechanism in knowledge representation gives ontology its advantage over traditional databases.

- ***Enhancing PDP-O classes description using OWL axioms***
An axiom in OWL ontologies is a statement that represents a basic piece of information, and may involve a class, property, and individuals. These axioms constitute explicit knowledge about plant pests and diseases, and are available in our system's knowledge base. Logic (i.e., Description Logic) provides the means to determine precisely the logical consequences from a set of axioms, while the reasoning engine (e.g., Pallet) allows the system to derive implicit knowledge from a set of explicitly asserted axioms. Therefore, by describing classes using OWL axiom we empowered our system to be more intelligent and infer new facts about explicit knowledge, thus we expanded the system knowledge base (further details about explicit knowledge extraction are discussed in Section 3.2.2). For instance, we defined $Infectious\_Plant\_Disease$ class using the following logical rule:

$$Infectious\_Plant\_Disease \equiv Plant\_Disease \sqcap \exists is\_Caused\_By.$$
$$(Bacteria \sqcup Fungi \sqcup Nematode \sqcup Phytoplasma \sqcup Viroid \sqcup Virus) \tag{1}$$

The rule (1) states that an infectious plant disease is a plant disease caused by infectious organisms (i.e., bacteria, fungi, nematode, phytoplasma, viroid, and virus).

In addition, we defined the *Plant_Fungi_Disease* class using the following logical rule:

$$Plant\_Fungi\_Disease \equiv Infectious\_Plant\_Disease$$
$$\sqcap \forall is\_Caused\_By.Fungi \tag{2}$$

The rule (2) states that plant fungi disease is an infectious plant disease caused by fungus. Consequently, the reasoning engine automatically infers that if an individual has a causal agent that is fungi, it is a fungal plant disease based on rule (2), thus an infectious disease based on rule (1).

- ***Relationship modeling for enhanced reasoning***
The hierarchical structure alone can not provide a full description of any class. To achieve a complete description, the properties must also be assigned to classes. PDP-O defines a set of properties that enables the system to identify plant pests and diseases and recommend suitable control methods. For example, *has_Symptom* describes the relation between a disease and symptoms expressed by a host plant. Because several diseases share multiple symptoms, making it challenging to make a proper diagnosis, to deal with this issue we defined the is_Appear_On property to describe the plant part where the symptom is observed, thus allowing us to distinguish diseases that share multiple symptoms. Furthermore, because knowledge related to environmental contexts such as temperature, humidity, and rainfall can enhance the accuracy of disease identification beyond considering only those symptoms visible to the human eye, we defined the $has\_Environmental\_Factor$ as super property of three object properties: $has\_Humidity\_Factor$, $has\_Rainfall\_Factor$, and $has\_Temperature\_Factor$. Similarly, because a significant variation in susceptibility to a specific disease may occur within cultivars of a plant species, we defined the $is\_Susceptible\_To$ property to describe the relation between a plant disease and the most susceptible varieties. Table 4 describes PDP-O's important properties, their domain, range, characteristics, and meaning.

Table 4
Domain, range, and meaning of PDP-O important properties.

Object Property	Domain	Range	Characteristic	Inverse Property	Meaning
has_Symptom	*Pest or Plant_Disease*	*Symptom*	*Asymmetric and Irreflexive*	*indicates*	Describes the relation between a disease or pest X presents abnormal change (Symptom) Y in a host plant
can_Be_Caused_By	*Plant_Disease*	*Organism*	*Asymmetric and Irreflexive*	*causes*	A disease Y occurred because of an organism X
is_Disease_Of	*Plant_Disease*	*Host_Plant*	*Asymmetric and Irreflexive*	*has_Disease*	A plant disease that has influence on host plant
is_Pest_Of	*Past*	*Host_Plant*	*Asymmetric and Irreflexive*	*is_Host_For*	An organism Y is past of host plant X
is_Appear_On	*Symptom*	*Plant_Part*	*Asymmetric and Irreflexive*	*has_Abnormal _Appearance*	Describes the relation between a symptom and associated plant parts
has_Environmental_ Factor	*Pest or Plant_Disease*	*Environmental_ Factor*	*Asymmetric and Irreflexive*	*is_Environmental_ Factor_Of*	A disease or pest Y occurred because of environmental factor X such as Humidity, Rainfall, Temperature and Soil_Factors
has_Part	*Plant_Part*	*Plant_Part*	*Transitive and Reflexive*	*is_Part_Of*	A plant part Y that can be identified as being composed of one or more parts
is_Control_By	*Plant_Disease or Pest*	*Control_ Method*	*Asymmetric and Irreflexive*	*is_Control_Of*	A treatment or action X that might prevent or reduce the effect of a disease or damage Y
is_susceptible_To	*Plant_Variety*	*Plant_Disease*	*Asymmetric and Irreflexive*	*is_Harmful_For*	A plant variety that is susceptible to plant disease

```
IF    has_Part   rdf:type   owl:TransitiveProperty
  AND IF
        Date_Palm   has_Part    Inflorescence.
    AND IF
            Inflorescence     has_Part    Spathe,
            Inflorescence     has_Part    Spadix.
        AND IF
                Spadix    has_Part     Spikelet,
                Spadix    has_Part     Flowers,
                Spadix    has_Part     Inflorescence_Axis.
 THEN
        Inflorescence    has_Part     Spathe,
        Inflorescence    has_Part     Spadix,
        Inflorescence    has_Part     Spikelet,
        Inflorescence    has_Part     Flowers,
        Inflorescence    has_Part     Inflorescence_Axis,
        Date_Palm        has_Part     Inflorescenc
        Date_Palm        has_Part     Spathe,
        Date_Palm        has_Part     Spadix,
        Date_Palm        has_Part     Spikelet,
        Date_Palm        has_Part     Flowers,
        Date_Palm        has_Part     Inflorescence_Axis.
```

Listing 1: Semantic rule and inferences of the transitive property *has_Part*.

- ***Enriching the meaning of PDP-O properties by attaching property characteristics***
  OWL allows the attachment of characteristics to object and data properties, making relationships between entities explicit and describing their meanings more precisely. Therefore, we specified the inverse property of each object property in PDP-O, regardless of its subPropertyOf level, and attached other characteristics such as *Symmetric, Asymmetric, Functional, Inverse Functional, Transitive, Reflexive, and Irreflexive* (see Table 4). For instance, the transitive property was used to represent the transferable relationship between entities. This states that if ‘x’ relates to ‘y’ via the property ‘P’ and ‘y’ relates to ‘z’ via the same property, it implies that ‘x’ relates to ‘z’ via ‘P’. In PDP-O, we define the property *has_Part* and its inverse property *is_Part_Of* as *owl:TransitiveProperty* because a plant is composed of main parts, which in turn are composed of sub-parts, and we want to represent each plant part independently. The semantic rule and inferences of the transitive property *has_Part* are explained by Listing 1.
  This type of modeling is important for two reasons. First, it enables the representation of plant morphology in a machine-understandable way. Second, it allows the modeler to determine whether a specific plant part displays abnormal symptoms, which is crucial for accurately diagnosing plant diseases.
- ***Populating PDP-O classes with sufficient instances (or individuals)***
  Instances are the most specific elements in the domain of discourse. In Protégé the term ‘instances’ and ‘individuals’ are used interchangeably. We enriched PDP-O with sufficient instances, most of which were captured by analyzing text-based content during the knowledge acquisition phase. Currently, PDP-O contains 555 individual instances added to the main classes that address most competency questions. We emphasized *Plant_Fungi_Disease*, *Insect_Damage*, *Organism*, *Plant_Part*, *Control_Method* and *Symptom*, as these are directly involved in disease identification and control, to give answers with sufficient information for decision support. Our focus included describing 18 fungal diseases and 14 insect pests with significant economic impact. Additionally, the ontology covers 146 symptoms associated with these diseases and pests. It is worth noting that, to overcome the overlap between the symptoms associated with plant diseases and pests, we associated each disease or insect pest with at least three distinct symptoms. This enabled the system to achieve a more accurate diagnosis. For example, the description of the inflorescence rot disease of date palms is presented as a knowledge graph in Fig. 6. The graph contains six classes (i.e., *Fungi, Symptom, Chemical_Control, Agricultural_Practice, Environmental_Factor*, and *Time*) involved in the description of this disease (which is defined as an instance of *Fungi_Disease_Of_Date_Palm*). Each of the classes contains some instances related to inflorescence rot disease associated with it through object properties. For example, considering that “infected inflorescences covered with white powdery” and “rot of flowers and spikelets” are distinct symptoms of inflorescence rot disease, we used *has_Symptom* to associate this disease with its symptoms.

3.2.4. Evidence-Based Explanation Model (EBEM) design and development

This phase presents our approach to designing and developing the Evidence-Based Explanation Model (EBEM). As previously mentioned, while the role of PDP-O is to model knowledge about plant diseases and pests, the role of EBEM is to provide evidence supporting the validity of AgrODSS outputs, such as diagnoses and recommendations. Several categories of explanation approaches are discussed in the literature, such as contextual-based, trace-based, and case-based [17,43,44]. In this work, our focus is on scientific evidence-based explanation, concerned with

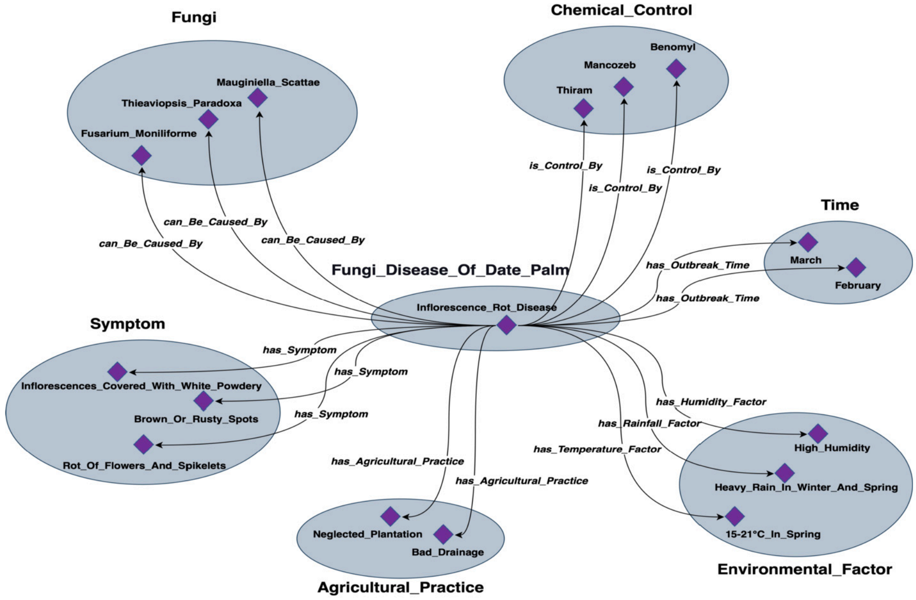

Fig. 6. A knowledge graph describes the inflorescence root disease of date palm.

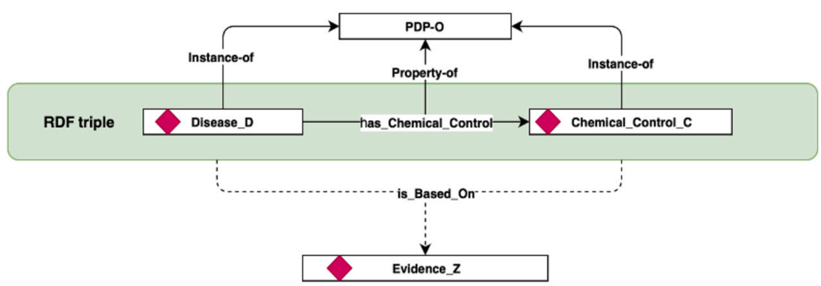

Fig. 7. Illustration of modeling process where each RDF triple in PDP-O asserted based on "Evidence" that supports it.

answering questions such as: "Is there evidence from the scientific work supporting ontology assertion (i.e., RDF statement)?".

- **EBEM design**
  Two design criteria have been considered: (1) to identify the evidence (i.e., a piece of text from scientific work) that supports an RDF statement asserted in our ontology (i.e., PDP-O), and (2) to provide metadata about the knowledge sources from which the evidence was extracted. To this end, we classified the information extracted from knowledge sources (see Section 3.2.2) into two types: (1) reasoning information, which is facts (or RDF statements) used to develop PDP-O (e.g., the disease name, symptoms, causal agents, and control methods); and (2) supporting information used to develop EBEM to provide evidence for the facts asserted in the PDP-O (e.g., text from guideline documents or research articles). To illustrate the design process, suppose a paper is published to describe a particular type of disease and its proper control method (e.g., disease D has chemical control C as backed by evidence Z). The first part of this information is captured and modeled in the PDP-O as an RDF triple. However, we want to annotate this RDF triple to state that evidence Z supports it. Fig. 7 provides an illustration of this idea.
- **EBEM implementation**
  As in PDP-O, EBEM was implemented using OWL in Protégé. OWL enables the representation of the intended explanations in this work in a machine-readable format, allowing modelers to model statements about other statements, a process known as reification [45]. Since EBEM is a semantic-based representation, we created the necessary classes, properties, and instances to represent explanations. EBEM developed around two central classes: *Explanation* and *Knowledge*. The *Explanation* class was created as a superclass, where each explanation type is a subclass of this class. Since our focus is on evidence-based explanation, this class has been specialized into a more specific class called *Scientific_Explanation*, which in turn has the *Evidence_Based_Explanation* class as a subclass. Instances of the last class represent evidence that supports RDF facts asserted in PDP-O. The *Knowledge* class was created as a sibling of the *Explanation* class. It has been specialized into one class, *Scientific_Knowledge*, which was created to semantically represent various types of knowledge sources as instances of this class, such as academic articles, books, thesis, proceedings, etc.
  To achieve more expressive semantic modeling, we define a set of object and datatype properties to establish relationships between classes or instances. The properties of *Scientific_Knowledge* class have been reused from Dublin Core[14] (DC) namespace, which provides a standard vocabulary to represent scientific publications. Examples of such properties include *dc:title, dc:date, dc:language, dc:source, dc:publisher, dcterms:identifier,* and *dcterms:hasVersion*. One of the important properties of *Evidence_Based_Explanation* is the object property *EBEM:is_Derived_From*, which associates the *Evidence_Based_Explanation* class with the *Scientific_Knowledge* class to establish the relation *"scientific evidence X is derived from knowledge source Y"*.

[14] https://www.dublincore.org/specifications/dublin-core/dcmi-terms/.

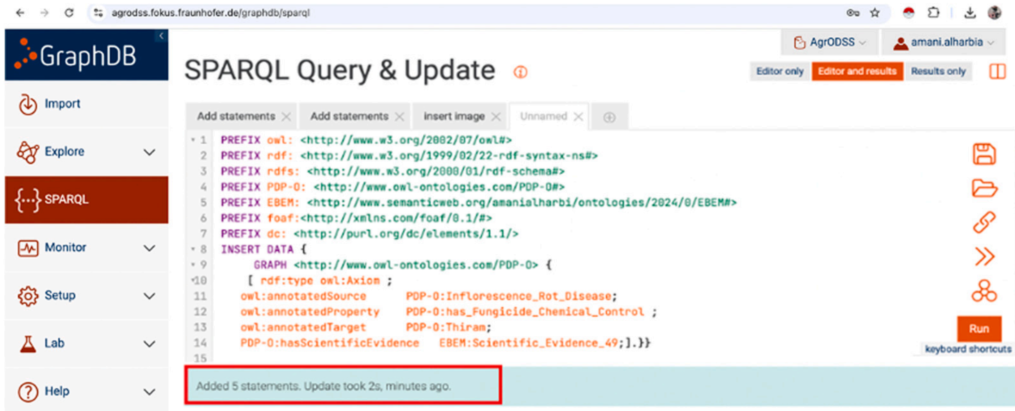

Fig. 8. An example of a SPARQL query to add OWL axiom annotations to the RDF statement: *"Inflorescence_Rot_Disease has_Fungicide_Chemical_Control Thiram"* which is supported by *Scientific_Evidence_49*.

- **PDP-O and EBEM linking process**

  Our goal here is to link the RDF statements asserted in PDP-O to the scientific evidence in EBEM that supports their assertion. To this end, the object property *has_Scientific_evidence* was defined in PDP-O, and its inverse property *is_Scientific_evidence_Of* was defined in the EBEM to link entities in the two models. Then, OWL axiom annotations are used to link each RDF statement in PDP-O with corresponding scientific evidence in EBEM. The following formula represents the general syntax of axiom annotations.

  [x rdf:type owl:Axiom;
  x owl:annotatedSource s;
  x owl:annotatedProperty p;
  x owl:annotatedTarget o;
  x PDP-O:has_Scientific_evidence SE;]

  Where *'x'* refers to the RDF statement which consists of *'s'*, which refers to the subject of *'x'*, *'p'* which refers to the predicate of *'x'*, and *'o'* which refers to the object of *'x'*. The last triple refers to the scientific evidence that supports *'x'*, associated by the property *hasScientificEvidence* and its value *'SE'*. We added these annotations using a SPARQL query in GraphDB (see Fig. 8). As shown in the figure, we used the INSERT DATA operation in the SPARQL query to add OWL axiom annotations to the RDF statements asserted in PDP-O and link them with the supporting evidence asserted in EBEM. The GRAPH clause specifies the URI of a particular graph to which one or more OWL axiom annotations are added; in our case, we provide the URI of PDP-O to this clause. A single INSERT DATA request can be used to add multiple OWL axiom annotations to a given graph. Fig. 9 presents a conceptual overview to illustrate the linking process between PDP-O and EBEM and describes the associations necessary to understand its idea.

3.2.5. Establishing AgrODSS web-based SPARQL endpoint

After developing PDP-O and the EBEM, we imported both into GraphDB. Our goal here was to establish a SPARQL endpoint as an interface for users to access AgrODSS from the front-end. In this section, also we demonstrate the effectiveness of AgrODSS by executing SPARQL queries through the SPARQL endpoint to obtain directly complex information to support agriculture decisions regarding disease and pest management. For this purpose, we formulated 19 CQs to be answered by the knowledge base, some of which are shown in Table 5. These questions were created in accordance with the CQs that define the system requirements (as outlined in Section 3.2.1, Table 3). By answering these questions we identified diseases or pests practically, recommended appropriate control methods, and gave scientific evidence to supports the recommendation. To illustrate how AgrODSS utilizes semantic technologies and ontological reasoning to answer CQs questions in Table 5, we present and discuss the following exemplary scenario:

Usage scenario:

"Suppose dark brown or black hard lesions appear on the leaf rachis and the palm's new leaves become twisted and malformed, along with round to oblong dark brown spots on the external surface of unopened spathes: what do these symptoms indicate? Furthermore, what type of problem do these symptoms suggest?"

This scenario represents the situation in which the user provides the system with more than one symptom observed on a date palm tree. Fig. 10 shows the SPARQL query executed to identify the problem presented in the above scenario, which is related to CQ1 in Table 5. This query searches for a disease or pest that influences a plant that has the scientific name "Phoenix Dactylifera" and produces three different symptoms: (1) "dark brown or black hard lesions" that appear on a plant part "leaf rachis", (2) "malformation" that appears on a plant part "new leaf", and (3) "round to oblong dark brown spots" that appears on a plant part described as "external surface of unopened spathe". It finds what these symptoms indicate and also what type of disease/pest these symptoms refer to.

The results retrieved from the previous query are shown in Fig. 11. From the result set, we can note that there is a single defined problem associated with the three symptoms provided, which is *Black_Scorch_Disease*. Since the query contains more specific information, this helps to narrow down the number of results to a single disease. Moreover, the results in Fig. 11 show additional information, we can see that *Black_Scorch_Disease* is a kind of *Plant_Disease*, *Infectious_Plant_Disease*, *Plant_Fungi_Disease*, and *Fungi_Disease_Of_Date_Palm*. The interpretation of this conclusion is as follows: because we classified the *Plant_Disease* class based on the infection process into *Infectious_Plant_Disease* and *Noninfectious_Plant_Disease*, then *Infectious_Plant_Disease* class has been classified based on the major causes, such as *Bacterial, Fungal, Viral, Phytoplasma,* and so on. In addition, each of these classes (i.e., *Plant_Fungi_Disease*) has been classified based on the host plant (i.e., *Fungi_Disease_Of_Date_Palm*). Therefore, based on class taxonomy and the logical rules defining these classes (as discussed in Section 3.2.3), the reasoner automatically inferred that *Black_Scorch_Disease* is of the type *Infectious_Plant_Disease*, *Plant_Fungi_Disease* and *Fungi_Disease_Of_Date_Palm*. These results answer the question CQ1 in Table 5 (What do the abnormal symptoms observed on a plant, or its parts, indicate?).

After the problem is diagnosed, the next step is to suggest the appropriate control or treatment. The queries shown in Fig. 12 were executed to provide users with recommendations on the appropriate methods to control *Black_Scorch_Disease*.

The query in Fig. 12a is related to CQ2 in Table 5, namely to recommend the appropriate chemical control of a particular pest or disease. Similarly, the query in Fig. 12b corresponds to CQ3 (What

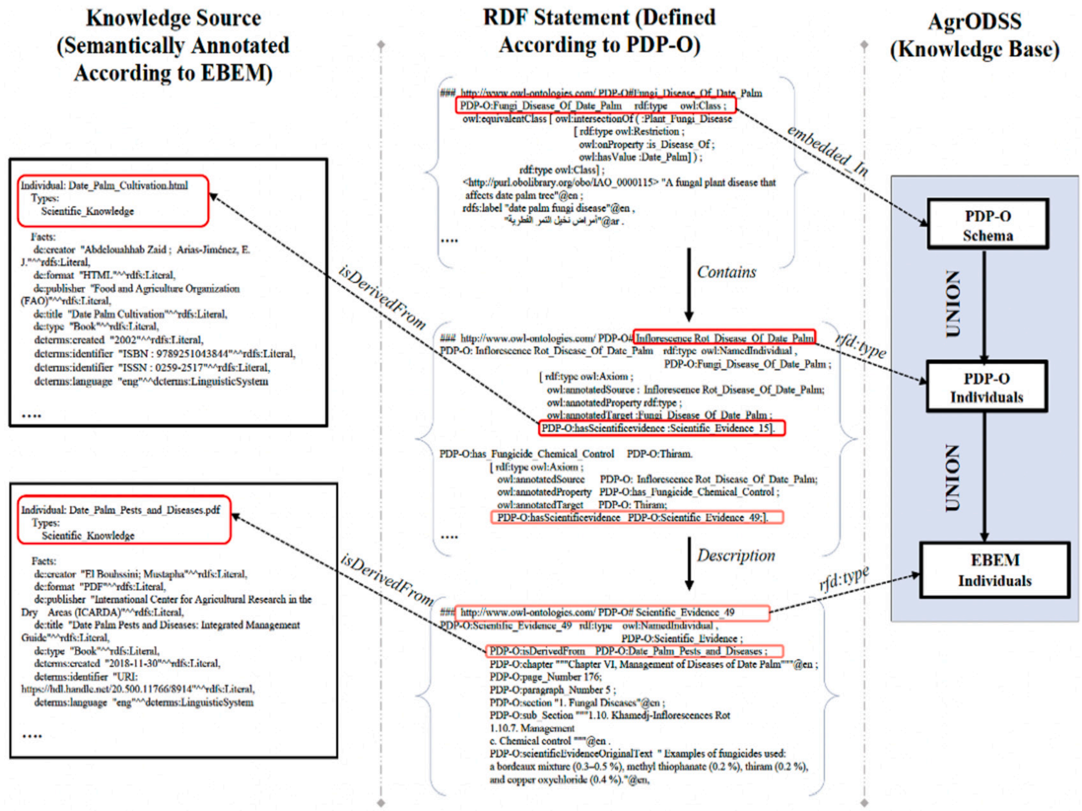

Fig. 9. A conceptual overview of PDP-O and EBEM Linking Process.

Table 5
Sample of CQs formulated to query AgrODSS knowledge base.

Number	Competency Questions
CQ1	What do the abnormal symptoms observed on a plant, or its parts indicate?
CQ2	What are the suitable chemical controls of a particular disease/past?
CQ3	What are the suitable culture controls of a particular disease/past?
CQ4	How can the recommended control method be applied?
CQ5	What evidence supports the recommended control method?
CQ6	What are the varieties or cultivar susceptible to this disease/pest?
CQ7	How symptoms associated with a particular disease or pest look like?
CQ8	What are the environmental factors that contribute to the emergence of a particular disease/past?

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX dp: <http://www.owl-ontologies.com/PDP-O#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX dc: <http://purl.org/dc/elements/1.1/>

SELECT DISTINCT ?Problem  ?ProblemType
WHERE { ?Problem dp:influence ?AffectedCrop.
   {?AffectedCrop dp:has_Scientific_name  ?SName. FILTER (regex(str(?SName),"Phoenix Dactylifera","i")) }
                 {?Symptom  dp:is_Appear_On dp:Leaf_Rachis.
                  FILTER (regex (str(?Symptom),"Dark brown or black hard lesions","i"))}
                  UNION {?Symptom  dp:is_Appear_On dp:New_Leaf.
                  FILTER (regex(str(?Symptom),"Malformation","i"))}
                  UNION {?Symptom  dp:is_Appear_On dp:External_Surface_Of_Unopened_Spathe.
                  FILTER (regex(str(?Symptom)," Round to oblong dark brown spots","i"))}
                  ?Problem dp:has_Symptom ?Symptom; rdf:type ?ProblemType.}
```

Fig. 10. SPARQL query for answering CQ1 in Table 5.

?Problem	?ProblemType
dp:Black_Scorch_Disease	dp:Plant_Disease
dp:Black_Scorch_Disease	dp:PDP_Top
dp:Black_Scorch_Disease	dp:Plant_Fungi_Disease
dp:Black_Scorch_Disease	dp:Fungi_Disease_Of_Date_Palm
dp:Black_Scorch_Disease	dp:Infectious_Plant_Disease
dp:Black_Scorch_Disease	owl:Thing

Fig. 11. Results of SPARQL query shown in Fig. 10.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX dp: <http://www.owl-ontologies.com/DPDAPO#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX dc: <http://purl.org/dc/elements/1.1/>

SELECT DISTINCT ?DiseaseName  ?Fungicide_Chemical_Control ?Chemical_Usage_Descrption
    WHERE { ?DiseaseName rdfs:label "black scorch disease"@en;
             dp:has_Fungicide_Chemical_Control ?Fungicide_Chemical_Control.
    ?p rdf:type owl:Axiom ;
     owl:annotatedSource dp:Black_Scorch_Disease;
     owl:annotatedProperty dp:has_Fungicide_Chemical_Control;
     owl:annotatedTarget ?Fungicide_Chemical_Control;
     dp:has_Fungicide_Usage_Descrption ?Chemical_Usage_Descrption.}
```

(a)

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX dp: <http://www.owl-ontologies.com/PDP-O#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX dc: <http://purl.org/dc/elements/1.1/>
#What are the cultural control methods of Black_Scorch_Disease?
#And provide implementation guidance if this information is available

SELECT DISTINCT ?DiseaseName  ?CulturalControls ?CulturalControlDescrption
    WHERE {
    ?DiseaseName rdfs:label "black scorch disease"@en;
          dp:has_Cultural_Control ?CulturalControls.
    ?p rdf:type owl:Axiom;
     owl:annotatedSource dp:Black_Scorch_Disease;
     owl:annotatedProperty dp:has_Cultural_Control ;
     owl:annotatedTarget ?CulturalControls ;
     dp:has_Cultural_Control_Descrption  ?CulturalControlDescrption.}
```

(b)

Fig. 12. Sample of queries to generate recommendations on the appropriate control methods.

are the suitable culture control of a particular disease/past?). The results retrieved from the previous queries are shown in Fig. 13. The query in Fig. 13a returned four control methods (*Thiophanate_Methyl*, *Copper_Oxychloride*, *Mancozeb*, and *Metalaxyl-M*) recommended to control *Black_Scorch_Disease*. These control methods are from the class *Fungicide*. The query in Fig. 13b returned six control methods recommended to control *Black_Scorch_Disease*, which are from the class *Cultural_Control*. In addition, the results of the previous queries show usage for the recommended control methods, answering the question CQ4 in Table 5 (How can the recommended control method be applied?). It is worth mentioning that AgrODSS offers another type of control method (i.e., biological control); however, for demonstration purposes, we show only two types of control methods (chemical and cultural).

In the second step above, AgrODSS provides recommendations to control the problem diagnosed in the first step. As we aimed to demonstrate the validity of these recommendations and increase users' knowledge, AgrODSS performs an additional step, which is to provide scientific evidence that supports these recommendations. For example, in Fig. 13a AgrODSS recommends the chemical substance *Mancozeb* to control *Black_Scorch_Disease*, so what is the scientific evidence that supports this recommendation? The query in Fig. 14 was performed to answer this question. Fig. 15 shows the results of the previous query.

We can see from the results in Fig. 15 the piece of text from which the RDF statement was formulated, the title of the knowledge source (i.e., book) from which the text was extracted, the authors of the scientific work, and the location (title of the chapter) of the text in the knowledge source. These results answer question CQ5 in Table 5. By presenting the supporting evidence, AgrODSS helps increase user trust and validate the generated recommendations, as users can easily compare the SPARQL query results with answers from domain-specific documents. Moreover, it increases users' knowledge of disease and pest management and makes scientific works accessible to target stakeholders. For more information they can easily refer to the domain-specific documents obtained by the SPARQL query. Additionally, presenting supporting evidence not only makes recommendations valid from user standpoints, but also serves a crucial role in assisting developers with ontology debugging. Domain ontologies contain information about entities extracted from multiple knowledge sources. In this context, knowing the scientific basis of each assertion is vital if errors are detected or the knowledge sources change, making it easy to update ontology content as knowledge of the domain evolves.

For non-technical users, GraphDB hides the complexity of the technology and enables full-text searching for any resource in the AgrODSS knowledge base to explore it without writing SPARQL queries. For example, if the user searches for *Black_Scorch_Disease* they can view the results as a knowledge graph (see Fig. 16). We can see from the visual graph on the left side of the figure further information about *Black_Scorch_Disease*, such as the most susceptible varieties which answers question CQ6 in Table 5, and also shows other symptoms associated with the disease. In addition, each node of the graph can be expanded for more information. For instance, if the user selects *Dark_Brown_Or_Black_Hard_Lesions_On_Leaf* as the symptom that matches their observation, then they can see information such as the plant parts affected by this symptom and symptom characteristics. The right panel of the graph displays symptoms with their textual description and images. Textual descriptions and images could assist in the diagnostic process to narrow down the possible diseases into those to be considered and those that can be eliminated. In addition, it becomes effortless to use, especially for farmers. These results answer question CQ7 in Table 5. Finally, the graph shows that causal agents of *Black_Scorch_Disease* include environmental factors (i.e., high humidity, silty soil, and moderate temperature) and biotic factors (i.e., *Chalara_Paradoxa* and *Ceratocystis_Paradoxa*).

	DiseaseName	Fungicide_Chemical_Control	Application_Method	Application_Rate	Chemical_Usage_Descrption
1	dp:Black_Scorch_Disease	dp:Thiophanate_Methyl	"Spraying"@en	"100-150 g/100 L water, about (10 L) of pesticide."@en	"After finishing pruning the infected leaves, sanitize the pruning shears and cover the pruning wounds by spraying them with the pesticide three times between 3 to 4 weeks each."@en
2	dp:Black_Scorch_Disease	dp:Copper_Oxychloride	"Spraying"@en	"100 ml / 100 L of water"@en	"Disinfect wounds and prune cuts and surrounding tissues resulting from pruning leaves , with a copper compound."@en
3	dp:Black_Scorch_Disease	dp:Mancozeb	"Spraying"@en	"250-300 g/100 L water, about (10 L) of pesticide."@en	"After finishing pruning the infected leaves, sanitize the pruning shears and cover the pruning wounds by spraying them with the pesticide three times between 3 to 4 weeks each."@en
4	dp:Black_Scorch_Disease	dp:Metalaxyl-M	"Spraying"@en	"100-150 g/100 L water, about (10 L) of pesticide."@en	"After finishing pruning the infected leaves, sanitize the pruning shears and cover the pruning wounds by spraying them with the pesticide three times between 3 to 4 weeks each."@en

(a)

	DiseaseName	CulturalControls	CulturalControlDescrption
1	dp:Black_Scorch_Disease	dp:Avoid_Injuries_Of_Palms_Parts	"Avoid injuries of young palms and the apical region of the tree during pruning and harvest."@en
2	dp:Black_Scorch_Disease	dp:Avoid_Planting_Of_Infected_Offshoots	"Avoid planting the contaminated offshoots and transplanting the infected young palms."@en
3	dp:Black_Scorch_Disease	dp:Avoid_Removing_Spines_By_Pulling	"Avoid removing the spines by pulling which causes injuries to rachis of leaves."@en
4	dp:Black_Scorch_Disease	dp:Ensure_Proper_Operation_And_Maintenance	"Good sanitation, pruning, collecting and immediately burning of infected palms, cleaning palm trees. Proper maintenance can reduce the incidence of disease and limit their extension."@en
5	dp:Black_Scorch_Disease	dp:Protect_Wounds_On_Palm_Parts	"Protect the cut wounds of leaves and healing by disinfectant products and especially the leaves of the crown top."@en
6	dp:Black_Scorch_Disease	dp:Remove_And_Burn_Of_Infected_Plant_Part	"Remove infected leaves from trees and offshoots as soon as the fruits are collected and burn them outside the farm, and not leave them close to trees so as not to be a source of infection. Covering the infection sites with Bordeaux paste, in autumn after harvesting, and repeating the process in early spring before the appearance of the spadix inflorescence"@en

(b)

Fig. 13. Results of SPARQL query shown in Fig. 12.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX dp: <http://www.owl-ontologies.com/DPDAPO#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX dc: <http://purl.org/dc/elements/1.1/>

SELECT DISTINCT ?DiseaseName ?ScientificEvidenceText  ?ScientificSourceTitle
?SourceCreator ?EvidenceLocation
WHERE {  ?DiseaseName rdfs:label "black scorch disease"@en.
       ?p rdf:type owl:Axiom;
       owl:annotatedSource dp:Black_Scorch_Disease ;
       owl:annotatedProperty dp:has_Fungicide_Chemical_Control;
       owl:annotatedTarget dp:Mancozeb;
              dp:hasScientificevidence ?s.
     ?s dp:isDerivedFrom ?ScientificSource.
     ?s dp:scientific_Evidence_Original_Text ?ScientificEvidenceText;
               dp:chapter ?EvidenceLocation.
    ?ScientificSource dc:title ?ScientificSourceTitle;
                           dc:creator ?SourceCreator.}
```

Fig. 14. Example of SPARQL query corresponding to CQ5 in Table 5 (What scientific evidence supports the recommendation *"black scorch disease has chemical control Mancozeb"*?).

	DiseaseName	ScientificEvidenceText	ScientificSourceTitle	SourceCreator	EvidenceLocation
1	dp:Black_Scorch_Disease	"c. Chemical control - Disinfect wounds and prune cuts and surrounding tissues resulting from pruning leaves with a copper compound (e.g., copper oxychloride 0.4 %). - Spray the tree with fungicide such bordeaux mixture (0.3 %), methyl thiophanate (0.2%), polyram thiram (0.2 %), and Mancozeb (0.2 %). - Other chemical products are: lime-sulphur solution, copper sulphate lime mixture, dichlone, thiram or any new copper-based fungicides."@en	"Date Palm Pests and Diseases: Integrated Management Guide"^^<http://www.w3.org/2000/01/rdf-schema#Literal>	"El Bouhssini; Mustapha"^^<http://www.w3.org/2000/01/rdf-schema#Literal>	"CHAPTER VI : MANAGEMENT OF DISEASES OF DATE PALM"@en

Fig. 15. Results of SPARQL query shown in Fig. 14.

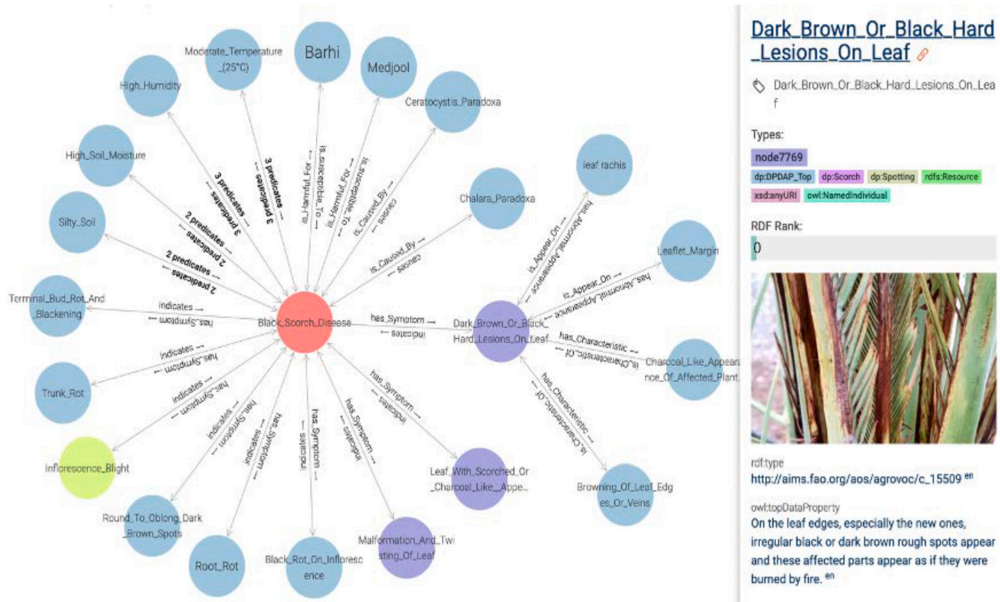

Fig. 16. Knowledge graph of *Black_Scorch_Disease* generated when the user start exploration using GraphDB.

Table 6
Results of AgrODSS evaluation by domain experts.

Category	Number of validated CQs	Results				
		Mean	SD	Relative weight (%)	Degree#	Rank
Disease/Pest	25	5.68	0.79	81.09	Agree	3
Control Methods	20	4.88	2.01	69.71	Somewhat agree	5
Symptom	15	5.87	0.84	83.84	Agree	2
Causal Agents	20	6.13	0.55	87.53	Strongly agree	1
Others	10	5.67	0.64	81.04	Agree	4
Total	***90***	***5.65***	***0.97***	***80.66***	***Agree***	

4. AgrODSS: ontology and system evaluation

This section presents our evaluation approach to assess key aspects of AgrODSS. In this work, the Pellet reasoner 2.2.0 and OntoDebug 0.2.2 (Protégé plugins) were consistently used to verify the ontology's coherence and consistency. However, human evaluation is essential to assess the accuracy and effectiveness of AgrODSS in supporting user decisions. This evaluation was conducted by answering the CQs executed in SPARQL query forms. A satisfactory result for CQs is a way to assess the achievement of objectives of an ontology-based project [46]. A total of 90 CQs were validated for this test, divided into five categories related to the knowledge aspect covered by PDP-O, mainly disease or pest, symptoms, causal agents, control methods, and others (i.e., the most affected plant parts by a given disease or pest, most susceptible varieties to a given disease or pest, and the active times of an insect pest). Then, the results obtained by executing SPARQL queries were submitted to the domain experts for validation using a structured questionnaire. The questionnaire included 90 closed-ended questions (corresponding to the number of CQs) and relied on a 7-point Likert Scale range from (1 = Strongly disagree) to (7 = Strongly agree), which allowed domain experts to express how much they disagree or agree on each answer. We asked domain experts to rate the results generated by the system in terms of "Accuracy". Accuracy means *"the degree to which an ontology provides the correct results with the needed degree of precision, and can be measured by the number of CQs that received the correct answers"*[47]. The AgrODSS passes the competency validation test if all CQs have answers and are graded at least as 'Somewhat agree'.

A total of 11 domain experts were involved in this evaluation, including 7 entomologists and 4 pathologists *(detailed information about domain experts involved in this evaluation, CQs with corresponding SPARQL queries, results obtained by the AgrODSS system, and the results of domain experts' evaluation of each category can be found in Supplementary data A)*. To ensure expert engagement in the evaluation process, online workshops were held to explain the overall goals of the system and the requirements for the evaluation process. These workshops also included initial evaluations, where we presented the ontology structure, demonstrated inferences made by the reasoner, and showcased the results of selected SPARQL queries.

Table 6 gives the summary results of evaluation by domain experts. The evaluation results demonstrate that AgrODSS had promising results. The overall accuracy is 80.66%, achieving 87.53% accuracy for causal agent recognition, 81.09% accuracy for disease and pest identification, 83.84% accuracy for symptoms that have been correctly associated with the corresponding disease and pest, and 69.71% accuracy for recommending the appropriate control methods. Also, results in Table 6 show that recognizing the causes (abiotic or biotic) that contribute to the emergence of disease achieved the highest accuracy. Meanwhile, recommending the appropriate control methods for a given disease or pest achieved the lowest accuracy. Although the recommended control method is suitable (i.e., chemical), it needs a more professional answer as so many aspects govern the effective use of chemicals. For example, the application rates vary according to the application method; the concentration in the immersion method is often higher than for direct spraying. Also, the application rate and method depend on the stage of the insect's life cycle; for example, some insecticides are effective when the insect is in the larva stage yet ineffective against the adult insect, or they differ in the application method or concentration rate. Besides, pests may have developed resistance against some pesticides over time. To address this issue, we needed to interview a group of domain experts to establish a set of rules to be more precise regarding chemical substances and restrict their use for each case.

Finally, Table 6 shows that the remaining categories (disease/pest, symptoms, and others) achieved similar accuracy (Agree). The reason behind not reaching the greatest accuracy (i.e., Strongly agree) is the similarity and overlap of symptoms produced by the various types of casual agent (i.e., fungi, bacteria, and insects), which leads to confusion and poses a difficulty in correctly diagnosing a disease. For example, CQ: What does a dark brown stripe that appears on the dorsal side of the rachis from the base to the top indicate? (in Disease/Pest Category) returns a total of three possible problems: *Bayoud_Disease*; *Fusarium_Wilt_Disease*; and *Reddish_Brown_Parallel_Spot_Disease*. These results were rated by domain experts as "two Agrees", with one "Strongly agree" by three pathologists, and was rated as "Disagree" by one entomologist, due to the overlap between symptoms produced by various types of casual agents.

5. Conclusion and future work

Agricultural production is constantly threatened by various diseases and pests that affect crops, leading to significant economic losses and rising concerns about food security. The identification and control of plant pests and diseases is a complex decision and knowledge-handling problem. Multiple factors affect this decision, ranging from environmental conditions to biological causes. Consequently, in this work, we present an Agriculture Ontology-Based Decision Support System (AgrODSS), which aims to assist decision-making regarding plant disease and pest identification and control. AgrODSS architecture consists of two semantic-based models. First, we designed and developed Plant Diseases and Pests Ontology (PDP-O), which captures key concepts, terms, and relationships related to plant diseases and pests and represents them in a machine-understandable format. Additionally, PDP-O provides an in-depth computational schema enriched with sufficient RDF data for intelligent decision-making. Second, we designed and developed an Evidence-Based Explanation Model (EBEM) that points to evidence from related literature to demonstrate the validity of the system outputs. Furthermore, a use case is presented with real-life data regarding date palm pests and diseases to demonstrate the effectiveness of AgrODSS.

AgrODSS was evaluated practically with 11 domain experts, including entomologists and pathologists. It obtained encouraging results with an overall accuracy of 80.66% in identifying of disease and insect pests that affect date palms. Although the current version of AgrODSS obtained encouraging results, several issues must be addressed to provide better decision support. For instance, the current version is centered on a specific crop (date palm), which left our system unable to deal with diseases and pests affecting other crops. This is due to manually instantiating the ontology that led to the insufficiency of data and rules covered by the PDP-O. However, the PDP-O can be easily extended to deal with other crops, diseases, and insect pests. In this sense, we seek to build a Natural Language Processing (NLP) tool to extract relevant data from available unstructured knowledge sources for automatically enriching the ontology by adding new instances, relations, and rules. This tool will also assist in keeping the PDP-O up to date and make it easy to update the ontology content as the knowledge in the domain evolves.

There are several research directions for future work. First, the current version of AgrODSS is available only as a SPARQL endpoint. We plan to make it more human-friendly by designing and developing a mobile application that allows various stakeholders to benefit from it to make informed decisions. Second, once the mobile application is complete, the next step is to evaluate the system's usability and determine user satisfaction through field trials (i.e., farmers who use AgrODSS in a real environment to perform observations and identify a disease). Third, PDP-O can be improved by linking it to the Global Agricultural Open Data Cloud (GAODC) to make local data interoperable with global efforts and maximize the data available to decision-makers. For example, it could integrate PDP-O with chemical databases such as PubChem [48] and ChEBI [49] to include more details on chemical substances. Finally, we need to consider that agricultural information has strong local characteristics related to local climate, soil, culture, and local species. Therefore, we plan to integrate AgrODSS with web services such as location and weather services to provide timely information and location-based decision support.

CRediT authorship contribution statement

Amani Falah Alharbi: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Muhammad Ahtisham Aslam:** Writing – review & editing, Validation, Supervision. **Khalid Ali Asiry:** Writing – review & editing, Supervision, Resources. **Naif Radi Aljohani:** Writing – review & editing, Visualization, Supervision. **Yury Glikman:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.atech.2024.100659. It is composed of: (1) a Word file including information about the cross-sectional survey conducted for system requirements elicitation, including survey design and findings, (2) a Word file including a Glossary of Terms (GT), or a list of domain concepts and relationships extracted from existing ontologies and reuse by our ontology, (3) a Word file including information about domain experts involved in the ontology and system evaluation, CQs with corresponding SPARQL queries, results obtained by the AgrODSS system and the results of domain experts' evaluation.

Data availability

I have shared a link to the ontology file in the manuscript file.

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