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SAFE NUSANTARA: A semi-automatic framework for engineering and populating a Nusantara Food Ontology

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Abstract
Constructing a comprehensive food ontology, particularly for culturally diverse cuisines like Southeast East Asian (Nusantara), is hindered by the variability of online recipes and the scarcity of structured data. This research introduces SAFE Nusantara, a novel semi-automated system designed to build and populate a Nusantara food ontology by extracting relevant terms from diverse online sources in Indonesian and Malaysian languages. By leveraging a combination of techniques, including topic modelling, natural language processing, and knowledge graph techniques, SAFE Nusantara addresses the challenges of data format diversity and language specificity. The system has demonstrated significant improvements in the accuracy of food classification and has the potential to enhance food recommendation systems and cultural heritage preservation efforts.

Keywords: Artificial Intelligence, Knowledge representation and reasoning, Ontology Engineering

I. INTRODUCTION

Nusantara, a Southeast Asian region encompassing Indonesia, Malaysia, Singapore, and Brunei Darussalam, is renowned for its diverse and delectable culinary heritage [1]. Nusantara has rich assets in foods and is well-known for its various delicious foods [2]. The shared cultural roots among these nations have led to the development of similar dishes, albeit with distinct regional variations. For instance, while both Indonesia and Malaysia have *rendang* and *nasi lemak*, their recipes and specific ingredients may differ, such as the *nasi uduk* in Indonesia or *nasi lemak* in Malaysia. Furthermore, Indonesian and Malaysian *rendang* have different recipes. For example, in the rendang recipe, the Indonesian recipe usually mentions *daging sapi*(beef), while the Malaysian recipe mentions *daging lembu*(beef) as the main ingredient.

Food is an integral part of the culture, serving as a powerful identifier of place and region [3], [4]. The Internet is replete with online resources offering a wealth of information on Nusantara cuisine, including recipes, nutritional details, and culinary traditions. Popular platforms like Cookpad[1], Malaysian Food Composition

[1] cookpad.com/id

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Database[2] and Nutrition Kitchen[3] provide a rich source of culinary data. However, the diverse and unstructured nature of online food information, coupled with the use of varying terminologies, presents significant challenges for data integration and knowledge extraction. To address these challenges, this paper proposes a novel approach to develop a comprehensive ontology for Nusantara cuisine. Subsequently, this study aims to answer the following research questions:

RQ1: How can we create a comprehensive ontology for Nusantara cuisine that captures the nuances and variations within this diverse culinary landscape?

RQ2: How can we effectively populate the ontology using a semi-automatic approach, leveraging the wealth of online food information?

By developing a robust ontology for Nusantara cuisine, we can contribute to (1) the preservation and dissemination of culinary knowledge, contributing to the preservation of cultural identity, (2) facilitate food information retrieval, which improves search capabilities and facilitate the discovery of specific recipes and culinary traditions and (3) support the development of innovative food applications, such as new dishes and culinary experiences by providing a structured knowledge base.

While several studies have successfully developed food ontologies and databases to address issues related to food composition, distribution, nutrition, and traceability [5], [6], [7], [8] these efforts have not fully addressed the specific needs of Nusantara cuisine. For example, *Rendang* cuisine. There are a lot of online resources that explain about the composition of Rendang, but none of them in the format of an ontology. Additionally, due to the dataset's characteristics, researchers need to disambiguate and identify the concepts and relationships from various sources on the Internet to develop an ontology for Nusantara food. As a result, this study was motivated by numerous Nusantara recipes to support tasks such as information retrieval or data integration.

FoodOn, a well-established food ontology, supports food traceability from farm to table [9]. Besides, FoodOn provides information about animal and plant food sources, categories, and other information, including preservation and packing methods. It leverages the LanguaL[4] thesaurus, an international framework for food description that provides unique codes for multilingual terminology and unique codes [10]. While FoodOn offers a solid foundation, its language coverage is primarily limited to English and a few European languages. This study focuses on the specific linguistic nuances of Nusantara languages, particularly Malay and Indonesian.

Furthermore, to the best of our knowledge, no prior study on automatically populating food ontology focuses on closely related languages (such as Indonesian and Malaysian). Previous research, such as [11], has explored the extraction of traditional food entities from Indonesian texts. However, this work primarily focuses on identifying food names and does not delve into the deeper semantic relationships between ingredients, preparation methods, and cultural contexts. The lexical resource approach, employed in studies like [12], has shown promise in ontology population from multilingual sources. However, these studies have not specifically addressed the unique linguistic challenges posed by closely related languages like Malay and Indonesian. While resources like WordNet Bahasa [13] and the Melayu grid [14] offer potential, their coverage of specific culinary terms and concepts may be limited, which suggests a need to develop a new ontology to address this issue.

The following sections describe related studies followed by our methodology, including the research procedure. Subsequently, we reported our results and discussion, addressing our three primary research questions. Finally, we concluded our study and suggested future work and its limitations.

[2] https://myfcd.moh.gov.my/
[3] https://nutritionkitchensg.com/
[4] https://www.langual.org/default.asp

II. Literature Review

A. Ontology Construction

The definition of ontology is a data model in which the model represents a set of concepts and relationships between those concepts in a domain [15]. Researchers classified the ontology construction approach into manual, cooperative, and semi-automatic [16]. The Manual construction approach requires immense effort from experts because the approach solely relies on experts to define the ontology. On the other hand, the expert role in cooperative construction is not as much as in manual construction because experts only perform supervision. On the other hand, the semi-supervised approach involves minimal intervention from experts/humans because the system automatically performs most of the ontology construction process. Although the semi-supervised approach to ontology construction has emerged, the fully automatic process without any human intervention is still impossible because it still requires human experts [17], [18].

The manual process of constructing ontology requires extensive human effort, is very time-consuming, and is expensive. However, if we have a small number of experts and the data set availability is considerably low, the manual construction approach could be a better choice [19]. Therefore, in this study, we choose the manual approach to initiate the ontology construction process because we have an expert in the food and nutrition domains who can share her expertise and conduct the validation. Furthermore, we adopted the manual approach proposed by [20] in developing our ontology because researchers in ontology development extensively use it.

Since Large Language Model (LLM) became a world trend with the emergence of ChatGPT in 2022, many research iniatives try to make use of this technology for solving the problems in many domains, including ontology construction. OntoChat [21] is the first work that we investigate. It is a framework for conversational ontology engineering, supporting activities such as user story creation and competency question extraction. Other approaches try to construct ontology by extracting concepts and relationships from unstructured text using LLM [22], [23].

Ontology construction has several challenging tasks such as term typing, taxonomy discovery, and relation extraction. LLMs4OL [24] tries to solve this problem by increasing the number of parameters in the transformer-inspired models such as Flan-T5-XL and GPT-3.5. Key findings indicate that Flan-T5-XL achieved the best results in taxonomy discovery, although task-specific fine-tuning is necessary for practical application in ontology learning.

People also use LLM for populating an ontology. The authors in [25] employ Large Language Models (LLMs) like GPT-4 and Llama-3 to populate the Enslaved.org Ontology by extracting structured triples from unstructured text (e.g., Wikipedia articles). They guide the LLMs using modular ontology schemas integrated into prompts, simplifying complex ontological relationships (e.g., collapsing role chains into direct predicates like hasSex(Agent, Sex_Type)) to enhance extraction accuracy. The issues with all these ontology constructions assisted by LLM compare with manual methods are hallucination & inaccuracy, oversimplification, context dependency, explainability gaps, and scalability vs. precision trade-off. These approaches overlook the semantic relationship among classes, whereas our approach uses the help of human in the loop for guarantying that the semantic relationships are preserved.

B. Latent Dirichlet Allocation

The Latent Dirichlet Allocation (LDA) model Blei (2012) [26] was initially created and used to capture thematic properties of documents by modelling texts as a mixture of distributions over words, known as topics [27]. The approach is one of the best solutions for providing unsupervised learning to generate general context topics. Notably, statistical models of topics used by researchers such as [28], [29], [30], and [31] use probabilistic (latent) topics to represent semantic properties of words and documents, while word-topic and topic-document distributions are used to interpret the internal structure of the text. Furthermore, these models were employed to provide effective dimension-reduction techniques. On the other hand, studies such as [32] and [28] represent the document using a vector of topics rather than words. Since this model necessitates prefixing the number of topics in advance, we can refer to it as semi-supervised classification because the number of concepts is assumed to be given in advance while the related topics are unknown. In addition, the emulation of the generation of a document by the Dirichlet probability distribution indicates the LDA model's novelty. This distribution guarantees the generation of a probability vector for a multinomial law. First, the vector represents the documents in LDA and is generated by the Dirichlet distribution's parameter vector. The documents are represented as a random mixture of latent topics. Then, for each word w, a topic z is assigned. Then, on a thematic probability set, these topics will be modelled as a random mixture of words. Finally, these final distributions follow a Dirichlet parameter distribution.

Additionally, the LDA model initially developed on the "bag of words hypothesis". This hypothesis emphasizes the possibility of determining the topic of the text solely based on its vocabulary. Thus, regardless of the order of the words, the documents are estimated as a grouping of words. Hence, this allows for the discovery of latent topics, which correspond to a specific distribution of frequently grouped words and can be found in a massive archive of documents [26]. By clearing the topics, the LDA aims to detect the hidden thematic structure in a document.

In recent work, Sear et al. (2022) [33] extended the LDA framework into a dynamic topic model that incorporates temporal evolution of topics. Their approach uses a state-space representation for topic distributions, enabling the model to capture subtle shifts in language over time, particularly useful in domains such as online hate content where thematic patterns evolve rapidly. The authors demonstrate that dynamic LDA yields improved topic coherence in time-sensitive applications compared to static LDA.

Meanwhile, Yadav et al. (2025) [34] proposed a hybrid method that combines LDA with BERT embeddings and clustering techniques. This model leverages the contextual richness of transformer-based representations to enhance the interpretability of topics generated by LDA, particularly for noisy, large-scale text corpora. Their experiments on benchmark datasets indicate that this hybrid approach not only improves topic coherence but also reduces the need for extensive parameter tuning.

C. Ontology Enrichment

Ontology enrichment is a process carried out to meet the needs of dynamic ontology. Ontology is dynamic following the development of knowledge in the field. Therefore, several processes are carried out in ontology enrichment, namely adding new concepts, relationships and rules so that the population of existing ontology can continuously be updated and adapted as needed [35], [36].

In general, ontology construction using an ontology learning approach is also suitable for conducting ontology enrichment. However, automated approaches are challenging to be used in enrichment ontology. Hence, domain experts are needed to judge the result to perform ontology enrichment. So, ontology enrichment can adopt only semi-automatic techniques compared to the ontology construction approach. One of the well-known ontology enrichment methodologies is BOEMIE, (Fig. 1) which explains how to enrich an initial ontology with many new documents to produce an enriched ontology. To help the readers understand how BOEMIE work, let us take example a small initial ontology, namely Human. This Human ontology consist only two concepts, which are Male, and Female. Both concepts are very straightforward, Male is for all individuals that have gender male, whereas Female is for all individuals that have gender female. Now, assume that we have a document that stated we can categorize Male Person into three categories based on his age, as follows: boy, man, and grandpa. And the same document also stated that Female Person can be categorized based on her age into the following categories: girl, woman, and granny. Now, after we identified the new categories/concepts, and after we understand the meaning of each concept, we update the taxonomy of the Human Ontology by inserting boy, man, and grandpa as new concepts under concept Male. We also insert girl, woman, and granny under concept Female. Now, after we do the insertion, our enriched ontology has become larger (in total has eight concepts) than the initial ontology (only has two concepts).

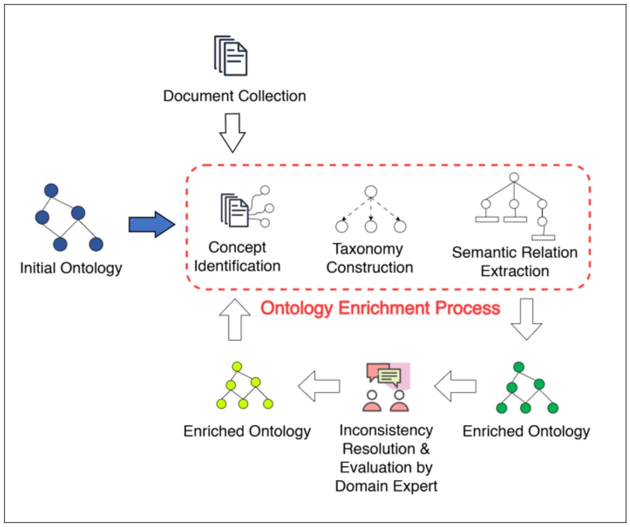

Fig. 1. BOEMEI Methodology for Ontology Enrichment Process [37]

Researchers classify the ontology enrichment approach based on the algorithm into four groups to perform the ontology enrichment process based on (1) similarity clustering, (2) the Set-Theoretic algorithm, (3) web corpus-based, (4) the learning algorithm [38] . Furthermore, similarity clustering approaches can classify the metadata and identify the concept and the hierarchy of the concept, whilst the set-theoretic approach defines the concept and finds the concept's relation. Finally, the corpus-based approach is the most used ontology enrichment because the required data is abundantly available online. Therefore, this approach can enrich the concept, relation, and rules. However, the learning algorithm approach continues to develop due to technology and data availability [38]. Therefore, the standard ontology enrichment approach combines web corpus-based and learning algorithms [39].

In addition, researchers used ontology knowledge mining to enrich ontologies. This approach is suitable for enriching if the existing ontology is large and complex. It aims to sharpen or make the ontology more specific [40]. So, choosing the best approach to enriching ontologies requires an early analysis of the initial ontology. The advanced approach can be used for complex and large ontologies, while the simpler one is more suitable for other methods.

III. Research Method

A. *Ontology Construction*

To construct our Nusantara cuisine ontology, we followed a seven-step methodology outlined by [20] . First, we defined the scope to encompass food and beverages from Indonesia, Malaysia, Brunei, and Singapore. Ontology would serve as the foundation for an information system to display food labels, ingredients, and nutritional information. As for the cooking processes, we will not handle this information. We formulated competency questions to guide the ontology's development, such as “What is the best drink after eating coconut milk?”, “Can tofu or tempeh replace beef protein intake?”, “What cooking oil has no cholesterol?”, “What is Nusantara food, which is savoury but has a low-fat content?”, “What can Nusantara foods be made from fish?” and “What foods are spicy but low in calories?”. Second, we reviewed existing food ontologies to identify reusable concepts and relationships, adapting them to the specific characteristics of Nusantara cuisine. For example, [41] posited that a food ontology for a nation should follow the eating habits of that nation (in Italy, the food recipes must be classified according to mealtime: breakfast, lunch, and dinner) and [42] which suggested there are object properties that distinguish Asian food from Western food, such as is_spicy (the spiciness level of food) or has_gravy (whether a food recipe have sauce or not). Third, we enumerated core terms and concepts by consulting a food expert from Padjajaran University and referring to Indonesia's official list of food ingredients[5]. Fourth, we defined 12 primary categories of Indonesian food as top-level classes, from cereal to vegetables and introduced flavour and Nutrition classes. This is because each recipe in the official list of Indonesian food ingredients has nutritional components such as water, energy, protein, fat, vitamin C, vitamin B1, and others. Fifth, we defined data properties to capture nutritional information, calling this initial ontology "DKPI ontology" and putting it on our GitHub. Sixth, we added domain and range constraints for the hasFlavor property. Finally, we utilised an entity extraction pipeline to extract food items and their attributes from diverse sources, including websites and PDF cookbooks. By following these steps, we aimed to create a comprehensive and accurate ontology of Nusantara cuisine.

B. *Latent Dirichlet Allocation*

To extract relevant entities from websites and PDF documents, we employed a combination of tools and techniques. For web scraping, we utilised the Scrapy framework[6] to define Spiders that crawled websites, extracted structured data, and followed links to discover new pages. For PDF extraction, we utilised PyPDF2[7], a library that parses PDF cookbooks and extracts information such as recipe titles, ingredients, and preparation steps. The extracted data was then organised into a structured dataset, forming the foundation for ontology construction and enrichment. The complete visual architecture of this ontology enrichment module is in Fig. 2.

C. *Ontology Enrichment*

We employed a three-stage or three flows approach to enriching ontology. The complete visual architecture of this ontology enrichment module is in Fig. 2.

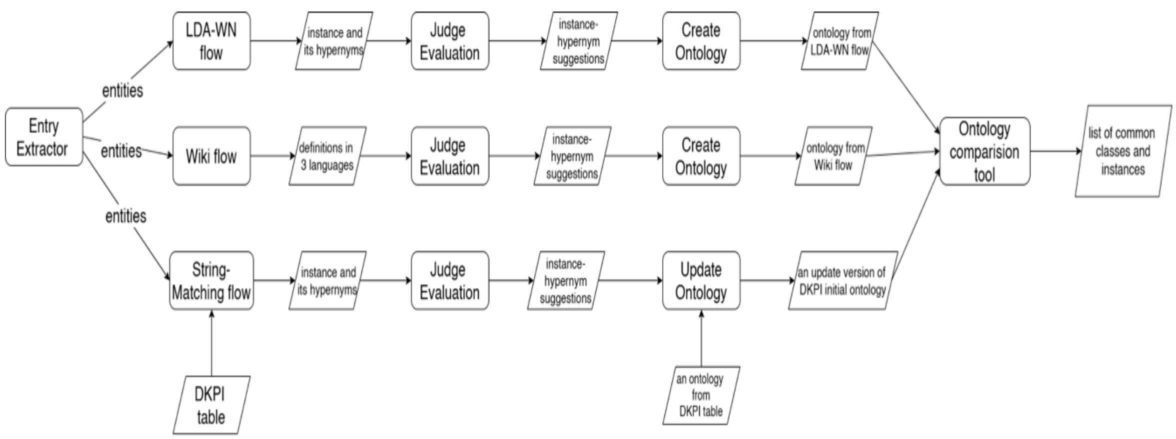

Fig. 2. The visual architecture of the ontology enrichment module

In the first stage (LDA-WN flow), we applied Latent Dirichlet Allocation (LDA) to identify thematic clusters within the extracted text data. We take a page description from a data set, clean the page description (e.g. removing the stop words), and then execute an LDA model by passing the cleaned page description, the number of topics, and several iterations. To help the user get a better group of terms/topics, we provide a user interface (see Fig. 3 for detailed algorithm) that allows a user to add more stop words and then repeat the iterations of running the LDA model. To do this, users must add the word that they want to remove from a cooking dataset. After that, the user needs to decide how many topics the LDA model should produce and specify the number

[5] https://kink.onesearch.id/Record/IOS2870.PKMAL000000000004123
[6] https://scrapy.org/
[7] https://pypi.org/project/PyPDF2/

of iterations it will perform. After setting the topic and iteration numbers, the user needs to press the button "Add words and clean" and, lastly, press the button "run model".

Procedure: Adding Stopword
Input:
- `new_stopword` : String
- `n_topics` : Integer
- `n_iter` : Integer

Output:
- Displayed topics from the LDA model

Begin
1. `dataset ← load_dataset()`
2. `stopwords ← default_stopwords`
3. // User clicks **"Add words and clean"**
4. `stopwords ← stopwords ∪ {new_stopword}`
5. `cleaned_data ← preprocess(dataset, stopwords)`
6. // User clicks **"Run Model"**
7. `lda_model ← LDA_Model(n_topics, n_iter)`
8. `lda_model.fit(transform(cleaned_data))`
9. `display(lda_model.topics())`

End Algorithm

Fig. 3. The Algorithm of Adding Stopwords and Repeating Iterations

Subsequently, we leveraged WordNet to find semantic relationships between terms, such as synonyms, hypernyms, and hyponyms. Next, we put all words, synonyms, hypernyms, and hyponyms into a single variable called udangWN. Subsequently, this variable, along with its empty ontology, is passed into a makeOntology function.

This function checks each word or recipe in udangWN and will check whether a wordnet service returns a hypernym. If the wordnet service does not return a hypernym for a word, then the service will create a "Nothing" class and then put the word as an instance of the "Nothing" class. The "Nothing" class itself becomes the subclass of the "Thing" / root class in an ontology (see Fig. 4). If the wordnet service successfully finds a hypernym for a word, then the service will put the hypernym as a new class under the "Thing"/root class. Moreover, the service will assign the word as an instance of that new class (see Fig. 5).

The next stage in this flow is the judging process. Domain experts reviewed the suggested class assignments and made necessary adjustments. In this process, the system will show a hypernym class for each recipe, and then the experts will decide whether they will accept this hypernym. If the experts accept, they will continue checking the other recipes. However, if the experts do not accept, they can suggest a new hypernym for a recipe. After the expert review process is completed, the last step is creating an ontology based on the result. We do this by using an owlready[8] library. For each recipe, owlready will take that recipe and set it as an instance and then map it with the hypernym that the experts suggested in the judging process (see Fig. 6).

[8] https://pypi.org/project/Owlready/

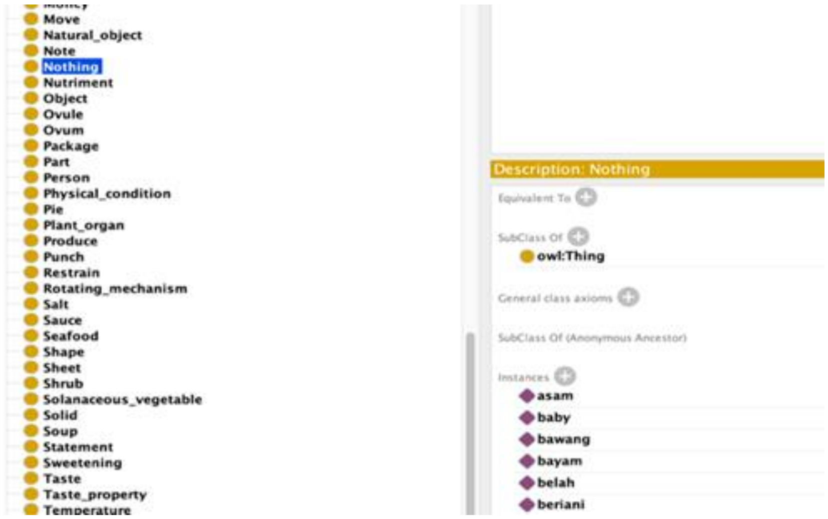

Fig. 4. Class "Nothing" with its instances

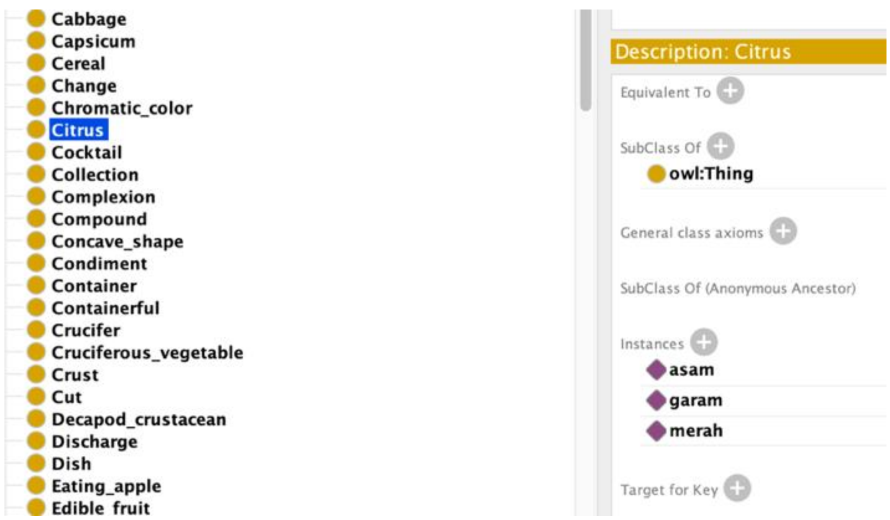

Fig. 5. Class Citrus with its instances

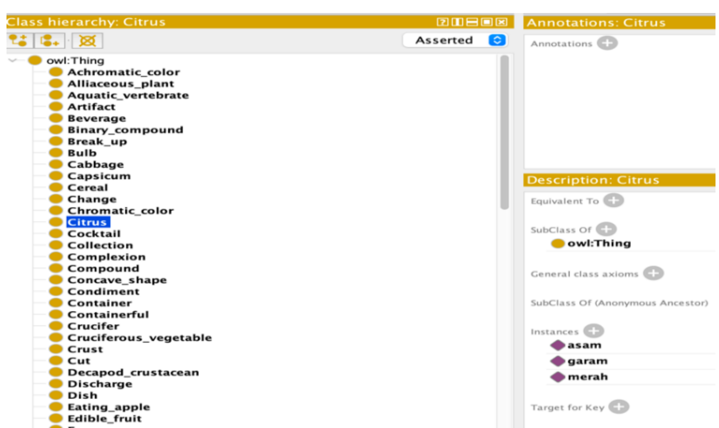

Fig. 6. The final ontology that our approach produces.

In the second stage (wiki flow), we utilized Wikipedia's API to extract definitions and related terms for food items. We take a title from a data set, clean the title, extract the terms from a title, and search for the definitions of that term by accessing a Wikipedia API. We use three different Wikipedias (Indonesia, Malaysia, and English Wikipedia) to provide a more comprehensive summary for a domain expert. Domain experts manually assign appropriate classes to the extracted terms. After suggesting classes for each term, the system will use this suggestion to create an ontology using the owlready library.

In the third stage, we compared food item names with entries in the Indonesian Food Composition Table (DKPI) to identify potential matches. In DKPI[9], there are 12 categories of Indonesian foods, and for each category, there are several food and beverage dishes. We do string matching between the recipe title and the name of the food dishes under a specific category in DKPI. Domain experts verified the suggested class assignments and made necessary adjustments. Suppose a recipe's title (for example: "Talas Bogor") matches the food's name in DKPI. In that case, the system will output the category's label (Umbi (Indonesia) / Tuber (English) as the hypernym for the recipe. The experts will decide whether to keep the category label as the hypernym. The experts also can suggest a new label for the hypernym of a recipe. After checking all suggestions from the system, the system will use these suggestions to update our DKPI ontology using the owlready library.

Finally, we developed a script to compare and integrate the ontologies generated from the three stages, identifying common classes and instances, resolving conflicts, and creating a unified ontology. By combining these techniques, we aimed to create a comprehensive and accurate ontology of Nusantara cuisine (Fig. 6). The input for this tool is three ontologies: one from the LDA-WN flow, one from the Wiki-flow, and one from the String-Matching flow.

D. Ontology Enrichment Research Procedure and Experimental Settings

This section details the experiment setup, dataset, and evaluation process used to assess the performance of our proposed methods for ontology enrichment.

1) Dataset. We utilized a dataset of 4,146 food recipes obtained from various Indonesian and Malaysian food websites recommended by food practitioners. These recipes represented a diverse selection of Nusantara cuisine from different regions. However, to streamline the evaluation process, a concise sample of recipes was chosen from each dataset (Table 1).

TABLE I
THE DATA SETS THAT WE USE

Label	Recipes	URL
Aziekitchen	1898	https://www.aziekitchen.com/
Sajian Dapur Bunda	419	https://sajiandapurbonda.blogspot.com/
Dapur Madiha	400	http://mamawandiha.blogspot.com/
Qasey	400	https://www.qaseyhoney.com/
Salamisimon	583	https://salamisimon1.blogspot.com/
Banyak resepi	46	https://banyakresepi.blogspot.com/
Tiffin	400	https://www.tiffinbiru.com/

2) Domain Experts Evaluation. Since our approach relies on semi-automatic methods, domain expert evaluation plays a crucial role in assessing accuracy. As mentioned by [43] and [18], fully automated evaluation of such methods is not feasible. Therefore, we recruited three domain experts in food nutrition from the Medical School of Padjadjaran University, Indonesia. These experts specialize in clinical and community nutrition, nutraceuticals, and epidemiology. Their task was to evaluate the accuracy of the hypernyms recommended by our approach for each recipe.

The procedures for this evaluation by domain experts are as follows:

[9] https://drive.google.com/file/d/12_yjWTRkIeu4LbJwe1nTRAR3qdzRX31H/view?usp=sharing

a. Participant recruitment: We approached three domain experts in food nutrition from Medical School, Universitas Padjadjaran, Bandung, to participate in the study.
b. Briefing session: Researchers explained the study goals and expectations to the experts, addressing any questions they might have.
c. Informed Consent Form: Participants reviewed and signed an informed consent form acknowledging their voluntary participation and the right to withdraw anytime. We also told the participants that their participation was voluntary and were not rewarded with money.
d. Instruction: Participants received detailed instructions on the evaluation process and whether time constraints were involved. The domain experts used our expert judging system10 (SAFE Nusantara) to evaluate three enrichment flows: WordNet, Wikipedia, and DKPI Table ("tabel 1981"). Fig. 7 provide screenshots of the judging interface.

Fig.7. A screenshot of the database selection

After choosing a database, the judging process is started. For each page, our system recommends some possible hypernym/categories of a recipe. If the expert agrees with our recommendation, they must click the Next button. However, suppose they disagree and would like to suggest a new category. In that case, they must fill in the edited text below the Suggested Categories with their suggestion and click the Next button. The scoring system works as follows: if an expert agrees with the hypernym that is recommended by our system, then our system's accuracy score is increased by one point. If the expert disagrees, then our system's accuracy score does not increase. If our system, for example, produces three hypernyms for a recipe, and the expert agrees with only one hypernym, then our system's accuracy score is increased by one-third point.

e. Debriefing Session: After completing the evaluation, researchers debriefed the participants, answered their questions, and expressed gratitude for their contribution.

3) Ontology Enrichment Evaluation. Each of the three enrichment flows (LDA-WN, Wiki, and DKPI) generates an ontology. To assess the effectiveness of the ontology enrichment process, we implemented the following algorithm:
a) Combine all three ontologies into a single directory.
b) Create a dictionary "compare_dict" to store all non-overlapping classes from the ontologies.
c) For each ontology and each class within it, check if the class already exists in "compare_dict." If not, add it to the dictionary.
d) Repeat step "c" until all classes from all three ontologies have been processed.

4) Evaluation and Comparison with Existing Approaches. We used a simple dataset called "simple wiki" to compare our approach with existing methods (SIREN and Gwolgen). Each tool (including ours) processed the simpleWIKI dataset. We collected the hypernym labels produced by SIREN and Gwolgen for each entry and compared them with the hypernyms generated by our approach.

IV. Results And Discussion

A. Evaluation by Domain Experts

To evaluate the accuracy of our system in recommending hypernyms for food recipes, we conducted a user study involving three domain experts in food nutrition. The experts assessed the accuracy of the hypernyms suggested by the system for each recipe.

The results for the LDA-WN flow were less than satisfactory, as illustrated in Table 2. Expert 1's average accuracy score was 23.38%, and expert 2's was 9.96%. This low performance was attributed to the limitations of the WordNet service, which struggled to provide accurate hypernyms for Indonesian and Malaysian food terms.

The accuracy of the Wikipedia flow was evaluated based on the system's ability to produce explanations for recipes. For example, given a recipe, namely "Rendang", our system will show an explanation from Wikipedia about Rendang in three languages (Ind, Mal, and Eng). For each recipe that our system is able to produce a Wikipedia explanation, our system's accuracy score is increased by one point. As shown in Table 3, the average accuracy scores for each judge (expert 1, expert 2, and expert 3) were 68.81%, 67.67%, and 62.60%, respectively. This score surpasses the average score of the LDA-WN flow (23.38% for expert 1 and 9.96% for expert 2). The improvement is attributed to the comprehensive descriptions available for nearly all food recipes in multiple languages, including English, Indonesian, and Malaysian, provided by the Wikipedia service.

TABLE II
THE RESULTS OF EXPERTS' EVALUATION FOR LDA-WN FLOW

The Dataset	Expert 1	Expert 2
aziekitchen-kambing	21.74%	0.0%
aziekitchen-sapi	22.03%	1.09%
aziekitchen-telur	21.18%	0.0%
aziekitchen-tempe	18.52%	0.0%
aziekitchen-udang	20.00%	0.68%
Banyak resepi	22.00%	0.0%
SajianDapurBonda	36.59%	67.96%
Salamisimon	25.00%	9.94%
Average accuracy	23.38%	9.96%

TABLE III
THE RESULTS OF THE EXPERT'S EVALUATION OF THE WIKIPEDIA FLOW

The Dataset	Expert 1	Expert 2	Expert 3
aziekitchen-kambing	79.63%	78.18%	48.39%
aziekitchen-sapi	77.78%	77.78%	77.78%
aziekitchen-telur	77.39%	76.57%	74.65%
aziekitchen-tempe	81.82%	72%	72%
aziekitchen-udang	84.66%	84.74%	82.99%
Banyak resepi	43.48%	43.48%	43.48%
SajianDapurBonda	48.22%	48.25%	46.54%
Salamisimon	54.99%	53.27%	47.34%
Tiffinbiru	61.01%	60.53%	57.5%
Qasey	43.82%	42.55%	39.25%
Mamawandiha	44.36%	44.3%	43.75 %
aziekitchen-tahu	82.51%	82.42%	72%
aziekitchen-ikan	90.86%	90.91%	83.5%
aziekitchen-ayam	92.76%	92.33%	87.25%
Average accuracy	68.81%	67.67%	62.60%

TABLE IV
THE RESULTS OF THE EXPERT'S EVALUATION OF THE DKPI FLOW

The Dataset	Expert 1	Expert 2	Expert 3
aziekitchen-kambing	75.77%	35.34%	41.20%
aziekitchen-sapi	66%	46%	68.66%
aziekitchen-telur	61.33%	61.23%	70.89%
aziekitchen-tempe	44.93%	44.20%	59.42%
aziekitchen-udang	62.89%	68.75%	41.75%
Banyak resepi	47.35%	35.60%	32.19%
SajianDapurBonda	46.76%	33.51%	43.36%
Salamisimon	41.45%	35.05%	42.31%
Tiffinbiru	48.37%	44.09%	51.13%
Qasey	38.29%	30.21%	43.02%
Mamawandiha	42.79%	37.52%	52.63%
aziekitchen-tahu	56.59%	57.10%	59.96%
aziekitchen-ikan	66.96%	69.78%	77.76%
aziekitchen-ayam	79.33%	76.38%	82.93%
Average	55.63%	48.20%	54.80%

For the DKPI flow, the definition of accuracy that we use is the number of hypernyms/categories that our system suggests are correct, according to the expert's judgment. The experts graded the hypernym recommendation according to the Indonesian Food Composition Table (DKPI).

The DKPI flow achieved an average accuracy of 55.63%, 48.20%, and 54.80% for the three experts, as illustrated in Table 4. While this performance is reasonable, it is limited by the reliance on syntactic matching and the lack of contextual understanding. For example, we parse each word for the Recipe *Telur Ikan Mayong Masak Lemak Cili Api* and then search each word in our DKPI table. The results of this search process are as follows: ['*Cili Api*=Vegetable', '*Lemak*=OilAndFat', '*Ikan*=Fish', '*Telur*=Egg']. Our system reports four hypernyms for that recipe. In contrast, the most important notion in the recipe is the word "*Telur*". The rest of the words: "*Ikan Mayong Masak Lemak Cili Api*" are only the seasonings for "*Telur*". The system might incorrectly classify a recipe as "vegetable" based on the presence of a vegetable ingredient, even if the primary ingredient is meat or fish. However, the experts can identify this context, so the correct hypernym for this recipe is only "Egg".

B. Ontology Enrichment Evaluation

In this stage, we aim to evaluate how effectively our approach enriches the initial ontology. Our initial ontology consists of 33 classes. It has three main classes: Flavour, Nutrient, and Recipe, and our ontology has an ontology depth of 3 levels. However, our ontology only has one object property, hasFlavour, and several data properties: hasAshComposition, hasCalciumComposition, hasCarbohydrateComposition, hasEnergy-Composition, hasFatComposition, hasFiberComposition, hasProteinComposition, hasWaterComposition. Please see Fig. 9 for the complete class hierarchy.

Once the three different ontologies were extracted from each stage, we compared these ontologies with the initial ontology, and we found out that our approach successfully enriched the initial ontology with 131 new classes and 3647 new individuals. Of these 131 new classes, 63 are related to the food domain, and the rest are classes that do not belong to the food domain. From this finding, we conclude that our approach can produce 190% new classes compared to the number of existing classes in ontology and thousands of new instances.

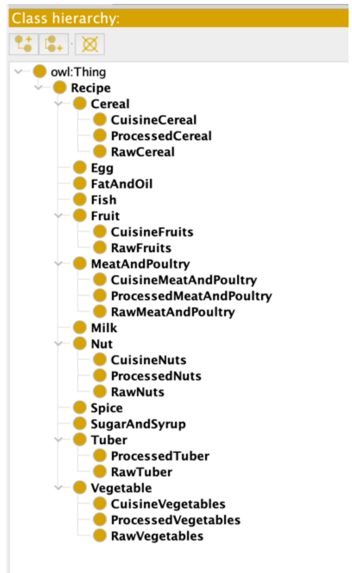

Fig. 9. The complete class hierarchy of our initial ontology

C. Evaluation Comparison with Existing Approaches

To evaluate the performance of our approach, we compared it with two state-of-the-art ontology learning methods: Gwolgen and SIREN [30]. We run our approach, and these two benchmarks are on the same machine. We chose simpleWIKI as the data set for these three tools. SimpleWIKI contains 628 entries from Wikipedia, and for each row, simpleWIKI has three (3) columns: number, title, and page description.

TABLE V
SHOWS GWOLGEN'S OUTPUT (WE ROUND THE CONFIDENCE SCORE TO THREE SIGNIFICANT FIGURES)

Assertion	Confidence	Expert Judgement
foods isA cereal	0.999	correct
foods isA meat	0.999	correct
fruit isA nut	0.999	incorrect
sugar isA syrup	0.999	incorrect
fruits isA food	0.999	incorrect
fruits isA vegetables	0.999	incorrect
fruit isA fruits	0.999	incorrect
fruits isA leaves	0.999	incorrect

The Gwolgen approach produces eight assertions. We read the first assertion in Table 5 as follows: food is the hyponym of cereal with a confidence level of 0.999. From Table 5, we could only collect four hypernym classes: foods, sugar, fruit and fruits. Furthermore, from these eight assertions, only two assertions are correct, according to our domain expert. While Gwolgen achieved a high confidence score, its accuracy was limited by its reliance on Wikipedia's knowledge base, which may not be comprehensive for specific domains like Nusantara cuisine.

Unlike Gwolgen, SIREN needs to process the initial ontology first to produce the labels of the hypernym. Therefore, we feed SIREN with the initial ontology of Nusantara Food. For each class in ontology, SIREN will produce a tsv file that contains pairs of labels (see Table 6 from fat.tsv as an example of the output of SIREN). In table 6, there are 8 pairs of labels. Let us take the second row of this table as an example. We read this row as follows: chemistry is an instance of food. For Gwolgen, we could collect five distinct hypernym classes: biology, food, fat, chemistry, and nutrition. Of these 8 assertions, only three are correct, according to our domain expert. SIREN required an initial ontology as input. However, its performance was hindered by its inability to accurately identify semantic relationships between terms, especially in the context of culinary terms.

TABLE VI
THE OUTPUT OF SIREN

Label 1	Label 2	instance of	Expert Judgement
nutrition	biology	none	incorrect
chemistry	food	instance	incorrect
nutrition	food	instance	incorrect
nutrition	fat	instance	incorrect
fat	food	instance	correct
biology	chemistry	none	incorrect
Fat	nutrition	instance	correct
fat	food	instance	correct

To compare our approach with Gwolgen and SIREN, we use the DKPI flow. By using DKPI flow, our approach produces ten distinct hypernym classes, such as meat and poultry, cereal, milk, fish, fruit, nut, vegetable, spice, tuber, sugar and syrup. This number of distinct hypernym classes excels SIREN and Gwolgen. For the accuracy of our approach, we ask a domain expert to decide whether the hypernyms that are generated by our system are correct or not. Based on the expert's judgement, our approach scores 60.25% (GWOLGEN scores 25%, whereas SIREN scores 27.27%). GWOLGEN and SIREN are ontology learning models that work very well in analyzing the relationship between the labels of classes if the resources for those classes in Wikipedia or other data sources are abundant. Our proposed ontology enrichment approach demonstrated promising results in expanding and refining the Nusantara cuisine ontology. While the LDA-WN flow had limitations, the Wikipedia and DKPI flows proved effective in suggesting accurate hypernyms and enriching the ontology with new classes and instances.

We used a simple dataset called "simple wiki" to compare our approach with existing methods (SIREN and Gwolgen). Each tool (including ours) processed the simpleWIKI dataset. We collected the hypernym labels produced by SIREN and Gwolgen for each entry and compared them with the hypernyms generated by our approach.

V. CONCLUSION

This paper presents a semi-automatic framework, SAFE Nusantara, for engineering and populating a Nusantara Food Ontology. Our approach combines multiple techniques, including LDA-WN, Wikipedia, and DKPI flow, to extract relevant information and enrich the ontology. While our approach has shown promising results, there are limitations. The LDA-WN flow, for instance, relies heavily on the availability of accurate and comprehensive information in WordNet, which may be limited for regional cuisines like Nusantara. The DKPI flow, while effective for basic categorization, struggles to capture the nuanced semantic meanings of recipes. Regarding populating the initial ontology, our approach adds almost 200% new classes and thousands of new instances. Also, in recommending hypernym classes, our approach excels Gwolgen and SIREN.

To address these limitations, future research could focus on (1) Contextual Understanding by developing techniques to understand the context of a recipe beyond simple keyword matching to improve the accuracy of hypernym suggestions, (2) Machine Learning Integration to Incorporate machine learning models to refine the ontology enrichment process, such as using neural networks for semantic similarity analysis and knowledge graph embedding techniques for relationship extraction, (3) Cross-lingual Knowledge Transfer by exploring techniques to leverage knowledge from other languages, such as English, to enhance the enrichment of the Nusantara food ontology and (4) User-Centric Design by developing user-friendly interfaces to facilitate the manual validation and refinement of the ontology.

By addressing these challenges and exploring future directions, we aim to further enhance the capabilities of the SAFE Nusantara framework and contribute to the advancement of knowledge representation and reasoning in the domain of culinary heritage.

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