Knowledge Graph Construction for Rice Pests and Diseases

Muhammad Ariful Furqon, Saiful Bukhori

[a] Universitas Jember, Indonesia
[1] ariful.furqon@unej.ac.id*
* corresponding author

ARTICLE INFO

Article history
Received 12 Apr 2023
Revised 28 June 2023
Accepted 12 July 2023

Keywords
Knowledge graph
Rice diseases
Rice Pests
Ontology

ABSTRACT

The agricultural industry in Indonesia confronts the simultaneous task of augmenting food production to satisfy escalating demand while proficiently handling crop losses caused by pests and diseases. This study introduces a novel approach that leverages knowledge graphs to transform traditional, expert-based knowledge into a dynamic and interconnected system for addressing rice pests and diseases. The process of constructing a knowledge graph consists of (1) domain extraction; (2) ontology design; (3) class definition; (4) property definition; (5) instance definition; and (6) build knowledge graph. The construction process entails retrieving data from the DBpedia through SPARQL queries, constructing a knowledge graph using an iterative approach, and designing ontologies. This involves defining essential classes like plants, pests, diseases, and pathogens, formalizing properties, and defining individuals. The ontology is transformed into a knowledge graph using Neo4J. Therefore, the knowledge graph will enhance decision-making and modeling processes in rice pests and diseases.

1. Introduction

The world population is projected to increase by more than 35 percent by 2050. Indonesia has a population of 275 million, with an annual growth rate of 1.3% [1]. As the population of Indonesia increases, the amount of consumption of rice as the country's leading staple food also increases. Agriculture is also the foundation for developing and expanding Indonesia's Gross Domestic Product (GDP) [2]. Indonesia is also known as an agricultural country with extensive cultivation of food crops [3]. Indonesian agriculture consists of various plants, with the leading staple food of Indonesian people being rice. However, the most significant loss for farmers is crop failure caused by pests and diseases. Pests and diseases management pose crucial obstacles, imposing substantial strain on the productivity of crops [4]. Agricultural practitioners always face the formidable challenge of combating pests and diseases, which have the potential to cause severe damage to crops and diminish overall productivity [5]. The problem is worsened by insufficient pest control methods and a lack of knowledge on integrated pest management [6].

The knowledge base related to plant pests and diseases is still traditional and based only on plant experts, causing the information obtained to be limited and static [7], [8]. However, agricultural production and related studies of insect pests and plant diseases generate enormous volumes of data [9]–[13]. One of the biggest challenges related to knowledge management in the agricultural domain is integrating large amounts of information effectively [14]. One approach that can be used to integrate information is to use a knowledge graph [15]–[17]. Semantic interoperability of knowledge graphs is based on comprehensive and efficient exchange and integration of pest and disease data [18]. Thus, knowledge acquisition and large-scale pest and disease management methods can be modeled using the knowledge graph [17].

In recent years, there has been an increasing interest in utilizing knowledge graphs in agriculture. Knowledge graphs offer a systematic approach to structuring and connecting information, facilitating analysis, and extracting insights [19]. A knowledge graph can be enhanced by utilizing existing data sources and integrating new information, such as plants, pesticides, and fertilizers [20]. The knowledge graph is a central repository for obtaining and interpreting this information, facilitating the optimization of agricultural production structure [21]. Moreover, using knowledge graphs goes beyond the scope of crop pest and disease control [22].

Applying knowledge graphs in smart agriculture involves converting fragmented agricultural big data into a comprehensive knowledge graph [23]. The knowledge graph contains diverse facets, including plant bug pests and diseases, plant variations, and smart agriculture applications [7], [24]. By visualizing links and interconnections within the knowledge graph, farmers and agricultural specialists can acquire valuable insights to enhance crop yields, manage resources efficiently, and understand the agricultural landscape [22]. This encompasses data regarding crops, meteorological trends, soil composition, pest and disease control, and various other aspects [25]. By consolidating all this information in a single location, farmers and agricultural specialists can enhance their decision-making process and apply precise crop management and pest/disease control methods.

The utilization of knowledge graphs for diagnosing rice diseases is an up-and-coming area of agricultural research and technology [26]. The specific objective of this research is to construct a novel knowledge graph model that can assist farmers in identifying rice pests and diseases. By organizing and integrating pertinent data, knowledge graphs can optimize the capacity to diagnose, prevent, and effectively manage diseases in rice fields [27]. The utilization of knowledge graphs is anticipated to have a growing significance in the intersection of data science and agriculture, particularly in enhancing the well-being of rice crops, thereby contributing to national food security [28].

2. Method

A knowledge graph is a directed, labeled graph that connects two or more points (nodes) represented by vertices and edges [29]. A knowledge graph is a directed labeled graph with 4-tuples, denoted in equation 1 below.

$$G = (N, E, L, f) \tag{1}$$

Where N is the set of nodes, $E \subseteq N \times N$ is the set of edges, L is a set of labels, dan $f: E \rightarrow L$as an assignment function from edges to labels. Knowledge graphs connect two or more interconnected entities and objectively describe concepts, entities, events, and their relationships [30]. Concepts refer to conceptual representations of objective things formed about sets, categories, and types of objects. Event refers to an event such as plant disease, prevention, and control behavior. Entities are the essential elements in a knowledge graph, including objects such as plants, diseases, pathogens, symptoms, disease locations, and pesticides. Relationships are objective relationships between describing concepts, entities, and events. Examples of relationships are disease causes, control methods, selection, and application methods [7].

The construction of a knowledge graph for rice pests and diseases is a methodical procedure that entails collecting, arranging, and categorizing information in a format based on graphs [31]. The methodical procedure to construct a knowledge graph for rice pests and diseases in this study is visualized in Figure 1 below.

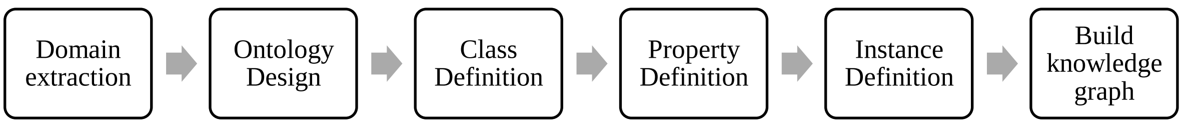

Figure 1 Knowledge graph construction method

Initially, the process of domain extraction commences by gathering pertinent data within the study domain, as exemplified in constructing a knowledge graph [32]. Furthermore, ontology design entails the creation of the ontology, which will serve as the fundamental framework for knowledge [33].

Furthermore, the class definition specifies the elements depicted in the graph, such as entities, concepts, or objects associated with the research domain of rice pests and diseases [7]. Furthermore, defining property entails precisely determining the characteristics or connections between items inside the ontology [34]. Furthermore, the process of instance definition involves mapping specific and tangible items within the study area onto the ontology that has been constructed. Lastly, the final step entails constructing the knowledge graph using tools such as Neo4j. During this phase, the previously established entities, relationships, and attributes are translated into a graph structure [35]. This graph allows for exploring and comprehending the connections between concepts and data inside the research area of rice pests and diseases.

3. Results and Discussion

When constructing a knowledge graph model, it is necessary to have a representation or instance of each entity and sub-entity [36]. Knowledge extraction was performed by executing queries on the DBpedia Open Knowledge Graph Database. DBpedia is a collaborative community that extracts organized information from content generated in different Wikimedia projects [37]. The organized information resembles an open knowledge graph that is universally accessible and may be retrieved online. A SPARQL query is required to retrieve information from DBpedia [38]. The SPARQL protocol, also known as the Resource Description Framework (RDF) query language, is utilized to construct linked data from an RDF dataset generated in DBPedia [39]. The SPARQL query will yield data on rice pests, which will be incorporated into rice pest instances or individuals. The results of the SPARQL query run in **Algorithm 1** to collect information about rice pests are illustrated in **Table 1**.

ALGORITHM 1: SPARQL QUERY OF RICE PESTS ON DBPEDIA

```
results []
for triple in dataset do
    if triple.subject.label ← "List of rice diseases" in English then
        URI ← triple.object
        diseases ← getLabel(URI, 'en', dataset)
        description ← getAbstract(URI, 'en', dataset)
        if diseases is not empty and description is not empty then
            results.append([URI, diseases, description])
        end if
        if length(results) >= 1000:
            exit loop
        end if
    end if
end for
for result in results do
    print(result)
end for
```

Table 1. SPARQL query results of Rice Pests

URI	Description
http://dbpedia.org/resource/Ricepests	"Rice pests"@en
http://dbpedia.org/resource/Chiasmini	"Chiasmini is a tribe of leafhoppers in the subfamily Deltocephalinae. Chiasmini contains 21 genera and over 300 species. Some species of Chiasmini in the genus Nephotettix are agricultural pests and transmit rice Tungrovirus in southeast Asia."@en
http://dbpedia.org/resource/Mythimna_separata	"Mythimna separata, the northern armyworm, oriental armyworm or rice ear-cutting caterpillar, is a moth of the family Noctuidae. It is found in China, Japan, South-east Asia, India, eastern Australia, New Zealand, and some Pacific islands. It is one of the major pests of maize in Asia. The species was first described by Francis Walker in 1865."@en

Once the data has been gathered, the subsequent task involves constructing a knowledge graph by incorporating entities, concepts, and relationships derived from the obtained data. Ensuring the knowledge graph's consistency, accuracy, and appropriateness within its intended domain is crucial

[40]. The method is iterative, allowing for updates and improvements to the knowledge graph as knowledge advances and needs change. Constructing a robust knowledge graph enables the organized presentation of information inside a particular area, facilitating enhanced analysis, modeling, and decision-making processes [41]. The approach employed for constructing knowledge graphs of rice pests and diseases involves using the semantic web, specifically ontology. A knowledge graph provides flexibility and adaptability in representing real-world connections [42]. On the other hand, an ontology serves as a formal, domain-specific specification, defining classes, properties, and relationships with a focus on semantic precision and logical inference [43]. The relationship between them is complementary, with ontologies guiding the schema and semantics of knowledge graphs. The collaboration enhances semantic interoperability, enriching the knowledge graph with formal definitions and supporting logical reasoning [44], [45].

The study involved constructing a knowledge graph by developing an ontology using Protégé. Protégé is a freely available open-source platform for constructing domain models and developing knowledge-based applications using ontologies [46]. The subsequent stage in the process is ontology planning, which builds upon the previously established knowledge domain definition of pests and diseases of rice plants. Ontology design refers to creating a formal structure for representing knowledge in a specific field [47]. Ontologies arrange concepts, entities, and their interconnections, creating a systematic framework for comprehending and organizing information within a specific field [48]. The outcomes of establishing a conceptual ontology for rice pests and diseases yield numerous primary categories, specifically: (1) plants; (2) pests; (3) diseases; (4) symptoms; (5) pathogens; (6) pest control; and (7) disease treatment. The ontology hierarchy of rice pests and diseasess is illustrated in **Fig. 1**.

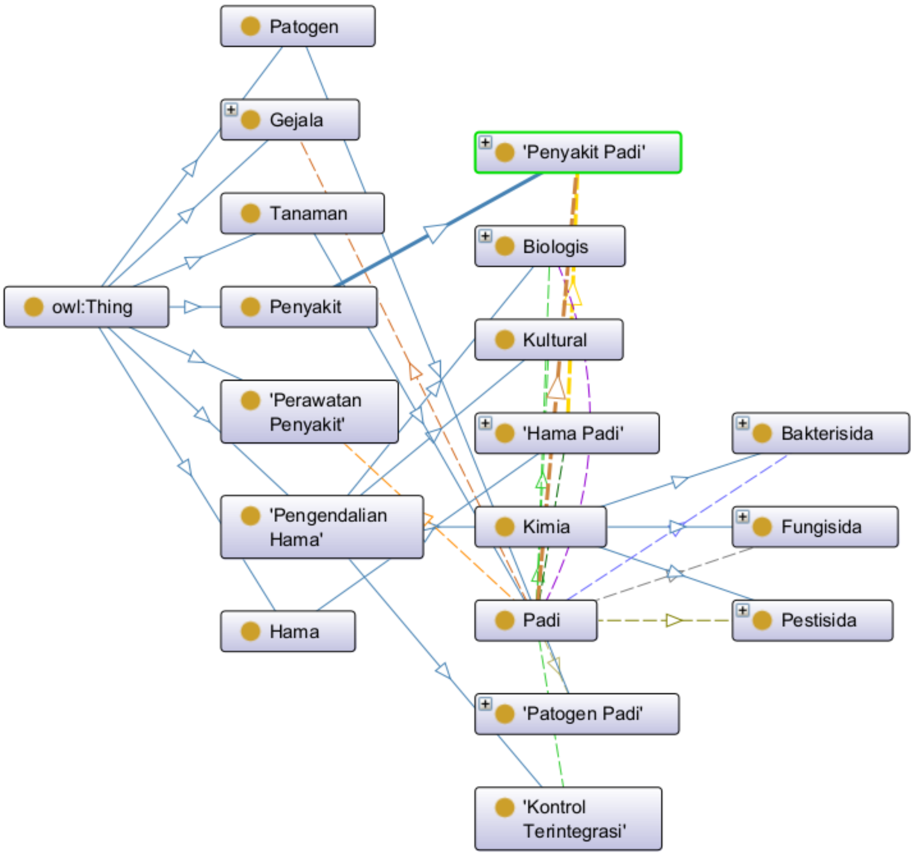

Fig. 1. Rice Pests and Diseases Ontology

Defining properties in an ontology is a crucial procedure for establishing and articulating the connections between classes in the knowledge domain shown in the ontology. Properties encompass the qualities or features of entities inside the ontology and delineate the connections between classes or between classes and individuals [49]. Classes need more relationships to provide adequate information [36]. Properties are crucial for establishing connections between classes in an ontology

[50]. Two categories exist, specifically object properties and data type properties. Object properties establish connections between individuals, whereas data type properties establish connections between individuals and data values [51]. Defining property objects in the ontology of rice plant pests and diseases entails establishing the connections between object classes linked to the entities of pests and diseases affecting rice plants. Object attributes establish connections between classes, enabling the association of entities with other entities within the ontology. **Table 2** defines the object properties utilized in the ontology.

Table 2. Object Properties of Rice Pest and Disease Ontology

Object Property	Domain	Range
givenBiologicalAgent	Rice	Biological
givenBactericide	Rice	Bactericide
givenFungicide	Rice	Fungicide
givenPestControl	Rice	Chemical Integrated Control Biological Cultural
givenTreatment	Rice	Disease Treatment
givenPesticides	Rice	Pesticide
haveSymptoms	Rice	Symptoms
causeDisease	Rice Pests	Rice Disease
sufferPathogen	Rice	Rice Pathogens
sufferDisease	Rice	Rice Disease
sufferPest	Rice	Rice Pests

Defining individuals or instances in the rice pest and disease ontology involves constructing a formal representation of knowledge on actual entities associated with the domain. During this phase, a procedure takes place to generate tangible entities or instances that symbolize actual entities in the field of pests and diseases in rice plants. Instances on an ontology are distinct manifestations of established classes, describing tangible items in the real world [52]. Describing persons in this ontology involves assigning a descriptive and pertinent name to each represented thing, such as "Planthoppers," which accurately denotes individual planthopper pests peculiar to rice plants. Moreover, individuals can possess distinct qualities and properties that offer a more comprehensive understanding of the characteristics of rice plant pests and diseases.

Once all individuals have been identified, the subsequent step involves transforming the ontology into a knowledge graph using Neo4J [53]. Ontology conversion to Neo4j involves transforming the ontology structure into a graph format seamlessly integrated with the Neo4j graph database. Neo4j is a graph database management system utilized for storing, administering, and manipulating data in a graph [54]. Converting an ontology to a Neo4J graph database entails determining the entities, classes, and characteristics inside the ontology that will be transformed into a Neo4J graph database. The ontology is converted to the Neo4J database using NeoSemantics [55]. The process of ontology conversion utilizing NeoSemantics entails the utilization of a Neo4j extension known as n10s to import and transform ontology data into a Neo4j graph database. NeoSemantics is precisely engineered to facilitate the manipulation and analysis of RDF and OWL data [56]. The outcomes of converting the ontology into a knowledge graph format are depicted in **Fig. 2**.

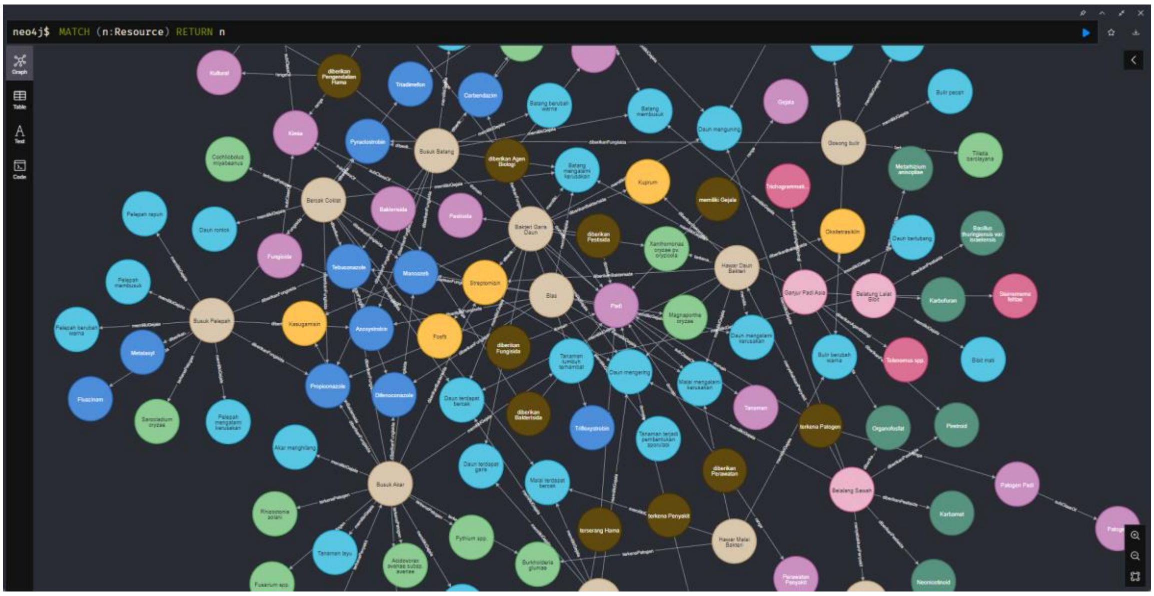

Fig. 2. Rice Pests and Diseases Knowledge Graph

The Neo4j visualization of the rice pest and disease knowledge graph is a complete framework for effectively classifying, storing, and assessing information on pests and diseases that impact rice plants. The knowledge graph uses Neo4j's graph database features to employ nodes for representing elements such as rice plants, pests, and diseases. Relationships are used to capture complex interactions between these entities. The hierarchical structure enables the flexible storing and retrieval of data, enabling detailed analysis of the interrelated attributes and connections within the agricultural ecosystem. The graph's layout facilitates user navigation and data querying, helping researchers, farmers, and stakeholders to make well-informed decisions regarding pest and disease management in rice cultivation. Knowledge graph visualization enhances comprehension of intricate patterns by visually intuitively depicting the complex network of interactions among pests, diseases, and rice plants.

4. Conclusion

This study process involves the construction of a knowledge graph model with a primary focus on rice pests and diseases. The process begins by extracting information from the DBpedia Open Knowledge Graph Database using SPARQL queries, which form the basis of the knowledge graph. Following that, the knowledge graph is methodically built by combining entities, concepts, and relationships obtained from this data while consistently using an iterative methodology to accommodate evolving knowledge and changing requirements in the field. Protégé is crucial in the development and structuring of ontologies. The ontology planning process involves defining and organizing various essential classes, such as plants, pests, diseases, symptoms, pathogens, pest control, and disease treatment, which comprise the ontology's hierarchical structure. Formalizing properties within the ontology improves the clarity of interactions between classes and entities, allowing for a clear distinction between object and data type properties. The ontology's concept of individuals provides comprehensive representations of concrete beings within the domain. In the end, the ontology is converted into a knowledge graph using Neo4J, with the help of NeoSemantics. This creates a well-organized repository that efficiently stores information about rice pests and diseases, their connections, and characteristics. As a result, decision-making and modeling processes in this field are enhanced.

Further research in developing knowledge graphs for specific areas, such as rice pests and diseases, involves a comprehensive and diverse strategy. The process involves augmenting the semantic complexity of the graph using natural language processing, merging it with other pertinent knowledge graphs to obtain comprehensive insights, utilizing machine learning for predictive analysis, creating user-friendly interfaces for broader accessibility, and consistently enhancing data quality and verification procedures. For the continuous development of these knowledge graphs, it is crucial to have collaboration between different disciplines, the ability to scale, support for several languages, ethical issues, and means for receiving feedback. This comprehensive strategy aims to provide researchers, policymakers, and farmers with essential and current information to effectively tackle the issues associated with controlling rice pests and diseases.

Acknowledgment

This research is financially supported by Grant Number 3378/UN.25.3.1/LT/2023, Institute for Research and Community Service, Universitas Jember

Declarations

Funding statement. Institute for Research and Community Service, Universitas Jember by Grant Number [3378/UN.25.3.1/LT/2023]
Conflict of interest. The authors declare no conflict of interest.
Additional information. All information is private for this paper.

Data and Software Availability Statements

The RDF file from the construction of the rice pest and disease knowledge graph used in this research is available at https://github.com/Ariful2607/Rice-Pest-Disease-Ontology.

References

[1] M. Jamaludin, "Indonesia's Food Security Challenges: How Food SOE Optimizes its Role?," *Research Horizon*, vol. 2, no. 3, pp. 394–401, 2022.

[2] C. Duffy *et al.*, "Agroforestry contributions to smallholder farmer food security in Indonesia," *Agroforestry Systems*, vol. 95, no. 6, pp. 1109–1124, Aug. 2021, doi: 10.1007/S10457-021-00632-8/TABLES/3.

[3] Sudirman, A. P. Windarto, and A. Wanto, "Data mining tools | rapidminer: K-means method on clustering of rice crops by province as efforts to stabilize food crops in Indonesia," *IOP Conf Ser Mater Sci Eng*, vol. 420, no. 1, p. 012089, Sep. 2018, doi: 10.1088/1757-899X/420/1/012089.

[4] M. B. Isman, "Challenges of Pest Management in the Twenty First Century: New Tools and Strategies to Combat Old and New Foes Alike," *Frontiers in Agronomy*, vol. 1, p. 503756, Dec. 2019, doi: 10.3389/FAGRO.2019.00002/BIBTEX.

[5] P. Karuppuchamy and S. Venugopal, "Integrated Pest Management," *Ecofriendly Pest Management for Food Security*, pp. 651–684, Jan. 2016, doi: 10.1016/B978-0-12-803265-7.00021-X.

[6] R. P. L. Durgabai, P. Bhargavi, and S. Jyothi, "PEST MANAGEMENT USING MACHINE LEARNING ALGORITHMS: A REVIEW," *International Journal of Computer Science Engineering and Information Technology Research (IJCSEITR)*, vol. 8, no. 1, 2018, [Online]. Available: www.tjprc.org

[7] L. Xiaoxue, "Review and Trend Analysis of Knowledge Graphs for Crop Pest and Diseases," *IEEE Access*, vol. 7, pp. 62251–62264, 2019, doi: 10.1109/ACCESS.2019.2915987.

[8] B. D. Grieve *et al.*, "The challenges posed by global broadacre crops in delivering smart agri-robotic solutions: A fundamental rethink is required," *Glob Food Sec*, vol. 23, pp. 116–124, Dec. 2019, doi: 10.1016/J.GFS.2019.04.011.

[9] R. H. L. Ip, L. M. Ang, K. P. Seng, J. C. Broster, and J. E. Pratley, "Big data and machine learning for crop protection," *Comput Electron Agric*, vol. 151, pp. 376–383, Aug. 2018, doi: 10.1016/J.COMPAG.2018.06.008.

[10] K. A. Garrett, "Big data insights into pest spread," *Nature Climate Change 2013 3:11*, vol. 3, no. 11, pp. 955–957, Oct. 2013, doi: 10.1038/nclimate2041.

[11] S. Himesh *et al.*, "Digital revolution and Big Data: A new revolution in agriculture," *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, vol. 13, 2018, doi: 10.1079/PAVSNNR201813021.

[12] J. C. Zhao and J. X. Guo, "Big data analysis technology application in agricultural intelligence decision system," *2018 3rd IEEE International Conference on Cloud Computing and Big Data Analysis, ICCCBDA 2018*, pp. 209–212, Jun. 2018, doi: 10.1109/ICCCBDA.2018.8386513.

[13] H. Murmu, M. Nazirul, I. Sarker, S. Islam, and E. Rozario, "Role of Big Data On Digital Farming," *Article in International Journal of Scientific & Technology Research*, 2020, Accessed: Feb. 04, 2023. [Online]. Available: www.ijstr.org

[14] K. H. Coble, A. K. Mishra, S. Ferrell, and T. Griffin, “Big Data in Agriculture: A Challenge for the Future,” *Appl Econ Perspect Policy*, vol. 40, no. 1, pp. 79–96, Mar. 2018, doi: 10.1093/AEPP/PPX056.

[15] Y. Liu, “DKG-PIPD: A Novel Method about Building Deep Knowledge Graph,” *IEEE Access*, vol. 9, pp. 137295–137308, 2021, doi: 10.1109/ACCESS.2021.3116467.

[16] H. Zhang, “Intelligent Retrieval Method of Agricultural Knowledge Based on Semantic Knowledge Graph,” *Nongye Jixie Xuebao/Transactions of the Chinese Society for Agricultural Machinery*, vol. 52, pp. 156–163, 2021, doi: 10.6041/j.issn.1000-1298.2021.S0.020.

[17] Y. Chen, J. Kuang, D. Cheng, J. Zheng, M. Gao, and A. Zhou, “AgriKG: an agricultural knowledge graph and its applications,” in *International conference on database systems for advanced applications*, 2019, pp. 533–537.

[18] M. Medici, D. Dooley, and M. Canavari, “PestOn: An Ontology to Make Pesticides Information Easily Accessible and Interoperable,” *Sustainability 2022, Vol. 14, Page 6673*, vol. 14, no. 11, p. 6673, May 2022, doi: 10.3390/SU14116673.

[19] M. A. Furqon, N. Fadilah Najwa, D. Hermansyah, and M. Zarkasi, “Jurnal Politeknik Caltex Riau Knowledge Graph Modeling in Healthcare: A Bibliometric Analysis,” 2022. [Online]. Available: https://jurnal.pcr.ac.id/index.php/jkt/

[20] L. Wang, J. Jiang, J. Song, and J. Liu, “A Weakly-Supervised Method for Named Entity Recognition of Agricultural Knowledge Graph”, doi: 10.32604/iasc.2023.036402.

[21] M. A. Furqon, G. Faisal, and N. F. Najwa, “Graph Database Modelling on Malay Architecture IFC Data,” in *Proceedings Article*, Alanya Hamdullah Emin Paşa University, 2021, pp. 50–55. doi: 10.38027/ICCAUA2021139n7.

[22] H. Yu, J. Shen, C. Bi, J. Liang, and H. Chen, “Intelligent diagnostic system for rice diseases and pests based on knowledge graph,” *Journal of South China Agricultural University*, vol. 42, no. 5, pp. 105–116, Sep. 2022, doi: 10.7671/J.ISSN.1001-411X.202101010.

[23] J. Dou, J. Qin, Z. Jin, and Z. Li, “Knowledge graph based on domain ontology and natural language processing technology for Chinese intangible cultural heritage,” *J Vis Lang Comput*, vol. 48, pp. 19–28, Oct. 2018, doi: 10.1016/J.JVLC.2018.06.005.

[24] M. Á. Rodríguez-García, F. García-Sánchez, and R. Valencia-García, “Knowledge-Based System for Crop Pests and Diseases Recognition,” *Electronics 2021, Vol. 10, Page 905*, vol. 10, no. 8, p. 905, Apr. 2021, doi: 10.3390/ELECTRONICS10080905.

[25] Y.-X. Shi *et al.*, “Constructing Crop Portraits Based on Graph Databases Is Essential to Agricultural Data Mining,” *Information 2021, Vol. 12, Page 227*, vol. 12, no. 6, p. 227, May 2021, doi: 10.3390/INFO12060227.

[26] H. Zhang, H. Si, X. Ma, L. Xi, and X. Xu, “Research and Application of Agriculture Knowledge Graph,” *ACM International Conference Proceeding Series*, pp. 680–688, Oct. 2021, doi: 10.1145/3501409.3501531.

[27] W. Jearanaiwongkul, C. Anutariya, and F. Andres, “A Semantic-Based Framework for Rice Plant Disease Management: Identification, Early Warning, and Treatment Recommendation Using Multiple Observations,” *New Gener Comput*, vol. 37, no. 4, pp. 499–523, Dec. 2019, doi: 10.1007/S00354-019-00072-0/FIGURES/8.

[28] A. Durrant, M. Markovic, D. Matthews, D. May, G. Leontidis, and J. Enright, “How might technology rise to the challenge of data sharing in agri-food?,” *Glob Food Sec*, vol. 28, p. 100493, Mar. 2021, doi: 10.1016/J.GFS.2021.100493.

[29] T. Trouillon, C. R. Dance, F. E. Gaussier, J. Welbl, S. Riedel, and G. Bouchard, “Knowledge Graph Completion via Complex Tensor Factorization,” *Journal of Machine Learning Research*, vol. 18, pp. 1–38, 2017, Accessed: Feb. 06, 2023. [Online]. Available: https://github.com/ttrouill/complex

[30] S. Auer, A. Kasprzik, V. Kovtun, M. Stocker, M. Prinz, and M. E. Vidal, “Towards a knowledge graph for science,” in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Jun. 2018. doi: 10.1145/3227609.3227689.

[31] J. Wang *et al.*, “A Survey on Application of Knowledge Graph,” *J Phys Conf Ser*, vol. 1487, no. 1, p. 012016, Mar. 2020, doi: 10.1088/1742-6596/1487/1/012016.

[32] B. Abu-Salih, “Domain-specific knowledge graphs: A survey,” *Journal of Network and Computer Applications*, vol. 185, p. 103076, Jul. 2021, doi: 10.1016/J.JNCA.2021.103076.

[33] H. Chen and X. Luo, “An automatic literature knowledge graph and reasoning network modeling framework based on ontology and natural language processing,” *Advanced Engineering Informatics*, vol. 42, p. 100959, Oct. 2019, doi: 10.1016/J.AEI.2019.100959.
[34] C. M. Fonseca, D. Porello, G. Guizzardi, J. P. A. Almeida, and N. Guarino, “Relations in ontology-driven conceptual modeling,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11788 LNCS, pp. 28–42, 2019, doi: 10.1007/978-3-030-33223-5_4/COVER.
[35] S. Ferilli, “Integration Strategy and Tool between Formal Ontology and Graph Database Technology,” *Electronics 2021, Vol. 10, Page 2616*, vol. 10, no. 21, p. 2616, Oct. 2021, doi: 10.3390/ELECTRONICS10212616.
[36] I. Osman, S. Ben Yahia, and G. Diallo, “Ontology Integration: Approaches and Challenging Issues,” *Information Fusion*, vol. 71, pp. 38–63, Jul. 2021, doi: 10.1016/J.INFFUS.2021.01.007.
[37] A. Ismayilov, D. Kontokostas, S. Auer, J. Lehmann, and S. Hellmann, “Wikidata through the eyes of DBpedia,” *Semant Web*, vol. 9, no. 4, pp. 493–503, Jan. 2018, doi: 10.3233/SW-170277.
[38] S. G. Pillai, L. K. Soon, and S. C. Haw, “Comparing DBpedia, Wikidata, and YAGO for web information retrieval,” *Lecture Notes in Networks and Systems*, vol. 67, pp. 525–535, 2019, doi: 10.1007/978-981-13-6031-2_40/COVER.
[39] C. Bizer, T. Heath, and T. Berners-Lee, “Linked Data - The Story So Far,” *Linking the World’s Information*, pp. 115–143, Jul. 2023, doi: 10.1145/3591366.3591378.
[40] X. Chen, S. Jia, and Y. Xiang, “A review: Knowledge reasoning over knowledge graph,” *Expert Syst Appl*, vol. 141, p. 112948, Mar. 2020, doi: 10.1016/J.ESWA.2019.112948.
[41] S. Ji, S. Pan, E. Cambria, P. Marttinen, and P. S. Yu, “A Survey on Knowledge Graphs: Representation, Acquisition, and Applications,” *IEEE Trans Neural Netw Learn Syst*, vol. 33, no. 2, pp. 494–514, Feb. 2022, doi: 10.1109/TNNLS.2021.3070843.
[42] J. Wang *et al.*, “A Survey on Application of Knowledge Graph,” *J Phys Conf Ser*, vol. 1487, no. 1, p. 012016, Mar. 2020, doi: 10.1088/1742-6596/1487/1/012016.
[43] A. Konys and Z. Drazek, “Ontology Learning Approaches to Provide Domain-Specific Knowledge Base,” *Procedia Comput Sci*, vol. 176, pp. 3324–3334, Jan. 2020, doi: 10.1016/J.PROCS.2020.09.065.
[44] Y. Jia, Y. Qi, H. Shang, R. Jiang, and A. Li, “A Practical Approach to Constructing a Knowledge Graph for Cybersecurity,” *Engineering*, vol. 4, no. 1, pp. 53–60, Feb. 2018, doi: 10.1016/J.ENG.2018.01.004.
[45] G. Lampropoulos, E. Keramopoulos, and K. Diamantaras, “Enhancing the functionality of augmented reality using deep learning, semantic web and knowledge graphs: A review,” *Visual Informatics*, vol. 4, no. 1, pp. 32–42, Mar. 2020, doi: 10.1016/J.VISINF.2020.01.001.
[46] M. El Asikri, S. Krit, and H. Chaib, “A brief survey of creating semantic web content with protégé,” *ACM International Conference Proceeding Series*, Jun. 2018, doi: 10.1145/3234698.3234704.
[47] L. Yang, K. Cormican, and M. Yu, “Ontology-based systems engineering: A state-of-the-art review,” *Comput Ind*, vol. 111, pp. 148–171, Oct. 2019, doi: 10.1016/J.COMPIND.2019.05.003.
[48] M. Husáková and V. Bureš, “Formal Ontologies in Information Systems Development: A Systematic Review,” *Information 2020, Vol. 11, Page 66*, vol. 11, no. 2, p. 66, Jan. 2020, doi: 10.3390/INFO11020066.
[49] P. Hashemi, A. Khadivar, and M. Shamizanjani, “Developing a domain ontology for knowledge management technologies,” *Online Information Review*, vol. 42, no. 1, pp. 28–44, 2018, doi: 10.1108/OIR-07-2016-0177/FULL/XML.
[50] P. Chhim, R. B. Chinnam, and N. Sadawi, “Product design and manufacturing process based ontology for manufacturing knowledge reuse,” *J Intell Manuf*, vol. 30, no. 2, pp. 905–916, Feb. 2019, doi: 10.1007/S10845-016-1290-2/FIGURES/10.
[51] N. Komninos, C. Bratsas, C. Kakderi, and P. Tsarchopoulos, “Smart city ontologies: Improving the effectiveness of smart city applications,” *Journal of Smart Cities*, vol. 1, no. 1, pp. 31–46, Mar. 2019, doi: 10.18063/JSC.2015.01.001.
[52] C. Steinmetz, A. Rettberg, F. G. C. Ribeiro, G. Schroeder, and C. E. Pereira, “Internet of things ontology for digital twin in cyber physical systems,” *Brazilian Symposium on Computing System Engineering, SBESC*, vol. 2018-November, pp. 154–159, Jul. 2018, doi: 10.1109/SBESC.2018.00030.

[53] X. Hao *et al.*, “Construction and Application of a Knowledge Graph,” *Remote Sensing 2021, Vol. 13, Page 2511*, vol. 13, no. 13, p. 2511, Jun. 2021, doi: 10.3390/RS13132511.
[54] M. Aldwairi, M. Jarrah, N. Mahasneh, and B. Al-khateeb, “Graph-based data management system for efficient information storage, retrieval and processing,” *Inf Process Manag*, vol. 60, no. 2, p. 103165, Mar. 2023, doi: 10.1016/J.IPM.2022.103165.
[55] P. Kapsalis, G. Kormpakis, K. Alexakis, E. Karakolis, S. Mouzakitis, and D. Askounis, “A Reasoning Engine Architecture for Building Energy Metadata Management,” *13th International Conference on Information, Intelligence, Systems and Applications, IISA 2022*, 2022, doi: 10.1109/IISA56318.2022.9904419.
[56] W. Jiang, L. Yan, Y. Tu, X. Zhou, and Z. Ma, “PG-explorer: Resource Description Framework data exploration with property graphs,” *Expert Syst Appl*, vol. 198, p. 116789, Jul. 2022, doi: 10.1016/J.ESWA.2022.116789.