OAK4XAI: Model towards Out-Of-Box eXplainable Artificial Intelligence for Digital Agriculture

Quoc Hung Ngo, Tahar Kechadi, and Nhien-An Le-Khac

School of Computer Science, College of Science
University College Dublin, Belfield, Dublin 4, Ireland

Abstract. Recent machine learning approaches have been effective in Artificial Intelligence (AI) applications. They produce robust results with a high level of accuracy. However, most of these techniques do not provide human-understandable explanations for supporting their results and decisions. They usually act as black boxes, and it is not easy to understand how decisions have been made. Explainable Artificial Intelligence (XAI), which has received much interest recently, tries to provide human-understandable explanations for decision-making and trained AI models. For instance, in digital agriculture, related domains often present peculiar or input features with no link to background knowledge. The application of the data mining process on agricultural data leads to results (knowledge), which are difficult to explain.

In this paper, we propose a knowledge map model and an ontology design as an XAI framework (OAK4XAI) to deal with this issue. The framework does not only consider the data analysis part of the process, but it takes into account the semantics aspect of the domain knowledge via an ontology and a knowledge map model, provided as modules of the framework. Many ongoing XAI studies aim to provide accurate and verifiable accounts for how given feature values contribute to model decisions. The proposed approach, however, focuses on providing consistent information and definitions of concepts, algorithms, and values involved in the data mining models. We built an Agriculture Computing Ontology (AgriComO) to explain the knowledge mined in agriculture. AgriComO has a well-designed structure and includes a wide range of concepts and transformations suitable for agriculture and computing domains.

Keywords: Explainable AI · Knowledge Map · Agriculture Computing Ontology · Knowledge Management · Digital Agriculture.

1 Introduction

Artificial Intelligence (AI) applications are present in many domains nowadays. These applications have a direct impact on human lives, such as healthcare,
self-driving vehicles, smart homes, the military, etc. The advances in AI and big data have led to the rise of explainable AI (XAI) and have gained much attention in recent years. Several studies have provided the main concepts, motivations, and implications of enabling explainability in intelligent systems [1, 3, 5]. Other studies have provided an overview of the existing XAI approaches and future XAI research opportunities. The concept of explainability is closely related to interpretability. XAI systems are interpretable if they can make human-understandable operations and decisions. Some previous studies considered the XAI goals as the need for interpretable AI models, such as trustworthiness, causality, transferability, informativeness, fairness, accessibility, confidence, interactivity, and privacy awareness [1, 3, 5]. Some others synthesized the definitions for the XAI goals and provided a set of WH-questions to classify explainability approaches, including what, who, why, what for, and how [2, 3].

XAI approaches can be used to explain one of the three stages: pre-model, in-model, and post-model [1, 7]. Pre-modelling targets a better understanding of the datasets, while post-model aims at model approximation and reporting of the results. Explainable modelling focuses on understanding how an AI model makes decisions. Many recent studies have focused on explainable modelling; however, it is not enough to understand the decision-making process in AI applications.

In agriculture, AI applications are constantly growing at a very high rate during the last decade. These include soil studies, weather forecasting, crop yield prediction, disease predictions, etc. For instance, there are several soil studies, building soil profiles [12], monitoring soil characteristics under the effects of other factors and crop yield[4], or using soil characteristics to predict other soil characteristics [14]. Although the number of XAI studies in digital agriculture is not too high, XAI for digital agriculture is necessary because agronomists and farmers do not have a strong background in machine learning and AI. [13] proposed an explainable AI decision support system based on fuzzy rules to automate field irrigation. Moreover, even though the number of knowledge models is small, the input and output attributes of forecasting models are different, and the number of agricultural features is large and diversified. The majority of these results (knowledge) are stored as pre-trained models, computer software, or scientific papers/reports. They also lack explanations to assist different users in accessing and understanding them.

In this paper, we propose an ontology-based knowledge map [6, 9] for representing and explaining the mined knowledge, which has been produced previously by the data mining process, including classification, regression, clustering, association rules, and other forms of mining. The main contribution of the model as an out-of-box approach for DM models is to support data scientists and agronomists in managing, understanding, and using mined results/knowledge for decision-making.

The next section overviews the OAK model as a foundational theory for the proposed approach and details the core of the ontology used in this study. Section 3 presents the proposed ontology-based knowledge map model for explainable AI, including its architecture and XAI transparency. We describe the implementation
process for validating the proposed model based on the knowledge repository in digital agriculture in Section 4. Finally, we conclude the paper and give some future research directions in Section 5.

2 OAK - Ontology-based Knowledge Map Model

2.1 Knowledge Definitions

We introduced the ontology-based Knowledge Map Model (OAK) to handle the knowledge extracted from a DM process [8, 9]. Before going into the details of the proposed approach, we give some key definitions of the OAK model. The model includes knowledge representation, ontology, knowledge map, concept, attribute, transformation, instance, state, and relation.

Knowledge represents the result of an experience or a data mining process, which uses some learning algorithms to predict a target based on the input dataset. Knowledge is of two types: processed knowledge and factual knowledge. The Processed Knowledge represents the result of a data mining process. This knowledge has some attributes that characterise it; input and output attributes and learning algorithms. Factual Knowledge is information validated by experts in the domain. It is characterised by some attributes, such as the transformation of input to output, its states/values, etc.

In the OAK model, the processed knowledge can be of four types: classification, regression, clustering, and association rule [8, 9]. Regression is a ML function that predicts a continuous outcome variable based on the values of the condition variables. This means that the Regression model ($k_{Reg}$) uses regression type algorithms ($t$, $t \in T_{DM}$, and $t$ to predict the value of the attribute (target of the model) based on its input attributes (conditions of the model) [9]. These are defined as follows:

$$k_{Reg} = (\{i\}, \{r\}, \{t\}, \{s\})$$

$$\{i\} = \{i_{regressor} \cup \{i_{condition}\} \cup \{i_{target}\} \cup \{i_{dataset}\} \cup \{i_{evaluation}\}$$

$$\{r\} = \{(i_{regression}, \text{hasAlgorithm}, i_{DM})\} \cup$$

$$\{(i_{regressor}, \text{hasRegressor}, i_{regressor})\} \cup$$

$$\{(i_{regressor}, \text{hasCondition}, i_{condition})\} \cup$$

$$\{(i_{regressor}, \text{predicts}, i_{target})\} \cup$$

$$\{(i_{condition}, \text{hasTransformation}, i_{DM})\} \cup$$

$$\{(i_{target}, \text{hasTransformation}, i_{DM})\} \cup$$

$$\{t\} = \{T_{DM} = \text{algorithm}(c) \in T_{DM}; c = \text{Regression}\} \cup$$

$$t_{DM} = f(i) : \mathbb{R}_x \rightarrow \mathbb{R}_y ; i \in \{i_{condition}\} \cup$$

$$\{t_D = f(i) : \mathbb{R}_x \rightarrow \mathbb{R}_y ; i \in \{i_{target}\}\}$$

$$\{s\} = \{\forall s \in S, \exists i \in \{i_{condition}\} : i \xrightarrow{hasState} s\} \cup$$

$$\{\forall s \in S, \exists i \in \{i_{target}\} : i \xrightarrow{hasState} s\}$$
The regressor $k_{\text{Reg}}$ is characterised by its main components, which are datasets, prediction targets, conditions, and evaluation information. In addition, the processed knowledge can have other attributes related to locations, research context, etc.

In summary, the proposed model includes all the information necessary to characterise a given knowledge (result) at any time within a data mining application. The model has an efficient knowledge representation that facilitates its storage and retrieval from the knowledge repository. However, it still needs an explainable mechanism to interpret the concepts as well as its processing steps. Therefore, an explainable knowledge base or a suitable ontology can be used in interpreting the mined knowledge within a given DM application.

2.2 Ontology: Role and Design

While the OAK model is designed to handle any domain knowledge, its ontology is specific to a given domain for efficient exploitation. One of the main objectives of ontology is to assist in the explanation and interpretation of the mined results. In the proposed approach, the ontology covers three main functions: 1) agriculture common concepts definition and representation, 2) concept transformations handling, and 3) Representation of the main types of relationships between concepts.

In this study, we developed and implemented an Agriculture Computing Ontology (AgriComO) that contains the most common classes (concepts), instances, attributes, and relations in crop farming. The AgriComO's architecture is derived from the knowledge map (KMap) model and contains the following components:

- **Concepts**: Concepts in the agriculture field, farmer, crop, organization, location, and product. The DM concepts include clustering, classification, regression, and association rule.
- **Transformations**: are predefined transformation functions of agriculture and DM (See Figure 1).
- **Relations**: They represent relationships between concepts/instances, and they also represent the analysis process to create the knowledge.

The AgriComO ontology describes agricultural concepts, their relationships, and lifecycles between seeds, plants, harvesting, transportation, and consumption. The concept relationships concern weather, soil conditions, fertilizers, and farms description. Moreover, AgriComO includes DM concepts, such as classification, clustering, regression, and association rules. The combination of agricultural and DM concepts represents mined knowledge efficiently. For instance, in the current implementation, AgriComO has 450 classes and over 3,381 axioms related to agriculture based on [10]. Finally, it provides an overview of the agricultural domain with its most general concepts.

AgriComO is the core ontology for building knowledge maps (KMaps) for digital agriculture and adopts an XAI-oriented design at the levels of the concepts and relationships. Therefore, every concept, transformation, and relation
Fig. 1: An overview of Agriculture Computing Ontology

in the ontology has at least two attributes; one for the title \(\text{rdfs:label}\) and the other for the description \(\text{rdfs:comment}\). Moreover, we provided extra attributes; \(\text{rdfs:isDefinedBy}\) and \(\text{rdfs:seeAlso}\) to provide external references for further information for each concept. These attributes are considered basic information for each entity in the ontology. The definitions, descriptions, and comments on concepts, transformations, and relations in the ontology provide transparency and explainability for AgriComO and the overall model.

- **URI** - Universal Resource Identifier.
- **rdfs:label** - name of concepts or instances.
- **rdfs:comment** - description of concepts, instances, relations, or transformations for explanation purposes.
- **dc:identifier** - formula, expression, or function to calculate and transform data if it has.
- **rdfs:isDefinedBy** - sources or creators of the concepts.
- **rdfs:seeAlso** - external references for further information for each concept.

In summary, a well-defined ontology design provides explainability to each concept in the DM applications and each instance value in the knowledge representation and its processing. It supports the OAK4XAI model (described in the next section) in interpreting the accurate meaning of concepts and values in knowledge items and in helping users understand their decision-making.
3 OAK4XAI Model & Architecture

3.1 OAK4XAI Architecture

The overall OAK4XAI architecture is developed around OAK [8]. It organises knowledge into two separate classes: knowledge and its explanation. The knowledge class manages a DM application result (item) based on its relationships with other concepts and entities and is defined in the KMap module. The knowledge explanations are stored in a pre-defined ontology (See Figure 2). This architecture handles both factual and mined knowledge [8]. We use a multi-layer approach where knowledge items are in the KMap, and their explanations are located in the ontology.

![Fig. 2: Architecture of OAK4XAI](image)

As mentioned in Section 2.2, AgriComO includes agriculture concepts and the DM domain. Each concept contains necessary descriptions and attributes to identify the concept and its data processing methods. They are defined under the prefix for AgriComO\textsuperscript{1} ontology. All knowledge representations (DM prediction models) in the agriculture knowledge maps repository (AgriKMaps) are represented and stored as KMaps with a prefix for the AgriKMaps\textsuperscript{2} knowledge repository.

3.2 Using OAK4XAI for Modeling and Explaining

The proposed approach converts the mined knowledge into its corresponding representation. This procedure is defined in the module Knowledge Wrapper. More precisely, it creates a representation for the mined knowledge using the

\textsuperscript{1} URI prefix for concepts of AgriComO: http://www.ucd.ie/consus/AgriComO#

\textsuperscript{2} URI prefix for instances of AgriKMaps: http://www.ucd.ie/consus/AgriKMaps#
model \( k = (\{i\}, \{t\}, \{s\}, \{r\}) \) (see Section 2) before converting it into RDF turtles and importing them into the RDF Triple storage. This consists of six steps: 1) identify the model; 2) identify concepts; 3) generate instances; 4) identify transformations; 5) generate states; and 6) generate scripts. The Knowledge Wrapper implementation depends on the type of knowledge items, such as *Factual Knowledge* items published in scientific papers or *Processed Knowledge* items extracted directly from DM modules.

A representation \( k \) includes a set of instances, transformations, states, and relations. 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. These transformations are linked to instances to represent the way data is processed in the prediction model. The set of states \( \{s\} \) is generated in Step 5. Note that not all knowledge representations have sets of states. If the knowledge items are factual knowledge items, they include values, and their representations contain states. Otherwise, the set of states is empty. Finally, the set of relations \( \{r\} \) is based on \texttt{rdf:type}, \texttt{AgriComO:hasTransformation}, \texttt{AgriComO:hasState}, \texttt{AgriComO:hasCondition}, and \texttt{AgriComO:predicts}, etc.

**Listing 1.1: Triples of Regressor_004**

```turtle
AgriKMaps:Regressor_004
  rdf:type owl:NamedIndividual ,
  AgriComO:Regressor ,
  AgriComO:KnowledgeModel ;
  rdfs:label "Regressor_004" .
AgriComO:definedIn
  AgriKMaps:Article_004 ;
AgriComO:hasAlgorithm
  AgriComO:Algorithm_DTR ,
  AgriComO:Algorithm_LR ,
  AgriComO:Algorithm_RF ,
  AgriComO:Algorithm_GBR ;
AgriComO:hasCondition
  AgriKMaps:SoilPH_004 ;
AgriComO:predicts
  AgriKMaps:SoilPH_004x ;
AgriComO:hasDataset
  AgriKMaps:Dataset_CONSUS_001 ;
AgriKMaps:SoilPH_004
  rdf:type owl:NamedIndividual ,
  AgriComO:SoilPH ,
AgriComO:hasTransformation
  AgriComO:Transformation_SoilPH_Max ,
  AgriComO:Transformation_SoilPH_Min ,
  AgriComO:Transformation_SoilPH_Avg ,
```

For example, when applying this modelling process, the knowledge item *Regressor_004*, published in article *Article_004* [11], can be converted into a set of triples. The brief triple example of *Regressor_004* (shown in Listing 1.1) shows that *Regressor_004* is used to predict soil pH and this attribute uses the soil pH transformation *Transformation_SoilPH_Max*, *Transformation_SoilPH_Min*, and *Transformation_SoilPH_Avg*.

The semantic interpretation of concepts, transformations, and values (such as *Transformation_SoilPH_Max*) in this knowledge item is done through the one-way retrieval process; from AgriKMaps to AgriComO and from AgriComO to
AgriComO. This means that using predefined information in the AgriComO ontology to interpret instances and processing in the AgriKMaps. The explanation process starts with an instance in AgriKMap. It browses the knowledge item to identify the concept class (prefix AgriComO) and its attributes.

3.3 XAI Transparency with OAK4XAI

In this section, we discuss the proposed model’s XAI functions by answering a set of WH-questions (What, What for, Who, When, Where and How) along with a summary as shown in Figure 3.

**What?** The OAK4XAI model focuses on representing and explaining the results of the DM analysis process. It supports four types of analyses: Classification, Clustering, Regression, and Association Rule.

**What for?** OAK4XAI can assist in describing the meaning of data, provide ways to transform raw data into input data for learning models and explain the results of the learning models. Therefore, this model helps to increase transparency, usability, trust, and confidence in mined knowledge, which are the XAI’s main goals.

**Who?** The model can explain the results of the ML algorithms to different types of users. More precisely. The implemented version of this model supports the following user groups:

---

**Fig. 3: OAK4XAI Model for explainable AI**

[Image of OAK4XAI model diagram]
Managers and executive boards understand an overview of knowledge items, including inputs, outputs, algorithms, training datasets, and results evaluation.

Data scientists and developers understand attributes, values, and labels used in the knowledge items (DM models).

Agronomists and experts understand states and processing steps of knowledge items, select then apply them in farming.

How? Recall that OAK4XAI contains a predefined ontology, which helps to explain the attributes in the knowledge representation. A representation is an entry of KMap with nodes for concepts, instances, transformations, states, and edges for relationships between them. All KMap entries are stored using the linked data technique. Finally, explainable interfaces provide different explanations to different user groups. Moreover, the explanations need to be written in suitable language (and with a description strategy) for the intended audience. These include:

- **Formal language** can be structured or syntax explanation, and it is based on structured and unique linked data in the knowledge repository layer. The linked data are sets of triples \( (\text{subject}, \text{predictive}, \text{object}) \). These triples can be transformed and interpreted in a certain format language.

- **Natural language**: written texts can be generated from the description of concepts and instances in the ontology. Each concept in the ontology has some attributes (\texttt{rdfs:label} and \texttt{rdfs:comment}), which support the model in a human-friendly explanation.

- **Graphic language**: visualizations can be supported by the explanation interface layers based on the knowledge repository layer.

Where? It is worth noting that OAK4XAI can explain data outside the mining steps, including the pre-model and post-model stages of the DM applications.

- **Pre-model**: With this model, the users can pre-process and transform the data and input it into learning models. Moreover, they have more options for improving the pre-processing and transformation steps by using predefined Transformation instances of the AgriComO ontology.

- **Post-model**: Trained models and final decisions contain data values, which need extra information and semantics. At this stage, different users may have different concerns (for example, why this decision was taken). This can be solved by exploring detailed information about each concept and extra information.

When? This model can be used to develop AI processes and XAI in three stages:

- **Designing**: planning pre-processing algorithms can help understanding data better by accessing predefined knowledge from the core ontology in the OAK4XAI model.
– **Implementation:** allowing scientists to have a deep understanding can contribute to the process of developing and improving machine learning models.
– **Knowledge Use:** explaining knowledge results can assist in understanding the model better.

4 Validation

4.1 Implementation

OAK4XAI is implemented using the linked data technique, the graph database server, and the web-based explanation application. The graph database server supports RDF triple storage and SPARQL protocol for query, while web-based explanation application (including Knowledge Wrapper module and Knowledge Browser module for visualization). The search engine searches for knowledge items from the AgriKMaps domain, while the explainable engine retrieves the domain knowledge from the predefined ontology, the AgriComO domain. All instances and concepts from AgriKMaps and AgriComO have a URI and they link together based on their URI. The graph database uses Apache Jena\(^3\) (for the native knowledge graph storage), SPARQL\(^4\) 1.1 (for SPARQL Engine), and Fuseki\(^5\) (for SPARQL Endpoint), while the Knowledge Browser is a web-based application for exploring knowledge and providing explanations.

4.2 Explanation

Knowledge Browser functions are twofold: it assists users in locating mined knowledge items based on their input queries or keywords and validates the explainability of the DM analysis process results.

Moreover, Knowledge Browser is a knowledge search engine, which looks for knowledge items (knowledge maps) in the RDF storage and queried input concepts and their roles. The retrieved results are represented and explained in many levels of detail, from general to details. Knowledge Browser is very efficient in finding knowledge items in the knowledge repository based on input queries, such as "predict soilPH" (with the result shown in Figure 4). The process includes:

– Finding knowledge items by search queries from AgriKMaps;
– Segmenting concepts into parts AI models;
– Generating SPARQL queries;
– Generating summaries of knowledge items from return triples.

The explanation content depends on users concerns when exploring given items. The explanation process with the OAK4XAI approach consists of the following steps:

\(^3\) https://jena.apache.org/index.html
\(^4\) https://www.w3.org/TR/sparql11-query/
\(^5\) https://jena.apache.org/documentation/fuseki2/
Determine the concept in the knowledge item;
- Retrieve related attributes and descriptions from AgriComO ontology;
- Generate explanations interface (from return triples).

For example, to locate the knowledge item shown in Listing 1.1, the results of the query "predict SoilPH" are represented as summaries of knowledge items (AgriKMaps) (Figure 4a), and the details of their concepts and states are interpreted based on knowledge from the ontology (AgriComO) (Figure 4b/c). Details of the data processing stage (formulas and values) in the knowledge items are described in the predefined ontology, so their information can be represented and explained. Based on different user questions, the system has different levels of interpretations of the post-model stage of the knowledge items.

Moreover, the system also supports searching for concepts and related details in the ontology. This explainability can assist users in the pre-model stage of building the knowledge items. For example, Listing 1.2 provides the information of transformation Transformation_SoilPH_Max using in Regressor0004 (Listing 1.1) and other transformations (such as, Transformation_SoilPH_Tier11[^6] (defined by US. Department of Agriculture, Natural Resources Conservation Service) as a category of 11 types) for the soil pH attribute.

[^6]: [https://en.wikipedia.org/wiki/Soil_pH](https://en.wikipedia.org/wiki/Soil_pH)
Listing 1.2: Information of Transformations for Soil pH attribute

| Transformation | Definition | Values |
|----------------|------------|--------|
| Transformation_SoilPH_Max | The transformation returns the maximum value of Soil pH values in the sampling area, for example in the radius of 100m. | 0.0 - 14.0 |
| Transformation_SoilPH_Tier11 | This transformation returns a state of soil pH, defined by the United States Department of Agriculture Natural Resources Conservation Service, classified soil pH ranges as 11 types. | Ultra acidic < 3.5, Extremely acidic 3.5 - 4.4, Very strongly acidic 4.5 - 5.0, Strongly acidic 5.1 - 5.5, Moderately acidic 5.6 - 6.0, Slightly acidic 6.1 - 6.5, Neutral 6.6 - 7.3, Slightly alkaline 7.4 - 7.8, Moderately alkaline 7.9 - 8.4, Strongly alkaline 8.5 - 9.0, Very strongly alkaline > 9.0 |

In summary, with a predefined AgriComO ontology, OAK4XAI provides consistent information and definitions of concepts, algorithms, and values involved in a knowledge item. The explainability information enables researchers to communicate and compare the results of various classifiers and support stakeholders in making informed decisions for the implementation and usage of machine learning models.

4.3 Statistics

Numerous algorithms and transformation techniques have been extracted from several resources to support the outside-of-box explanation of DM applications in agriculture. They are collected manually from programming libraries, scientific articles, etc. A list of algorithms is collected from programming libraries, such as Scikit-learn\(^7\), NLTK\(^8\), Huggingface\(^9\), etc. Then, each algorithm requires necessary information, such as authors, definitions, reference information, and programming libraries. The algorithm structure of basic information or transformation is provided in Section 2.2. Moreover, well-known algorithms were defined in the AgriComO ontology. Similarly, all evaluation metrics for data mining processes and common pre-trained models were collected and put into the ontology. In the current implementation, AgriComO contains 176 algorithms, 110 pre-trained models, and 51 evaluation metrics, as shown in Table 1.

\(^7\) https://scikit-learn.org/stable/
\(^8\) https://www.nltk.org/
\(^9\) https://huggingface.co/docs/transformers/index
Table 1: Statistics of Main Indices and Transformations in AgriComO

| Indices            | Examples                          | Count |
|--------------------|-----------------------------------|-------|
| Agronomic Indices  | Soil, weeds, nutrient, water indices | 310   |
| Agroclimatic Indices | GDD, AFD, CDD, FX               | 172   |
| Vegetation Indices | LAI, NDVI, GDVI, RVI, SAVI, SAVO | 322   |
| Ecological Indices | Water Index: WZI, WFI            | 15    |
| Pretrain Models    | GoogLeNet, AlexNet               | 110   |
| Mining Algorithms  | Linear, DT, ANN, RF, LSTM, LASSO | 176   |
| Evaluation Metrics | Accuracy, CCR, Jscore, F1, R2, RSME | 51    |
| Data Transformations | RGB or BW for Colour, SoilPH Types | 326   |
| **Total**          |                                   | **1,310** |

5 Conclusion and Future Work

We proposed the OAK4XAI model that consists of an ontology-based knowledge map and a knowledge management system. The OAK4XAI architecture has the potential to be expanded to other knowledge domains. The knowledge items can easily be imported into the knowledge management system. The knowledge management system implements a knowledge browser to access and explore knowledge of any kind and with different levels of interpretations depending on the DM applications.

We defined an agriculture ontology, AgriComO, and populated it with the most well-known algorithm for mining agricultural data. AgriComO provides definitions and information for concepts, algorithms, and states in crop farming. We believe that the proposed model and its ontology can provide consistent information and explanation not only for DM applications in agriculture but also for other domains by pre-defining their corresponding ontology.

In future work, we will focus on two areas: a) implement the explanation interface as a service, to interact with several user groups. It will take user questions as input and retrieve the corresponding knowledge, and b) extend the proposed model to include several ML algorithms for prediction based on explainable approaches.

Moreover, we plan to represent the result of several predictive algorithms in agriculture, such as decision trees, Bayesian analysis, or support vector machines with rule-based extraction. Representations will be compatible with different explanation interfaces, and then develop a reasoning module to decide the most appropriate explanation.

Acknowledgment This work is part of CONSUS and is supported by the SFI Strategic Partnerships Programme (16/SPP/3296) and is co-funded by Origin Enterprises Plc.
References

1. Amina Adadi and Mohammed Berrada. Peeking inside the black-box: a survey on explainable artificial intelligence (xai). *IEEE Access*, 6:52138–52160, 2018.
2. Arjun R Akula, Sinisa Todorovic, Joyce Y Chai, and Song-Chun Zhu. Natural language interaction with explainable ai models. In *CVPR workshops*, pages 87–90, 2019.
3. Alejandro Barredo Arrieta, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Benenetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-López, Daniel Molina, Richard Benjamins, et al. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information Fusion*, 58:82–115, 2020.
4. Thomas Bishop and Alex McBratney. A comparison of prediction methods for the creation of field-extent soil property maps. *Geoderma*, 103(1-2):149–160, 2001.
5. David Gunning. Explainable artificial intelligence (xai). *Defense Advanced Research Projects Agency (DARPA), nd Web*, 2(2), 2017.
6. Nhien-An Le-Khac, M-Tahar Kechadi, and Joe Carthy. Admire framework: Distributed data mining on data grid platforms, 2017.
7. Christoph Molnar. *Interpretable machine learning*. Lulu. com, 2020.
8. Quoc Hung Ngo, Tahar Kechadi, and Nhien-An Le-Khac. OAK: Ontology-based knowledge map model for digital agriculture. In *Future Data and Security Engineering: 7th International Conference (FDSE)*, volume LNCS 12466. Springer, 2020.
9. Quoc Hung Ngo, Tahar Kechadi, and Nhien-An Le-Khac. Knowledge representation in digital agriculture: A step towards standardised model. *Computers and Electronics in Agriculture*, 199:107127, 2022.
10. Quoc Hung Ngo, Nhien-An Le-Khac, and Tahar Kechadi. Ontology based approach for precision agriculture. In *International Conference on Multi-disciplinary Trends in Artificial Intelligence*, volume LNCS 11248, pages 175–186. Springer, 2018.
11. Quoc Hung Ngo, Nhien-An Le-Khac, and Tahar Kechadi. Predicting soil ph by using nearest fields. In *29th SGAI International Conference on Artificial Intelligence*, volume LNCS 11927, pages 480–486. Springer, 2019.
12. Wei Shangguan, Yongjiu Dai, Baoyuan Liu, Axing Zhu, Qingyun Duan, Lizong Wu, Duoying Ji, Aizhong Ye, Hua Yuan, and Qian Zhang. A China data set of soil properties for land surface modeling. *Journal of Advances in Modeling Earth Systems*, 5(2):212–224, 2013.
13. Nikolaos L Tsakiridis, Themistoklis Diamantopoulos, Andreas L Symeonidis, John B Theocharis, Athanasios Iossifides, Periklis Chatzimisios, George Pratos, and Dimitris Kouvas. Versatile internet of things for agriculture: an explainable ai approach. In *IFIP International Conference on Artificial Intelligence Applications and Innovations*, pages 180–191. Springer, 2020.
14. Fei Wang, Shengtian Yang, Wei Yang, Xiaodong Yang, and Ding Jianli. Comparison of machine learning algorithms for soil salinity predictions in three dryland oases located in Xinjiang Uyghur Autonomous Region (XJUAR) of China. *European Journal of Remote Sensing*, 52(1):256–276, 2019.