Knowledge Representation in Digital Agriculture: A Step Towards Standardised Model

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\section*{ABSTRACT}

In recent years, data science has evolved significantly. Data analysis and mining processes become routines in all sectors of the economy where datasets are available. Vast data repositories have been collected, curated, stored, and used for extracting knowledge. And this is becoming commonplace. Subsequently, we extract a large amount of knowledge, either directly from the data or through experts in the given domain. The challenge now is how to exploit all this large amount of knowledge that is previously known for efficient decision-making processes. Until recently, much of the knowledge gained through a number of years of research is stored in static knowledge bases or ontologies, while more diverse and dynamic knowledge acquired from data mining studies is not centrally and consistently managed. In this research, we propose a novel model called ontology-based knowledge map to represent and store the results (knowledge) of data mining in crop farming to build, maintain, and enrich the process of knowledge discovery. The proposed model consists of six main sets: concepts, attributes, relations, transformations, instances, and states. This model is dynamic and facilitates the access, updates, and exploitation of the knowledge at any time. This paper also proposes an architecture for handling this knowledge-based model. The system architecture includes knowledge modelling, extraction, assessment, publishing, and exploitation. This system has been implemented and used in agriculture for crop management and monitoring. It is proven to be very effective and promising for its extension to other domains.

\section*{1. Introduction}

In this era of digital agriculture, crop farming can take advantage of all the advances in Information and Communication Technologies. The data collection becomes routine. This study collects large amounts of data from different perspectives. Data science and machine learning are at the core of agricultural data analyses and decision-making processes. In recent years, the knowledge discovered from the data analysis processes is the most diverse and dynamic in digital farming. In other words, digital agriculture benefited significantly from data mining, data analytics or, in the general term, “data science”. Several data-driven studies have been conducted on several agricultural elements, including soil, weather, crop yield, disease, fertilisers, etc., with the view to derive models that govern the phenomenon behind agricultural processes, forecasting, or optimising the usage of resources. Moreover, significant farming knowledge also derived from farmers’ and agronomists’ experiences. These can be incorporated into some advanced models to increase the reliability and precision of digital agriculture.

The application of data science to digital agriculture enabled some studies which were not possible in the past. These include data construction, forecasting models and validation of some hypotheses about efficient farming techniques. In this context, there are several computational soil studies, for example, building datasets of soil profiles Shangguan, Dai, Liu, Zhu, Duan, Wu, Ji, Ye, Yuan and Zhang (2013), monitoring soil characteristics under effects of other factors and crop yield Bishop and McBratney (2001), or using soil characteristics to predict other soil characteristics Wang, Yang, Yang, Yang and Jianli (2019). Another common application of knowledge mining in agriculture is crop yield prediction, for example, predicting yield or wheat yield based on soil attributes, weather factors, and management factors Aggelopoulou, Bochtis, Fountas, Swain, Gemtos and Nanos (2011), Liu, Goering and Tian (2001), Pantazi, Moshou, Alexandridis, Whetton and Mouazen (2016). Finally, another important application of knowledge mining is disease prediction or protection plan. For instance, detecting nitrogen stresses in the early crop growth stage of corn fields Maltas, Charles, Jeangros and Sinaj (2013), or detecting and classifying sugar beet diseases Karimi, Prasher, Patel and Kim (2006) is crucial for the farmers.

Data mining or data analysis process has four typical tasks; clustering, classification, regression, and associations. Some of these are heavily used. So far, data classification and regression are widely used in digital agriculture. Data classification is used to detect diseases Karimi et al. (2006), predict crop yield (e.g., low, medium, high) Papa-georgiou, Aggelopoulou, Gemtos and Nanos (2013). Regression techniques are mainly used to find correlations or models between crop yields and other different attributes Aggelopoulou et al. (2011), Bishop and McBratney (2001). Although the data analysis process is more or less straightforward, however, it faces many challenges; the number of input parameters is usually very large, the data quality and its variety, and the lack of prior knowledge and tangible
hypotheses. The latter can be dealt with by incorporating some know-how in the data science process itself, however, this know-how is not always available as an input. These known results or models are often published in scientific articles and reports. They are not ready to be incorporated into advanced data analysis methodologies. They need to be extracted from these scientific reports and publications, they need to be represented in a form that they can be exploited, and they need to be stored in a common and unified format to facilitate their exploration and retrieval.

The main requirement of such knowledge representation is that the mined results are not consistent among different sources of knowledge. For example, one can have two different knowledge representations from two separate data mining studies used to predict farming conditions to maximise the crop yield of winter wheat. The concepts of high crop yield in two knowledge representations in Papageorgiou et al. (2013) and Natarajan, Subramanian and Papageorgiou (2016) are different. They depend on the way they were defined based on the datasets and their context. Therefore, the results may not be consistent. This issue can also occur with input attributes. In addition, the farming knowledge represented as ontology is static, and it is difficult to apply to various regions having diverse farming conditions. The knowledge represented as rules-based in expert systems does not scale well because it is not easy to refine the rules and check the coherence of all the rules. Finally, the knowledge mined from data mining processes is dynamic and flexible, so their representations may be different among data mining processes. For instance, several data mining results are stored as rules while others as vectors or trained models.

This study extended the definition of the Ontology-based Knowledge map (OAK) model described in Ngo, Kechadi and Le-Khac (2020) to include more new entities, such as State, Relation, Concept, Attribute, Transformation (Data Transformation and Computing Algorithm), Instance, and Lexicon in the OAK model. The extended definition is much more robust and inclusive to model any types of knowledge. We also provided a new definition of knowledge representation to include the results of any data mining (DM) technique, such as clustering, classification, and association rules mining. These include DM process, Fact Knowledge, and Analysis technique (Classification, Clustering, Regression, Association Rule algorithms). This makes it not only easy to infer the knowledge but also easy to extract it from external documents, such as journal papers. The study extended the OAK architecture to include six more modules; Knowledge Miner, Knowledge Modelling, Knowledge Extraction, Knowledge Assessment, Knowledge Publishing, and Knowledge Exploitation. We provided new evaluation, verification, and validation processes for the proposed model. We proposed a novel knowledge assessment within the OAK model. This study built a prototype for a knowledge repository that can hold up to 500 knowledge representations extracted from 1,000 articles and reports. Finally, we developed an innovative Knowledge Browser to identify knowledge by concepts and roles. This browser is also used to evaluate the ability of the proposed model to handle knowledge. The contribution of this extended model is to support data scientists and agronomists in discovering knowledge and representing their mined knowledge.

The next section gives an overview of knowledge concepts and how to create knowledge in the domain of agriculture. Section 2 describes the details of the OAK model, which includes relevant definitions, architecture and its main modules. Section 3 presents the implementation of the main components in the OAK architecture, whereas Section 4 deals with experiments and the evaluation of the OAK model. Finally, the paper gives a conclusion and several future works in Section 5.

2. OAK - Ontology-based Knowledge Map Model

This study proposes a model for representing knowledge extracted from data mining and analysis techniques. The proposed model consists of eight components: knowledge representation, ontology, knowledge map model, concept, transformation, instance, state, and relation. Moreover, it also has two more elements, lexicon and hierarchy, which are structured factors of the model. In the following content, we define the model and its components. Let’s define each of these components.

**Definition 1 (Domain Concept).** A Domain Concept set $\mathbb{C}_D$ is a set of typical concepts used in domain $\mathbb{D}$.  
$$\mathbb{C}_D = \{c_D : \text{where, concept } c_D \text{ is used in domain } \mathbb{D}\}$$  
(1)

For example, in a specific domain, typical concepts in $\mathbb{C}_D$ can be crop, crop yield, soil, temperature.

**Definition 2 (Computing Concept).** A Computing Concept set $\mathbb{C}_{DM}$ is a set of data mining concepts $\mathbb{C}_{DM}$ to delegate to data mining tasks.  
$$\mathbb{C}_{DM} = \{c_{DM} : \text{where, concept } c_{DM} \text{ is used in data mining}\}$$  
(2)

**Definition 3 (Concept).** A Concept set $\mathbb{C}$ is a union of Domain Concepts $\mathbb{C}_D$ in domain $\mathbb{D}$ and Computing Concepts $\mathbb{C}_{DM}$ to delegate to data mining tasks.  
$$\mathbb{C} = \mathbb{C}_D \cup \mathbb{C}_{DM}$$  
(3)

For example, data mining concepts in $\mathbb{C}_{DM}$ can be clustering, classification, regression, and association rule. $\mathbb{C}_{DM}$ also has relevant concepts, such as dataset, evaluation and toolkit to represent related concepts of the mined knowledge items.

**Definition 4 (Data Transformation).** A Data Transformation set $\mathbb{T}_D$ is a set of functions $f(a)$, which are used to transform the value of concept $c$ in $\mathbb{C}_D$ from range $\mathbb{R}_x$ to range $\mathbb{R}_y$; where $\mathbb{R}_x$ and $\mathbb{R}_y$ are value ranges of concept $c$.  
$$\mathbb{T}_D = \{f(c) : \mathbb{R}_x \rightarrow \mathbb{R}_y ; c \in \mathbb{C}_D\}$$  
(4)
Definition 5 (Computing Algorithm). A Computing Algorithm set \( T_{DM} \) is a set of algorithms \( \{ \text{algorithm}(c) \} \), which are used in the data mining tasks.

\[
T_{DM} = \{ \text{algorithm}(c) : \mathbb{R}_{\{ \text{condition} \}} \rightarrow \mathbb{R}_{\{ \text{target} \}} ; c \in C_D \}
\]  

(5)

where, \( \mathbb{R}_{\{ \text{condition} \}} \) and \( \mathbb{R}_{\{ \text{target} \}} \) are value ranges of concept \( c \).

For example, \( T_{DM} \) can be Decision Tree, Neural Networks (algorithms for Classification or Regression), or Apriori, FP-growth (algorithms for Association Rule), etc.

Definition 6 (Transformation). A Transformation set \( T \) is a union of Data Transformations \( T_D \) and Computing Algorithms \( T_{DM} \).

\[
T = T_D \cup T_{DM}
\]  

(6)

For example, the pH value can be from 0 to 14, therefore the basis transformer function is itself (i.e. \( f(x) = x \), where \( x \) is the pH attribute), and defined as Transformation_SoilPH in the ontology AgriComO, described in Section 3.1). Moreover, a transformation \( f(x) \) can convert a value to a new value in a different range, e.g. \( [0 .. 1] \) or to a new label in the list with predefined Equation 4 (defined as Transformation_SoilPH_Tier5 in the ontology, used in Ngo, Le-Khac and Kechadi (2019)).

\[
f(x) = \begin{cases} 
\text{"Strongly acidic"} & pH \leq 5 \\
\text{"Acidic"} & 5 < pH < 7 \\
\text{"Neutral"} & pH = 7 \\
\text{"Alkaline"} & 7 < pH \leq 10 \\
\text{"Strongly alkaline"} & 10 < pH 
\end{cases}
\]  

(7)

This transformation is one of many functions of the concept of soil pH. They can be fixed if they are commonly used in knowledge items, or they can be defined when in use. In general, if one concept \( c \) is used to analyse and create knowledge, this concept will have one or more transformations.

\[
c \in C_D, \exists t \in T_D : c \xrightarrow{\text{hasTransformation}} t
\]  

(8)

Definition 7 (Domain Instance). A Domain Instance set \( I_D \) is a set of instances \( i \), which represents an individual of a domain concept \( c \) in a knowledge representation.

\[
I_D = \{ i : \exists c \in C_D ; i \xrightarrow{\text{isA}} c \}
\]  

(9)

For example, SoilPH_006 and Yield_006 are instances of concept SoilPH, Yield respectively.

Definition 8 (Computing Instance). A Computing Instance set \( I_{DM} \) is a set of instances \( i \), which represents an individual of a computing concept \( c \) in a knowledge representation.

\[
I_{DM} = \{ i : \exists c \in C_{DM} ; i \xrightarrow{\text{isA}} c \}
\]  

(10)

For example, Classifier_006, Cluster_007, Dataset_001 are instances of concept Classifier, Cluster, Dataset respectively.

Definition 9 (Instance). An Instance set \( I \) is a union of domain instances \( I_D \) and computing instances \( I_{DM} \).

\[
I = I_D \cup I_{DM}
\]  

(11)

Definition 10 (State). A State set \( S \) is a set of states \( s \), which are real values of instance \( i \) when applying transformation \( t \):

\[
S = \{ s : \exists i \in I : i \rightarrow s \}
\]  

(12)

So, if one concept \( c \) is used to analyse as well as create knowledge and its value is used in the knowledge representation, this concept will have one or more transformations and this value will belong to some instance.

\[
\forall s \in S, \exists i \in I, \exists c \in C, \exists t \in T : i \rightarrow c,
\]  

(13)

For example, SoilPH_006 can have state 4.5 or 7.5 if the transformation of SoilPH_006 is Transformation_SoilPH. Moreover, SoilPH_006 can have state "Strongly acidic", "Acidic", "Neutral", "Alkaline", or "Strongly alkaline" if the transformation of SoilPH_006 is Transformation_SoilPH_Tier5. Transformation_SoilPH and Transformation_SoilPH_Tier5 are two different transformations as explained above.

Definition 11 (Relation). The Relation set \( R \) consists of a set of relations \( r \) between two concepts \( (c_1, c_2) \); two instances \( (i_1, i_2) \), between concept \( c \) and instance \( i \), between concept \( c \) and transformation \( t \), or between instance \( i \) and state \( s \):

\[
R = \{ (c_1, r, c_2) \} \cup \{(i_1, r, i_2)\} \cup \{(c, r, i)\} \cup \{(c, r, t)\} \cup \{(i, r, s)\}
\]  

(14)

The knowledge relation set \( R \) contains at least four relation types: subClassOf, isA, hasTransformation, and hasState. Relation subClassOf is between two concepts, \( (c_1, c_2) \). Relation isA is between an instance and a concept, \( (i, isA, c) \). Relation hasTransformation is between a concept and a transformation, \( (c, hasTransformation, t) \). Relation hasState is between an instance and a state, \( (i, hasState, s) \). Moreover, the relation set \( R \) can have many other relation types, which are used to present the relationships between concepts or between instances.

Definition 12 (Ontology). Ontology \( O \) is a set of three elements, including concepts \( C \), relations \( R \), and transformations \( T \):

\[
O = (C, R, T)
\]  

(15)

Definition 13 (Knowledge Representation). A Knowledge Representation set \( K_R \) is a set of four elements, including instances \( \{ i \} \), relations \( R \), transformations \( T \), and states \( S \):

\[
K_R = (\{ i \}, R, T, S)
\]  

(16)

And each representation \( kr \) is an individual of \( K_R \):

\[
kr = \{ (i), \{ r \}, \{ t \}, \{ s \} \}
\]  

(17)

Definition 14 (Knowledge Map Model). Knowledge Map Model \( K_M \) is a set of five elements \( (C, I, R, T, S) \), which
are corresponding sets of concept c, instance i, relation r, transformation t, and state s.

\[ \mathcal{K}_M = (\mathcal{C}, \mathcal{I}, \mathcal{R}, \mathcal{T}, \mathcal{S}) \]  

(18)

**Definition 15 (Lexicon).** The Lexicon \( \mathcal{L} \) consists of a set of terms (lexical entries) for five elements of \( \mathcal{K}_M \), containing concepts \( (\mathcal{L}_c) \), instances \( (\mathcal{L}_i) \), relations \( (\mathcal{L}_r) \), transformations \( (\mathcal{L}_t) \), and states \( (\mathcal{L}_s) \). Their union is the lexicon:

\[ \mathcal{L} = \mathcal{L}_c \cup \mathcal{L}_i \cup \mathcal{L}_r \cup \mathcal{L}_t \cup \mathcal{L}_s \]  

(19)

**Definition 16 (Hierarchy).** The Hierarchy \( \mathcal{H} \) of the KMMaps is a concept tree, which consists of a set of concepts in the ontology and subClassOf relations.

\[ \mathcal{H} = (\mathcal{C}', \mathcal{R}') \]  

(20)

where,

\[ \mathcal{C}' \subseteq \mathcal{C}, \text{ and } \mathcal{R}' = \{ (c_x, \text{subClassOf}, c_y) \}, \quad c_x, c_y \in \mathcal{C}' \]

Based on Equation 14 and Equation 15, the hierarchy is a subset of the ontology; \( \mathcal{H} \subseteq \mathcal{O} \).

In general, the Lexicon \( \mathcal{L} \) provides the vocabulary of the knowledge map \( \mathcal{K}_M \), while the hierarchy \( \mathcal{H} \) provides its hierarchical structure.

### 2.1. Definitions for Knowledge Representation

**Definition 17 (Knowledge).** A Knowledge set (mined knowledge) \( \mathcal{K} \) is a set of processes, which use data mining functions (algorithms) and input conditions to predict or describe one or more output targets.

For example, using Linear Regression and weather conditions to predict diseases of crops. Or, knowledge is using K-Mean, weather conditions as well as the status of crop diseases from a given dataset to predict clusters of diseases.

\[ \mathcal{K} = \{ (\{ \text{algorithm} \}, \{ \text{condition} \}, \{ \text{target} \}) \} \]  

(21)

Knowledge has two detail levels, Process Knowledge and Fact Knowledge. Process Knowledge is used to represent knowledge for processes, while Fact Knowledge is used to detail these processes with specific knowledge and specific process cases.

\[ \mathcal{K} = \mathcal{K}_P \cup \mathcal{K}_F \]  

(22)

**Definition 18 (Process Knowledge).** A Process Knowledge set \( \mathcal{K}_P \) is a set of mined processes, which use data mining functions and input instances as conditions to predict one or more output attributes as targets.

\[ \mathcal{K}_P = \{ (\{ \text{algorithm} \}, \{ \text{condition} \}, \{ \text{target} \}) \} \]

(23)

where, \( \text{algorithm} \in \mathcal{T}_\text{DM}, \text{condition} \in \mathcal{I}_D, \text{target} \in \mathcal{I}_D \)

It means, the knowledge uses a set of computing algorithms \( (\{ \text{algorithm} \} \in \mathcal{T}_\text{DM}) \), and a set of instances \( (\{ \text{condition} \} \in \mathcal{I}_D) \) as conditions to predict output instances \( (\{ \text{target} \} \in \mathcal{I}_D) \) in domain \( D \).

And, each process knowledge representation \( k_p \) is an individual of \( \mathcal{K}_P \). Based on Definition 13 Knowledge Representation, process knowledge representation \( k_p \) is defined as follows:

\[ k_p = \{ (\{ \text{process} \} \cup \{ \text{condition} \} \cup \{ \text{target} \}, \{ r \}, \{ \text{algorithm} \} \cup \{ \text{condition} \} \cup \{ \text{target} \}, \{ \} ) \} \]  

(24)

where, \( r = \{ (\text{process}, \text{hasAlgorithm}, \text{algorithm}) \} \cup \{ (\text{process}, \text{hasCondition}, \text{condition}) \} \cup \{ (\text{condition}, \text{hasTransformation}, \text{transformation}) \} \cup \{ (\text{process}, \text{predicts}, \text{target}) \} \cup \{ (\text{target}, \text{hasTransformation}, \text{transformation}) \} \)

For example, knowledge model \( k \) is used to predict CropYield based on conditions of Temperature, Rainfall, and SeedRate by using Principal Component Analysis (PCA) algorithm (for classification). It is presented as follows:

\[ k = \{ \{ \text{Classifier} : \text{Algorithm}_{\text{PCA}} \}, \{ \text{Temperature}_006, \text{Rainfall}_006, \text{SeedRate}_006 \}, \{ \text{Yield}_006 \} \} \]  

(25)

where, \( \text{Temperature}_006, \text{Rainfall}_006, \text{and} \text{SeedRate}_006 \) represent condition concepts Temperature, Rainfall, and SeedRate respectively, while \( \text{Yield}_006 \) represent the output concepts of the knowledge.

**Definition 19 (Fact Knowledge).** A Fact Knowledge set \( \mathcal{K}_F \) is a set of mined processes, which use data mining functions and input states of instances as conditions to predict one or more output states of instances as targets.

\[ \mathcal{K}_F = \{ (\{ \text{algorithm} \}, \{ \text{condition} \}, \{ \text{target} \}) \} \]

(26)

where, \( \text{algorithm} \in \mathcal{T}_\text{DM}, \text{condition} \in \mathcal{S}_D, \text{target} \in \mathcal{S}_D \)

\[ \exists \text{condition} \in \mathcal{I}_D, \text{target} \in \mathcal{I}_D : \]

\[ \text{condition} \rightarrow \text{target} \]

It means, the knowledge item uses the set of computing algorithms \( (\{ \text{algorithm} \} \in \mathcal{T}_\text{DM}) \), and a set of values \( (\{ \text{condition} \} \in \mathcal{I}_D) \) as conditions to predict output values \( (\{ \text{target} \} \in \mathcal{I}_D) \) in domain \( D \) as conditions to predict output values \( (\{ \text{target} \} \in \mathcal{I}_D) \) in domain \( D \).

Moreover, as mentioned in Equation 13, if one concept \( c \) with its state \( s \) is used the knowledge, this concept will have one or more transformations. Therefore, the extension of Equation 26 is:

\[ \mathcal{K}_F = \{ (\{ \text{algorithm} \}, \{ \text{condition} \}, \{ \text{target} \}) \} \]

(27)

where, \( \text{algorithm} \in \mathcal{T}_\text{DM}, \text{condition} \in \mathcal{S}_D, \text{target} \in \mathcal{S}_D \)

\[ \exists \text{condition} \in \mathcal{I}_D, \text{target} \in \mathcal{I}_D : \]

\[ \text{condition} \rightarrow \text{target} \]

\[ \text{condition} \rightarrow \text{condition} \]

\[ \text{target} \rightarrow \text{target} \]
And, each fact knowledge representation $k_f$ is a map individual of $k_F$. Based on Definition 13 Knowledge Representation, fact knowledge representation $k_f$ is defined as follows:

$$
k_f = ([f_{\text{fact}} \cup \{\text{condition}\} \cup \{\text{target}\}, \{r\}, \{f_{\text{algorithm}}\} \cup \{\text{condition}\} \cup \{\text{target}\}, \{s_{\text{condition}}\} \cup \{s_{\text{target}}\})$$

(28)

where, $r = ([f_{\text{fact}}, \text{hasAlgorithm}, \text{algorithm}]) \cup ([f_{\text{fact}}, \text{hasCondition}, \text{condition}]) \cup ([\text{condition}, \text{hasTransformation}, \text{transformation}]) \cup ([\text{condition}, \text{hasState}, \text{state}]) \cup ([f_{\text{fact}}, \text{predicts}, \text{target}]) \cup ([\text{target}, \text{hasTransformation}, \text{transformation}]) \cup ([\text{target}, \text{hasState}, \text{state}])$

For example, the knowledge item $k$ uses the Principal Component Analysis (PCA) algorithm to predict HighYield based on the values of Temperature, Rainfall, and SeedRate of 20°C, 100mm and 200, respectively. In which, HighYield is based on transformation Transformation_Yield_Tier3 to transform yield values.

$$
k = ([\text{Classifier} : \text{Algorithm}_{\text{PCA}}], \text{Temperature}_006 : \text{Transformation}_{\text{Temperature}}, 20^\circ C; \text{Rainfall}_006 : \text{Transformation}_{\text{Rainfall}}, 100\text{mm}; \text{SeedRate}_006 : \text{Transformation}_{\text{SeedRate}}, 200 \}; \text{Yield}_006 : \text{Transformation}_{\text{Yield}_{\text{Tier}3}, \text{HighYield}})$$

(29)

In general, different forms of mined knowledge, which can be represented in this model are divided into 4 types: Classification, Regression, Clustering, and Association as in the following definitions.

**Definition 20 (Classification).** Classification is a data mining function that assigns items in a collection to predefined target categories Tan, Steinbach and Kumar (2006).

It means a classification model $k_{\text{Classification}}$ uses data mining algorithms $(t, r \in T_{\text{DM}},$ and $t$ is used for classification tasks) to assign items in a collection to a target label (target of the model) based on their concept (conditions of the model). Each model contains three main elements, classifier, conditions, and targets as in the following definition.

$$
k_{\text{Classification}} = ([\text{classifier} : \text{algorithm}, \text{state}], \{\text{condition} : \text{transformation}, \text{state}\}, \{\text{target} : \text{transformation}, \text{state}\})$$

(30)

This classification model $k_{\text{Classification}}$ is represented in the OAK model (as defined in Definition 13 Knowledge Representation) as below:

$$
k_{\text{Classification}} = ([t], [r], [r], [s])$$

(31)

**Definition 21 (Regression).** Regression is a data mining function that predicts a continuous outcome variable based on the value of condition variables.

It means a regression model $k_{\text{Regression}}$ uses data mining algorithms $(t, r \in T_{\text{DM}},$ and $t$ is used for regression tasks) to predict the value of a concept $(\text{target of the model})$ based on their concepts (conditions of the model).

$$
k_{\text{Regression}} = ([\text{regressor} : \text{algorithm}, \text{state}], \{\text{condition} : \text{transformation}, \text{state}\}, \{\text{target} : \text{transformation}, \text{state}\})$$

(32)
Similarly, this regression model \( k_{Regression} \) is represented in the OAK model (as defined in Definition 13) as follows:

\[
k_{Regression} = \{(i), \{r\}, \{t\}, \{s\} \}
\]

\[
\begin{align*}
\{i\} & = \{\text{regressor} \} \cup \{\text{condition} \} \cup \{\text{target} \} \\
\{r\} & = \{\text{hasCondition}, i_{\text{condition}}\} \cup \{\text{hasAlgorithm}; i_{\text{algorithm}}\} \cup \{\text{predicts}, i_{\text{cluster}}\} \\
\{t\} & = \{\text{hasTransformation}, i_{\text{transformation}}\} \\
\{s\} & = \{\text{hasState}\}
\end{align*}
\]

**Definition 22 (Clustering).** Clustering is a data mining function that finds clusters of data objects that are similar in some sense to one another Tan et al. (2006).

It means a clustering model \( k_{Clustering} \) uses data mining algorithms \((i, t \in \mathbb{P}_{DM}, \text{ and } i \text{ is used for Clustering tasks})\) to group similar items in a collection into clusters (cluster of the model) based on their concepts (conditions of the model).

\[
k_{Clustering} = \{(\text{clustering} : \text{algorithm}, \text{state}), \{\text{condition} : \text{transformation}, \text{state}\}\}
\]

Similarly, this clustering model \( k_{Clustering} \) is represented in the OAK model (as defined in Definition 13) as below:

\[
k_{Clustering} = \{(i), \{r\}, \{t\}, \{s\} \}
\]

\[
\begin{align*}
\{i\} & = \{\text{clustering} \} \cup \{\text{condition} \} \cup \{\text{cluster} \} \\
\{r\} & = \{\text{hasAlgorithm} ; \text{algorithm}\}_i \cup \{\text{hasCondition} ; \text{condition}\}_i \cup \{\text{predicts}, \text{cluster}\}_i \\
\{t\} & = \{\text{hasTransformation}, \text{transformation}\}_i \\
\{s\} & = \{\text{hasState}\}
\end{align*}
\]

**Definition 23 (Association Rule).** Association Rule is a data mining function that discovers the probability of the co-occurrence of items in a collection. The relationships between co-occurring items are expressed as association rules Tan et al. (2006).

It means an association model \( k_{Association} \) uses data mining algorithms \((i, t \in \mathbb{P}_{DM}, \text{ and } i \text{ is used for association tasks})\) to predict the co-occurrence of items (target of the model) based on their concepts (conditions of the model).

\[
k_{Association} = \{(\text{association} : \text{algorithm}, \text{state}), \{\text{condition} : \text{transformation}, \text{state}\}\}
\]

This association model \( k_{Association} \) is represented in the OAK model (as defined in Definition 13) as below:

\[
k_{Association} = \{(i), \{r\}, \{t\}, \{s\} \}
\]

\[
\begin{align*}
\{i\} & = \{\text{association} \} \cup \{\text{condition} \} \cup \{\text{target} \} \\
\{r\} & = \{\text{hasAlgorithm} ; \text{algorithm}\}_i \cup \{\text{hasCondition} ; \text{condition}\}_i \cup \{\text{predicts}, \text{cluster}\}_i \\
\{t\} & = \{\text{hasTransformation}, \text{transformation}\}_i \\
\{s\} & = \{\text{hasState}\}
\end{align*}
\]

**Definition 24 (Extend Knowledge).** Extend Knowledge is a mined process, which uses data mining functions to predict a target outcome based on condition states (as defined in Definition 17) and the context (containing context and locations of experiences), the dataset for training, and evaluation result. Its visualisation is shown in Figure 2.

\[
k_{Extend} = \{(\text{model} : \text{algorithm}, \text{state}), \{\text{condition} : \text{transformation}, \text{state}\}, \{\text{target} : \text{transformation}, \text{state}\}, \{\text{evaluation} : \text{evaluationmetric}, \text{state}\}, \{\text{dataset} : \{\text{location}, \text{context}\}\}
\]

This extend knowledge model \( k_{Extend} \) is represented in the OAK model (as defined in Definition 13) as below:

\[
k_{Extend} = \{(i), \{r\}, \{t\}, \{s\} \}
\]

\[
\begin{align*}
\{i\} & = \{\text{extend} \} \cup \{\text{condition} \} \cup \{\text{target} \} \cup \{\text{dataset} \} \cup \{\text{location} \} \cup \{\text{context} \} \\
\{r\} & = \{\text{algorithm} \} \cup \{\text{condition} \} \cup \{\text{target} \} \cup \{\text{evaluationmetric} \} \\
\{t\} & = \{\text{transformation}, \text{state}\}_i \\
\{s\} & = \{\text{hasState}\}
\end{align*}
\]

where, \( r = \{\text{hasAlgorithm} ; \text{algorithm}\}_i \cup \{\text{hasCondition} ; \text{condition}\}_i \cup \{\text{hasTransformation}, \text{transformation}\}_i \cup \{\text{hasState} ; \text{state}\}_i \cup \{\text{predicts}, \text{cluster}\}_i \\
\{\text{hasDataset}, \text{dataset}\}_i \cup \{\text{hasLocation}, \text{location}\}_i \cup \{\text{hasContext}, \text{context}\}_i \cup \{\text{hasEvaluationMetric}, \text{evaluationmetric}\}_i \cup \{\text{hasState}, \text{state}\}_i \)

2.2. Architecture of Ontology-based Knowledge Map Model

As illustrated in Figure 3, the architecture of the OAK model consists of six components: (i) Knowledge Miner, (ii) Knowledge Modelling, (iii) Knowledge Extraction, (iv) Knowledge Assessment, (v) Knowledge Publishing and (vi) Knowledge Exploitation.

- **Knowledge Miner** is used to extract knowledge from data; this component can be a Data Mining or publishing knowledge resource as Scientific Paper & Research module.
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Figure 2: Main Data Mining Concepts in the Ontology.

- **Data Mining** refers to mining tools and techniques, which are used in analyzing datasets from various dimensions and perspectives, finding hidden knowledge and summarizing the identified relationships. These techniques are classification, clustering, regression, and association rules.

- **Scientific Papers** refers to publishing papers at scientific conferences or journals.

Depending on the source of the knowledge (from Data Mining tasks or from Scientific Papers) there are different ways to reproduce and represent that knowledge. If the knowledge is from the Data Mining module, they can be transformed using a rule-based module in the Knowledge Extraction module. Otherwise, if the knowledge is from scientific papers, the Knowledge extraction module uses natural language processing tools to extract them.

- **Knowledge Modelling** is a select data mining pattern based on the data mining algorithm and generates the data mining instances (such as classification, clustering, regression, and association rule instances for the corresponding data mining tasks) and links to data mining algorithms as the transformation objects of the data mining instances.

- **Knowledge Extraction** is the main module to transform the knowledge from the output of the knowledge miner module to the Knowledge Publishing module. This step is to identify concepts in mining results and locate them in the ontology. Basically, these concepts occur in the mined results as input features and predicting features, for example, *SoilPH*, *SeedRate*, *Nitrogen*, *Wheat*, and *MeanYield*. If the knowledge source is from scientific papers, this module is based on natural language processing tools to extract published knowledge from the articles, for example, entity extraction Ngo, Kechachi and Le-Khac (2021) or relation extraction Luan, He, Ostendorf and Hajishirzi (2018).

- **Knowledge Assessment** is the module to verify and rate the mined knowledge from the output of the knowledge miner module before importing them into the Knowledge Publishing module to store them. This module evaluates knowledge representations based on their contributed parts and grades them on a scale of 100, in which any knowledge representations with less than 50 should not be imported to the system.

- **Knowledge Publishing** is a graph database server, which supports RDF triple storage and SPARQL protocol for retrieval. This module receives the domain knowledge from the pre-defined ontology, the mined knowledge representations from the Knowledge Wrapper module, and then stores it in the RDF Triple Storage as a set of RDF turtles.

- **Knowledge Exploitation** are application components, which are used to search and represent knowledge as required by users.

The ontology-based knowledge map model includes two knowledge layers. The first layer is the background knowledge about agriculture, defined as a core KMap and built from a pre-defined agricultural ontology (mainly cropping knowledge in this project). This layer defines most of the concepts (agricultural entities related to crops) in the KMaps and common relations between them. The second layer includes knowledge representations of data mining results. This knowledge layer is extracted from the data mining process and imported by the Knowledge Wrapper module.

3. Implementation

To implement this empirical study and to realize the proposed model, this project is broken into four major phases including building an agriculture ontology, knowledge wrapper representing knowledge models from data mining results, and knowledge browser.

3.1. Agriculture Computing Ontology

There are several ontologies for agriculture. Each ontology has a specific purpose in agriculture studies rather than using it to handle knowledge in digital agriculture. For example, AGROVOC provides vocabularies in agriculture Caracciolo, Stellato, Morshed, Johannsen, Rajbhandari, Jaques and Keizer (2013), AgOnt aims to agriculture IoT Hu, Wang, She and Wang (2010), Citrus Ontology focuses on citrus fruits Wang and Wang (2018), or Plant Ontology (PO) describes plant anatomy, morphology and growth and development Cooper, Walls, Elser, Gandolfo, Stevenson, Smith, Preece, Athreya, Mungall, Rensing et al. (2012). Therefore, it is necessary to create a new ontology, which includes common agriculture concepts and their relationships with each other.

Basically, most ontologies describe classes (concepts), instances, attributes, and relations. Moreover, some ontologies also include restrictions, rules, axioms, and function terms. However, as a formal presentation of KMaps, we propose an ontology with the following components:

1.http://aims.fao.org/vesr-registry/vocabularies/agrovoc
• **Concepts**: Concepts in the ontology include concepts in agriculture and concepts for representing four main tasks of data mining. For example, agriculture concepts have field, farmer, crop, organization, location, and product, while data mining concepts have clustering, classification, regression, and association rule.

• **Transformations**: They are pre-defined transformation functions of agriculture concepts and existing data mining techniques for four main tasks of data mining.
  - Agriculture Transformation
  - Agroclimatic Indices
  - Spectral Vegetation Indices
  - Computer Algorithms
  - Evaluation Metrics

• **Relations**: ways in which concepts (and then instances) can be related to others. They are defined as the $\mathbb{R}$ set in definitions.

In this research phase, we propose an agricultural ontology for the purpose of using it in the knowledge map model. The agricultural ontology contains 4 sub-domains: agriculture, IoT, geography, and the business sub-domain (Figure 4). In addition, the ontology is also added concepts in the data mining domain as shown in Figure 2. These concepts and relations will be knowledge frameworks to transform mined knowledge from data mining tasks to the knowledge representations and import them into the knowledge maps.

After building a knowledge hierarchy, the ontology provides an overview of the agriculture domain and describes agricultural concepts, life cycles between seeds, plants, harvesting, transportation, and consumption. It also gives relationships between agricultural concepts and related concepts, such as weather, soil conditions, fertilizers, and farm descriptions. In addition, this ontology also includes data mining concepts, such as classification, clustering, regression, and association rule. Combined with agricultural concepts, these are used to represent mined knowledge. Currently, the ontology has 598 classes and over 18,176 axioms related to agriculture (as shown in Table 1, and partly presented in Ngo, Le-Khac and Kechadi (2018)). It provides an overview of the agriculture domain with the most general agricultural concepts. As a result, the AgriComO ontology can be used as the core ontology to build the knowledge maps for agriculture. Moreover, this ontology with agricultural hierarchy can help to integrate available resources to build larger and more precise knowledge maps in the agriculture domain.

### 3.2. Knowledge Wrapper

The procedure for mapping mined knowledge into a knowledge representation in the ontology-based knowledge map is defined in the **Knowledge Wrapper** module. The knowledge wrapper module is the main module to transform the mined knowledge into a knowledge representation $k$ (as
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defined by \( k = (\{i\}, \{t\}, \{s\}, \{r\}) \) in Definition 13, Section 2). Then, it is converted into RDF turtles and imported into the RDF Triple storage.

This module has six steps:

- **Step 1, Identify model**: Select data mining pattern based on the data mining algorithm and generate the data mining instances (such as classification, clustering, and association rule instances for the corresponding data mining tasks, as defined in Definition 20-23) and link to data mining algorithm as the transformation objects of the data mining instances (as defined in Definition 5).

- **Step 2, Identify concepts**: Identify agricultural concepts in mining results and locate them in the ontology. Basically, these concepts occur in the mined results as input features and predicting features, for example, SoilPH, SeedRate, Nitrogen, Wheat, MeanYield.

- **Step 3, Generate instances**: Generate agricultural instances of each located concept and link them to data mining instances (in Step 1) based on the framework of data mining tasks.

- **Step 4, Identify transformations**: Identify transformations of each concept in the mining results (as defined in Definition 4), locate them in the ontology part of the KMap, then link them to agricultural instances (in Step 3).

- **Step 5, Generate states**: Identify states of each concept in the mining results, generate states and link to instances (in Step 3) in the knowledge representation.

- **Step 6, Generate turtles**: Transform the knowledge representation into RDF turtles and import them into the RDF triple storage.

The set of instances \( \{i\} \) is created in Step 1 and Step 3, while the set of transformations \( \{t\} \) is created in Step 1 and Step 4. The set of states \( \{s\} \) is generated in Step 5, however, not all knowledge representations have sets of states. For example, in the model to predict crop yield, the input values only occur when the model is executed. Therefore, the set of states for this knowledge representation is nearly none. Finally, set of relations \( \{r\} \) is based on relation isA, hasTransformation, hasState, hasCondition, and predicts.

As a result, an example of Classifier_010 has shown that this knowledge item is a classifier and it is published in the article Article_010 Pantazi et al. (2016). This classifier uses cation exchange capacity, organic carbon, soil attributes (calcium, magnesium, nitrogen, soil moisture, and soil pH) to predict crop yield for wheat based on Counter-propagation Artificial Neural Network (CPANN), Supervised Kohonen Network (SKN), and XY-fusion network (XYF) algorithms. This knowledge has been conducted in the United Kingdom (Listing 1).

### 3.3. Knowledge Map Assessment

This section describes the knowledge assessment progress and result of the mined knowledge of agriculture in Section 4.1. We divide information in each knowledge map representation into three groups: Basic information, principal information and subordinal information. The rates of the three groups are 20%, 40% and 40% for basic, principal, and subordinal information, relatively, as below.

- **Basic information** (20%): general information of the knowledge, such as authors, title or time of research, resource of knowledge.

- **Principal information** (40%): major information of knowledge, such as algorithms, conditions, target, transformations for conditions and target.

- **Subordinal information** (40%): dataset, evaluation (metrics and values), locations and context of research.

In general, each knowledge representation will be rated around 50-60% if it has basic information for basic knowledge as in Definition 17. However, its grade can reach 100% if it has full information for extending knowledge as in Definition 24.

Table 2 shows the result of knowledge assessment based on 500 mined knowledge items, which are extracted from the knowledge resources as shown in Section 4.1.

### 3.4. Knowledge Publishing

We propose to use the native knowledge storage with the Triple store technology. Literally, Apache Jena\(^2\) is a native knowledge graph storage technology. It is used for SPARQL Engine with Fuseki\(^3\) for SPARQL Endpoint.

---

\(^2\)https://jena.apache.org/index.html

\(^3\)https://jena.apache.org/documentation/fuseki2/
In this module, both ontology and knowledge maps are transformed into RDF format. Concepts in AgriComO\(^4\) and instances in AgriKMaps\(^5\) have IRIs to identify. In addition, common concepts and relationships in AgriComO are considered to refer to elements of the DCMI\(^6\) (Dublin Core Metadata Initiative) for further sharing.

In the context of a management system, the query language for knowledge retrieval is SPARQL 1.1 Query Language\(^7\). Apache Jena also provides a REST API for the Knowledge Wrapper module, which can access to query and import knowledge representations. Moreover, Apache Jena also provides HTTP and the SPARQL protocols for directly queries on web pages. The SPARQL Endpoint is installed locally and can be accessed for web-based queries.

Specifically, SPARQL queries can be run on the SPARQL Endpoint with a web interface. For example, Figure 5 shows the results for the query "What are conditions and the target attribute of the knowledge model Regressor\(_{0001}\)\?". The SPARQL query for this question is shown below:

```sparql
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX AgriComO: <http://www.ucd.ie/consus/AgriComO#>
PREFIX AgriKMaps: <http://www.ucd.ie/consus/AgriKMaps#>
SELECT * 
WHERE { 
  AgriKMaps:Regressor\(_{0001}\) ?predictive1 ?object1 . 
  ?object1 ?predictive2 ?object2 
}
```

3.5. Knowledge Browser

Knowledge Browser is one of the knowledge exploitation applications. Knowledge Browser helps users to find mined knowledge items based on their input queries or keywords. Basically, the input queries can be a simple sentence, such as "predict crop yield in the United Kingdom" (with the result as shown in Figure 6). The process includes:

- Finding concepts from search queries,
- Segmenting concepts into parts knowledge models
- Generating SPARQL queries

4. Experimental Results

Overall, there is no approach to evaluate the whole model in knowledge management. In this study, each individual component of the proposed OAK model has been evaluated. Firstly, this project applied several approaches to validate and verify the proposed AgriComO ontology Bandeira, Bittencourt, Espinheira and Isotani (2016). Next, the project also completed several experiments on the knowledge management system to demonstrate the ability of the OAK model in knowledge management and handling mined knowledge in digital agriculture.

4.1. Knowledge Materials

Materials for mined knowledge representations are extracted from scientific papers published in two journals in the digital agriculture domain. The total number of the articles is 3,381 articles and it is filtered by a keyword list to select about 1,000 papers, which present data mining results (as shown in Table 3). The keyword list for filtering includes 10 keywords: agriculture, crop, wheat, oats, rice, fertiliser, Quoc Hung Ngo et al.:

Preprint submitted to Elsevier
Each article is considered to extract 9 elements of knowledge representation (as listed in Table 4). Basically, there are several parts that are extracted semi-automatically while other parts are manually extracted from the content of the article by using the Knowledge Wrapper module. As result, there are 500 knowledge representations extracted from the dataset and they are imported into the Knowledge Publishing module as knowledge maps of agriculture.

### 4.2. Agriculture Ontology Evaluation

Although ontologies are formal representations of knowledge and are widely used in computer science, there is no standard unity of benchmarks or metrics to evaluate them. However, there is a remarkable number of studies focused on evaluating them. Brank et al. Brank, Grobelnik and Mladenica (2005) summarised six levels for ontology evaluation. They are (i) Lexical, vocabulary; (ii) Hierarchy, taxonomy; (iii) Semantic relation; (iv) Concept, application; (v) Syntactic level; and (vi) Structure, design. There are several approaches for evaluating ontologies on different levels, such as lexical, vocabulary Maedche and Staab (2002), hierarchy, taxonomy Dellschaft and Staab (2008); Porzel and Malaka (2004), and semantic relation Porzel and Malaka (2004). These evaluation approaches are based on application or humans, while the study of Staab et al. Maedche and Staab (2002) evaluates ontologies based on a “golden standard” set. These approaches have certain limitations when each ontology has different purposes, and it is difficult to find a standard ontology as a “golden standard” ontology for evaluation.

Moreover, there are many different criteria used for ontology evaluation, including Accuracy, Adaptability, Clarity, Completeness/Incompleteness, Consistency/Inconsistency, Conciseness, Computational Efficiency, Expandability, Sensitiveness, Redundancy, and Transparency Vrandecic (2009); Staab and Studer (2010). Different approaches have different groups of these criteria, such as Gómez-Pérez used a group of 5 criteria (Completeness, Conciseness, Expandability, and Sensitiveness) Gómez-Pérez (2004), while J. Bandeira proposed FOCA methodology with a group of 6 criteria (Completeness, Adaptability, Consistency, Conciseness, Computational Efficiency, and Clarity Bandeira et al. (2016)).

To evaluate the proposed AgriComO ontology, this study divides the ontology evaluation process into two parts, validation and verification tests. Ontology validation examines the developed ontology to determine whether the correct ontology has been developed. Besides, ontology verification examines the developed ontology to determine whether the ontology has been developed correctly.

#### 4.2.1. Ontology Validation

To validate the Agriculture Computing Ontology (AgriComO), two approaches are used to implement the validation process. The first approach requires answering eight Competency Questions (CQs) (as shown in Table 5) Bezerra, Freitas and Santana (2013), while the second approach evaluates the ontology content with five criteria (Completeness, Consistency, Conciseness, Expandability, and Sensitiveness) as shown in Table 6) (Gómez-Pérez (2004).

In the first test of ontology validation, AgriComO ontology is evaluated based on eight CQs for a competency evaluation. CQs not only specify the requirements for the ontology in the ontology development lifecycle but also provide references for a competency evaluation. In the evaluation step, answering eight CQs in the list of CQs supports reviewing the proposed ontology with its requirements. It ensures that the final ontology has enough competency for use in the model. Each question is reviewed to provide the answer and make the decision Passed or Failed. The result for each CQ is Passed if the answer matches its assumption. If it does not match, the result is Failed. The ontology will pass the competency evaluation of this validation test if all CQs have answers and are graded as Passed.

Basically, eight CQs of the list have contributed to the ontology development progress and each step also aims to meet particular CQs. So, all CQs have results Passed.

---

**Table 3**

| Figure          | Count |
|-----------------|-------|
| Scientific Article | 3,381 |
| Crop Articles   | 1,972 |
| Data mining     | 1,007 |
| Classification  | 467   |
| Clustering      | 249   |
| Regression      | 189   |
| Association Rule| 95    |

**Table 4**

| Figure          | Description                                           |
|-----------------|-------------------------------------------------------|
| Knowledge task  | Extract the clustering, classification, regression or association type from the title. |
| Approaches      | Extract mining algorithms from abstract.              |
| Conditions      | Manually extract input attributes from the main section of the model. |
| Target          | Extract output attributes, predict label, or rule sets from the title. |
| Transformation  | Manually extract Transformations formulas of attributes. |
| Evaluation      | Extract from abstract or section Experience, refer to Evaluation Metrics in Transformations. |
| Dataset         | Extract information of dataset, the data size of experiences from section Material or Experience. |
| Location        | Extract locations of experiences from section Material. |
| Context         | Context of study and mined knowledge Manually extract from section Material. |
Table 5: Answering Competency Questions

| No. | Question                                                                 | Check |
|-----|---------------------------------------------------------------------------|-------|
| CQ1 | What types of mined knowledge models are represented in the system?       | Passed|
| CQ2 | What types of elements are represented in each mined knowledge model?    | Passed|
| CQ3 | What concepts of a given domain are represented as input/output attributes of the models? | Passed |
| CQ4 | What transformations of particular elements are used in mined knowledge models? | Passed |
| CQ5 | What types of relationships are represented in the system?                | Passed |
| CQ6 | How mined knowledge models represent the data values of model elements?  | Passed |
| CQ7 | How mined knowledge models record, transform, and transmit data?          | Passed |
| CQ8 | What types of mined knowledge models arise from the external aspects of the system and its improvement stages? | Passed |

Table 6: Content Evaluation Metrics

| No. | Criteria | Explanation | Result |
|-----|----------|-------------|--------|
| C1  | Consistency | AgriComO ontology contains all over 600 concepts and 1,300 transformations, which are consistent. | Yes |
| C2  | Completeness | AgriComO ontology reflects an image for scope of OAK model for representing data mining results in digital agriculture. | Yes |
| C3  | Conciseness | AgriComO ontology is free of any needless concepts or redundancies between concepts. | Yes |
| C4  | Expandability | AgriComO ontology is a well-defined and scalable ontology. | Yes |
| C5  | Sensitiveness | Small changes in AgriComO ontology are not observable for the current concepts. | Yes |

Table 7: Taxonomy Evaluation Metrics

| Criteria | Explanation | Check |
|----------|-------------|-------|
| C1. Inconsistency | All concepts are stated as specialisation themselves. | No |
| C2. Incompleteness | No wrongly defines concepts. | No |
| C3. Semantic errors | Incorrect semantic classification. | No |
| C4. Incomplete concept classification | All concepts are overlooked by classification. | No |
| C5. Partition errors | A partition between a set of concepts is omitted. | No |
| C6. Grammatical redundancy | More than one explicit definition. | No |
| C7. Identical formal definition | Concepts with same formal definition. | No |

Table 5 provides a summary of answers for the competency evaluation.

In the second test, the content of ontology is evaluated based on 5 criteria, including Consistency, Completeness, Conciseness, Expandability, and Sensitiveness (proposed by Gómez-Pérez (2004)). Each criterion is evaluated manually to answer Yes or No. The ontology will pass the content evaluation of this validation test if all criteria have answered Yes. After checking AgriComO ontology with all five criteria as well as their guides, the proposed ontology has the answer Yes for all criteria as shown in Table 6.

After the first part of the ontology evaluation, the AgriComO ontology has been proved the ability to be used in the OAK model as a core background knowledge for OAK KMaps Repository. It is also evaluated with 5 criteria to ensure that the ontology development is carried on correctly.

4.2.2. Ontology Verification

There are two approaches for ontology verification, including ontology taxonomy evaluation and FOCA methodology evaluation. In the first verification test, AgriComO ontology is evaluated based on the taxonomy of ontology. For ontology taxonomy evaluation, Lovrencic and Cubrilò (2008) proposed a set of criteria for evaluating the taxonomy. The taxonomy evaluation approach has three criteria (including Inconsistency, Incompleteness, and Redundancy). These three criteria are divided into seven sub-criteria (including circularity errors, definition errors, semantic errors, incomplete concept classification, partition errors, grammatical redundancy, and identical formal definition). These criteria and sub-criteria intend to find existing errors in the ontology. Each sub-criteria is verified to answer Yes or No. The ontology will pass the taxonomy evaluation of this verification test if all sub-criteria have answered Yes. For this test, AgriComO ontology has been reviewed to find inconsistency, incompleteness and redundancy errors based on the seven sub-criteria above. The summary result of this evaluation is presented in Table 7.

The result in Table 7 has shown that there is no inconsistency, incompleteness or redundancy error in the AgriComO ontology. This result reflects the detail and carefulness of the ontology development process. Every concept from the digital agriculture domain and computing domain has been reviewed and located in the ontology.

In the second verification test, the AgriComO ontology is evaluated based on the FOCA approach with the GQM metric (Bandeira et al. 2016). This test includes five goals...
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The ontology properties reflect characteristics of

Eight CQs are provided and answered clearly.

Concepts (classes and instances) are described

The ontology reused several concepts from the

Grade

The total quality of the proposed ontology is 0.95 and it is very close to 1, which means that this ontology has high quality and satisfies the requirements of an agriculture computing ontology used in the proposed OAK model. Moreover, the ontology also obtained six criteria from the FOCA evaluation, including Completeness, Adaptability, Conciseness, Consistency, Computational efficiency, and Clarity.

Overall, the AgriComO ontology has passed four ontology evaluation tests, including validation evaluation and verification evaluation. Passing four evaluation tests, the AgriComO has been verified with total 12 criteria, including Adaptability, Consistency, Completeness, Conciseness, Computational efficiency, Clarity, Expandability, Sensitiveness, Inconsistency, Incompleteness, and Redundancy.

4.3. Knowledge Browser Performance

To demonstrate the ability of the Knowledge Repository and Knowledge Browser, this study designs practical experiments in different end-user groups: data scientists and agronomic users.

Although agronomists and data scientists have a wide range of concerns in digital farming, these concerns can be classified into several tasks of data mining in digital agriculture, such as yield prediction, early disease prediction, or nitrogen content estimation. Agronomists and agricultural

Table 8

Verification of Questions in the GQM Model

| Goal | Question | Explanation | Grade |
|------|----------|-------------|-------|
| G1   | Q1       | The document defines the ontology objective, the ontology stakeholders, and the use of scenarios | 100   |
| G1   | Q2       | Eight CQs are provided and answered clearly. | 100   |
| G1   | Q3       | The ontology reused several concepts from the SSN Ontology, Plant Ontology, etc. | 25    |
| G2   | Q4       | The type of the ontology is application ontology. | 50    |
| G2   | Q5       | Did the ontology impose a maximum ontological commitment? | -     |
| G2   | Q6       | The ontology properties reflect characteristics of concepts in the agriculture domain. | 100   |
| G3   | Q7       | One of mechanisms for building the ontology is top-down mechanism, therefore, there are no contradictions. | 100   |
| G3   | Q8       | There are no redundancies. | 100   |
| G4   | Q9       | The reasoner Pellet 1.5.2 (Protege plugin) has been run and check the consistency of the ontology (classes and instances with their properties, characteristics, and constraints). | 100   |
| G4   | Q10      | The ontology can be stored as OWL, RDF format, and imported into RDF SPARQL Endpoint for querying and reasoning. | 100   |
| G5   | Q11      | The documentation provides modelling samples of data mining tasks for agriculture. | 100   |
| G5   | Q12      | Concepts (classes and instances) are described by dc:identifier, rdfs:label, and dc:description relations. | 100   |
| G5   | Q13      | All concepts are provided at least the dc:identifier, rdfs:label, and dc:description relations to define their definitions. | 100   |

* $\text{G}1, \text{G}2, \text{G}3, \text{G}4$ respectively, 0 if otherwise.
* $\text{N}1$ is 1 only if some Goal was impossible for the evaluator to answer all the questions, 0 if otherwise.
* $\text{S}b, \text{C}o, \text{Re}, \text{Cp}$ is 1 if total quality score considers Goal $\text{G}1, \text{G}2, \text{G}3, \text{G}4$ respectively, 0 if otherwise.

"The result of the total quality of the proposed ontology is 0.95 and it is very close to 1, which means that this ontology has high quality and satisfies the requirements of an agriculture computing ontology used in the proposed OAK model. Moreover, the ontology also obtained six criteria from the FOCA evaluation, including Completeness, Adaptability, Conciseness, Consistency, Computational efficiency, and Clarity."
production managers from Origin Enterprises PLC\textsuperscript{5} also provided a list of the greatest potential to gain from precision farming and digital agriculture as follows Agrii (2020):

- Saving costs based on limited inputs
- Finding crop yield potential earlier
- Identifying farming problems earlier
- Providing a map of production costs and gross margin
- Improving performance from every part of the field
- Developing tools for support decision making
- Reducing human errors from farming progress
- Reducing time consumption on farming activities

In the list above, the last 2 bullet points are heavily related to agriculture machinery, while the rest of the list are similar problems of data mining in digital agriculture with different factors of interest. Based on these concerns, this study has created a list of common queries from data scientists working on digital agriculture and agronomists using data mining results. Again, this list contains a lot of questions, but they are compiled into a list of 10 queries, which can be delegated to a wide number of similar questions. They are as follows:

**Queries from data scientist users:**

- **Q1.** What is the basic information about wheat crop?
- **Q2.** What concepts are used in knowledge item Regressor\textunderscore 0015?
- **Q3.** What models can use nitrogen to predict and what to predict?
- **Q4.** What models can be used to predict wheat yield?
- **Q5.** What potential methods can be used to process Temperature in knowledge items?

**Queries from agronomic users:**

- **Q6.** What are the relationships between Wheat and Leaf Rust disease?
- **Q7.** What potential characteristics or states can be used to predict high yield?
- **Q8.** How crops can get a high yield when grown in the UK?

**Extra queries from testing:**

- **Q9.** What is relevant information of Multi-Linear Regression?
- **Q10.** What are knowledge items related to dataset PlantVillage?

Basically, using a list of 10 queries to test the knowledge management system is a practical approach for evaluating the system. It partly presents the ability of the proposed OAK model in handling mined knowledge in digital agriculture. However, this section will analyse and prove that the list of these 10 queries is enough to access all elements and roles of the OAK model. Other different queries can be inherited and generated from these ten queries.

In general, several questions can be answered by the first layer of knowledge, the AgriComO ontology. For example, queries Q1, Q5, Q6, and Q9 can be partly answered by the knowledge in AgriComO ontology. However, all the above queries can be completely answered by the OAK model when it has enough knowledge in the knowledge repository. Moreover, only KMaps can help to answer questions Q4, Q7, and Q8 effectively.

According to Definition 14 Knowledge Map Model of OAK Model (Section 2), there are 5 elements that contributed to knowledge representations, including Concept, Instance, Relation, Transformation, and State (Remark: \(\mathbb{K}M = (C, I, R, T, S)\)). Definition 24 Extend Knowledge of OAK Model (Section 2.1) also provides 8 types of instances presented in knowledge representations, including KMap, Algorithm, Condition, Target, Dataset, Evaluation, Location, and Context). Therefore, these experiments will evaluate the accuracy in the retrieval of different elements in different roles of instances based on given queries as follows:

- **Elements in OAK model:** Concept, Instance, Relation, Transformation, and State (Section 2).

- **Roles of Instances:** KMap, Algorithm, Condition, Target, Dataset, Evaluation, Location, and Context (Section 2.1).

To demonstrate the effectiveness of the proposed Knowledge Repository, this study carries out a set of 10 queries, which will focus on looking up basic knowledge or expert knowledge (Q1, Q5, Q6, and Q9) and finding mined knowledge items from existing relevant data mining studies (Q2, Q3, Q4, Q7, Q8, and Q10). These experiments analyse queries to provide the solution and SPARQL queries, which can execute in SPARQL Endpoint to have results. All queries are formalised, generated SPARQL queries and then executed in SPARQL Endpoint. They are also searched on Knowledge Browser with corresponding keywords. For example, query Q3 is processed as follows:

**Query:** Q3.

What models can use nitrogen to predict and what to predict?

**Formalise:** QF3. What are knowledge items \(M_i\), which use condition \(c\) (for example, Nitrogen), to predict? [DM models]

**Solution:** Finding all instances, which have relation hasCondition and objects, which are instances of concept Nitrogen, then query all information related to returned results (Listing 3).

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\textsuperscript{5}Origin Enterprises Public Limited Company is a company focused on consumer foods, crop nutrition, feed ingredients, marine proteins, and oils. This company has manufacturing and distribution operations in Ireland, the United Kingdom and Poland. Origin Enterprises PLC is also an enterprise partner of CONSUS project.
Listing 3: SPARQL Query for QF3

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX AgriComO: <http://www.ucd.ie/consus/AgriComO#>
PREFIX AgriKMaps: <http://www.ucd.ie/consus/AgriKMaps#>

SELECT ?subject
WHERE {
  ?subject AgriComO:hasCondition ?object .
  ?object rdf:type AgriComO:Nitrogen .
}
```

Listing 3 shows the SPARQL query for QF3. It is executed on SPARQL Endpoint and got 25 knowledge items from AgriKMaps Repository (Figure 7, (1)). However, this SPARQL query can expand to have more information on related elements. They are processed to present as a web page in Knowledge Browser with query "predict based on Nitrogen" (Figure 7 (2)).

To evaluate the correctness and completeness of the proposed OAK model, we created an access matrix to review the representation and access ability of the model (as shown in Table 9). This table includes five different elements of OAK Model in eight different roles. Moreover, these elements and roles are considered in two different groups when executing queries, including input parameters and output results. For each query (from Q1 to Q10 for two groups of experiments), each element in the OAK model and each role of instances will be checked (✓) if it is used, accessed, or returned in the results. Column Check at the last column shows the result of each item based on the whole list of queries. It is checked (✓) if it has at least one check from any query.

The result of this reviewing process has shown in Table 9. It can be easily seen that every element of the OAK model and every role of instances have been used, accessed, or returned in the results based on the set of ten queries (from Q1 to Q10 above). Moreover, queries for knowledge items easily access and get results of all elements of the OAK model and instances (as attributes of the prediction knowledge models) with different roles.

In the list of queries, there are two typical queries that results contain all the elements of the OAK Model. Specifically, query Q1 shows information of all related elements (whole 5 elements in the OAK model) of the input concept. This query requests domain information from the AgriComO ontology, therefore, its result does not contain knowledge items (as shown in column Q1 of Table 9). The second query is query Q2, which returns information of all related elements and roles (whole 5 elements and 8 roles of instances (if exist) in the OAK model) of the input knowledge item (as shown in column Q2 of Table 9). Search queries returned a list of matched knowledge instances. From this list, all related elements/roles can be accessed when expanding the SPARQL queries, such as Query Q3, Q4, Q7, Q8, and Q10. Although the list of queries has 10 queries, they have accessed all elements as well as roles of instances presented in the proposed OAK model. They also retrieved different types of knowledge successfully in the Knowledge Repository.

In this study, there are over 500 mined knowledge items, which are prepared in Section 4.1. All of them can be

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**Table 9**

| Element | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Check |
|---------|----|----|----|----|----|----|----|----|----|-----|-------|
| Input Element | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓   | ✓     |
| Concept | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓   | ✓     |
| Instance | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓   | ✓     |
| State | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓   | ✓     |
| Transformation | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓   | ✓     |
| Relation | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓   | ✓     |

**Table 9** Access Matrix based on Different Elements and Roles for Each Query
accessed by using Query 2 (QF2) and show all of their information. All 500 mined knowledge items are located in class AgriComO:DataMining and its four sub-classes (corresponding to 4 data mining tasks) in the AgriKMaps Repository. The results of search queries are based on this set of knowledge items. All of them can be accessed by using QF2 and show all of their information. As defined in Definition 24 Extend Knowledge in Section 2.1, knowledge items will have Algorithm, Condition, Target, Dataset, Context, Location, Dataset, and Evaluation. Queries for knowledge items can expand with more detailed requirements. For example, Query Q4 will extend with Context of the knowledge items.

The results in Table 9 show that the Knowledge Repository with the processing ability of SPARQL supports accessing all different elements of the OAK model as well as all different roles in knowledge representations. Moreover, it also illuminates that the OAK model accurately processes, stores, and represents the mined knowledge items.

The results of queries demonstrate the performance of the OAK model and the knowledge repository and provide ideas for further works. For example, query Q3 or query Q10 create a group of similar knowledge items.

5. Conclusion

While significant research work has been committed to knowledge extraction from large datasets, little effort has been devoted to knowledge reuse and mining. We presented a generalised model for knowledge representation, storage, and exploration. The model, called ontology-based knowledge map, has been demonstrated in the agricultural domain, but it can be extended to many other application domains. The model consists of eight primary and two secondary components. The model is flexible enough to represent any knowledge and mined results. We also presented a formal model justifying the components and the process of building such a model.

Furthermore, we presented a complete architecture for the ontology-based knowledge map model and gave numerous examples about how to represent mined knowledge in digital agriculture. In addition to the core modules, the architecture includes knowledge miners, knowledge wrappers, knowledge publishing, and knowledge browser modules based on a pre-defined ontology.

We have implemented a fully operating prototype around an agricultural ontology to provide domain knowledge and a knowledge management system. The system stores knowledge and supports efficient knowledge exploration and retrieval. The current implementation is very adaptive and easy to use.

The prototyped ontology-based knowledge map model is promising and has the potential to be extended to other application domains. Despite its flexibility, efficient storage system, and knowledge retrieval, the proposed model relies heavily on the quality of the inputs and repositories (previous ontology). We plan to design an evaluation methodology to evaluate not only the model performance, its robustness and scalability, but also the quality of input knowledge items of the knowledge repository.

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