Building a Simple COVID-19 Knowledge Graph in Bahasa Indonesia: A Preliminary Study

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***Abstract*—COVID-19 is an acute respiratory disease that has become a pandemic worldwide. Many studies have been conducted to enhance our understanding of COVID-19. However, the abundance of information obtained from these studies has resulted in information overload. In this study, we purposed a simple COVID-19 Knowledge Graph in Bahasa Indonesia as a way to reconstruct knowledge to combat this information overload. We used Bahasa Indonesia in our study to explore its potential for constructing a Knowledge Graph (KG). The construction of our KG involved manual curation of medical literatures and annotation of entities and relationships by the domain experts. The KG was implemented using Neo4J version 5. We successfully demonstrated our COVID-19 KG, which consists of 240 nodes and 276 relationships with 15 and 14 node and relationship labels respectively. Accessing the information within the KG is made effortless through the use of Cypher queries in Neo4J. Further research is still needed to develop the KG into a larger and better one. However, our COVID-19 KG can serve as a basis for further development.**

***Index Terms*—COVID-19, knowledge graph, Bahasa Indonesia**

I. Introduction

Coronavirus disease 2019 (also known as COVID-19) is an acute respiratory infectious disease caused by the SARS-CoV-2 virus [1], [2]. COVID-19 was first identified as an outbreak in the city of Wuhan, Hubei province, China and has since become a pandemic worldwide. COVID-19 is a highly contagious disease that can be transmitted through the air (airborne disease) and can cause a range of symptoms from mild to severe. Some signs and symptoms of COVID-19 include fever, cough, shortness of breath, sore throat, nausea, vomiting, and headache [2].

To understand COVID-19, researchers and academics have conducted intensive research on COVID-19. This research is published through academic journals or scientific conferences. Every new piece of information produced by this research is added to our current knowledge. As a result, the research findings provide information that shapes our current understanding of COVID-19. However, on the other hand, the abundance of information has resulted in a phenomenon known as ”information overload” [3].

”Information overload” is a phenomenon that occurs due to the abundance of information, resulting in an explosion of information. The phenomenon of information overload happens due to the continuous addition of information over time. In addition to the addition of information, information overload can also occur due to multiple sources of information, difficulties in organizing information, irrelevant or unimportant information, and a lack of time to understand all the available information [3].

To address the increasing volume of information and to better organize it, there is a growing interest in the development of knowledge graphs as a comprehensive means of organizing this information. A Knowledge Graph (KG) is a graph data that contains ”real-world knowledge”, where nodes represent ”real-world entities” and edges represent the ”relationships” between those ”entities” [4]. Nodes can also be referred to as vertices, while relationships can be called edges [5]. Therefore, KG can be represented using the following notation.

$$G(V, E) \tag{1}$$

where G represents the KG, V as the set of entity vertices (where each member is denoted by $v_1, v_2, v_3, ..., v_n$), and E as the set of entity edges (where each member is denoted by $e_1, e_2, e_3, ..., e_n$). Furthermore, each edge e_n represents a relationship r between the source entity e_v^s and the target entity e_v^t, which can be represented as (e_v^s, r, e_v^t).

In the medical context, an example of a node can be an object such as a disease or a symptom. On the other hand, a relationship example could be ”HAVE_SYMPTOM,” which represents a relationship of a symptom of a disease. Thus, a constructed KG example in this context is shown in Figure 1.

KG technology has become increasingly popular and developed recently due to the advancements in graph technology and the demand for making data meaningful. Furthermore, the use of graphs in KG enables the integration, management, and

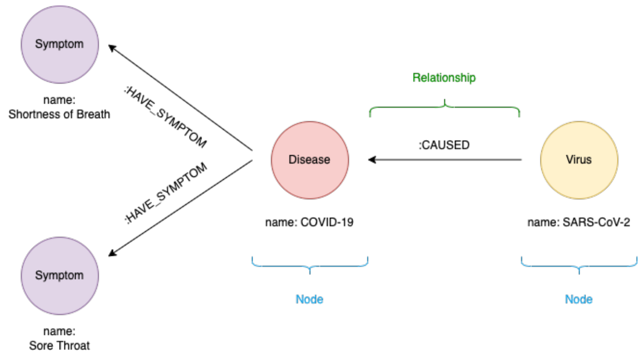

Fig. 1. Example of a knowledge graph

extraction of information from various sources on a large scale [6].

In this study, we present our preliminary study on constructing a COVID-19 KG using Bahasa Indonesia (the Indonesian language). Our motivation arises from the interest in organizing COVID-19 information into a comprehensible concept model while promoting the use of Bahasa Indonesia in KG development. Our contributions encompass the definition of the KG schema, including node and relationship labels and their interconnections, as well as the KG that captures COVID-19 information using the schema.

This paper is structured into sections, including an introduction, related work, methodology, results, and conclusion. The related work section provides an overview of KG usage in biomedical domains. The methodology section outlines the techniques employed in designing and implementing the KG. In the results section, we present the study's findings, concluding with a summary in the conclusion section.

II. Related Work

Recently, there has been a growing interest in using KG in the biomedical field. Researchers have conducted numerous studies concerning the implementation and potential utilization of KG in biomedicine. The example of KG utilization in biomedicine can range widely, from creating intelligent systems to enhance healthcare services, developing models to comprehend diseases, exploring drug interactions, to providing personalized care for patients.

In drug-drug interaction analysis, Hamed et al. [7] used the KG to predict various drug combinations for the COVID-19 case. Hamed et al. [7] used the KG in their study to reconstruct knowledge regarding drugs, genes, and diseases information from various biomedical literature. Furthermore, they used the KG to identify the risks of drug interactions, thereby generating predictions of drug combinations that can be further considered by scientists in the further investigations.

KG can also be used for diagnosing a disease. A study by Chai [8] used KG to diagnose thyroid disease. In this study, KG was used as additional information in training the diagnosis model. The results indicated that the use of KG and deep learning yielded better prediction results for diagnosing the disease. Moreover, KG can also be used to provide better health information. For instance, a study by He et al. [9] used KG to visualize interactive dietary supplement information.

To gain a comprehensive understanding of COVID-19, numerous attempts have been made to reconstruct the desired COVID-19 Knowledge Graph (KG). Gütebier et al.'s study [10] successfully created a "CovidGraph," which serves as a large-scale COVID-19 KG encompassing information from publications, patents, clinical trials, as well as biomolecular and systems biology data related to COVID-19. This graph comprises approximately 36 million nodes and 60 million relationships. Similarly, Wise et al.'s research [11] resulted in the creation of a COVID-19 Knowledge Graph (CKG) using the CORD19 Open Research Dataset, which includes 336,887 entities and 3,332,151 relationships. A slightly different approach was taken by Domingo-Fernández et al. [12] in constructing a COVID-19 KG by using selected journals to establish a cause-and-effect knowledge model of COVID-19 pathophysiology.

III. Method

A. Knowledge Graph Modeling

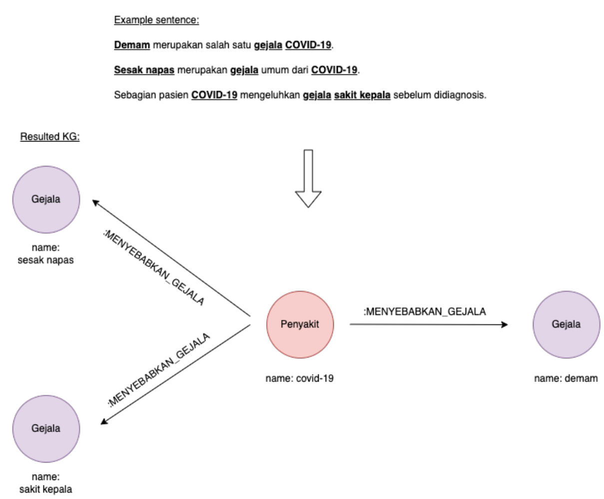

Fig. 2. Our KG construction process

The KG modeling was conducted using a domain expert-based approach, which involved the participation of domain experts in discussions and analyses for creating both the KG schema and the KG itself. As the source of the information, we selected scientific literature discussing COVID-19. This literature includes national guidelines, original articles, review articles, and meta-analyses related to COVID-19. The literature used in the modeling process is presented in Table I.

First, we identified, studied, and understood the literature. We highlighted sentences containing high-level information about COVID-19 from each of literature used. This information may include definitions, risk factors, pathogenesis, pathophysiology, complications, and management strategies of the COVID-19. These highlighted sentences then undergo further analysis.

TABLE I
REFERENCES USED TO BUILD THE COVID-19 KG

Authors	Title	Type of Reference
[13]	Pedoman tatalaksana covid-19	National guideline
[14]	Etiology of community-acquired and hospital-acquired pneumonia associated with COVID-19	Original article
[15]	A comprehensive review of various categories of face masks resistant to COVID-19	Review article
[16]	Differential diagnosis of coronavirus disease 2019 from community-acquired-pneumonia by computed tomography scan and follow up	Original article
[17]	Coronavirus disease 2019 (COVID-19): multisystem review of pathophysiology	Review article
[18]	COVID-19: current understanding of its pathophysiology, clinical presentation and treatment	Review article
[19]	Viral replication of SARS-CoV-2 could be self-limitative - the role of the renin-angiotensin system on COVID-19 pathophysiology	Review article
[20]	More than 50 long-term effects of COVID-19: a systematic review and meta analysis	Meta analysis
[21]	Efficacy and safety of three new oral antiviral treatment (molnupiravir, fluvocamine, and paxlovid) for COVID-19: a meta analysis	Meta analysis
[22]	Mechanism and adverse effects of COVID-19 drugs: a basic review	Review article

Next, we analyzed the highlighted sentences. First, we identified the nodes. To identify the nodes, we extracted keywords from each sentence, where the keyword is the subject or object in the subject-predicate-object (SPO) sentence structure. For example, in the sentence *"COVID-19 disebabkan oleh virus SARS-CoV-2"*, the resulting keywords are *"COVID-19"* and *"SARS-CoV-2"*. Next, to determine the label of node, human annotation based on expertise will be carried out. For example, the keyword *"COVID-19"* belongs to the node label *"Penyakit"*, while *"SARS-CoV-2"* is *"Virus"*. All labels of nodes are written lower cased in Bahasa Indonesia.

Next, we conducted an identification of relationships. To identify these relationships, we applied human common sense analysis to the sentences, and then determined the suitable relationship to represent each sentence. For example, in the sentence *"Demam merupakan salah satu gejala COVID-19"* and *"COVID-19 menyebabkan gejala-gejala seperti sesak napas, sakit kepala, demam, dan diare"*, the appropriate relationship to represent the relationship is *"MENYEBABKAN_GEJALA"*. Each relationship is written in Bahasa Indonesia using capital letters without spaces (every space is replaced with an underscore, if any).

Finally, we constructed a KG from these sentences by following the predetermined labels of nodes and relationships. The KG construction was done by humans, who transformed each sentence into the established labels of nodes and relationships. For example, the sentence *"Demam merupakan salah satu gejala COVID-19"* would be represented as (COVID-19)-[MENYEBABKAN_GEJALA]->(Demam) in the graph. Figure 2 shows the overview of this process.

B. Implementation and Evaluation Strategy

We use Neo4J Graph Database version 5 to implement our KG. The creation of the KG is done through Cypher, which is a query language for Neo4J [23]. In addition, Cypher allows us to perform data retrieval queries from the graph. For evaluation strategy, we conducted several tests to query the graph. Our evaluation aims to ensure that the graph can be modeled well.

C. Problem Limitations

As this is a preliminary study, we have established the problem limitations in our study as follows.

- The source of COVID-19 information is limited to what is mentioned in Table I.
- Our KG will only cover the areas of etiology, pathogenesis, pathophysiology, risk factors, complications, and treatments of COVID-19 in general.
- The annotation process for nodes and relationships is done manually by humans. Therefore, there is a potential for errors or biases in their determination.

IV. RESULT

We have successfully built a simple COVID-19 KG using Bahasa Indonesia (Figure 3). Tables II and III show the entity nodes and relationships as the KG schema used in building our KG. The node and relationship labels have been created through discussions and analysis involving domain experts, resulting in the generation of 15 node labels and 14 relationship labels. Furthermore, our KG consists of 240 nodes and 276 relationships. As additional information, the node count refers to the total number of nodes within the KG, while the relationship count represents the total number of relationships connecting pairs of nodes.

During the development of our KG, one keyword may be assigned to more than one node label. For example, the keyword *"sinovac"* is assigned to both the *"Terapi"* and *"Vaksin"* node labels. Furthermore, each node may also have more than one different relationship. For example, the node *"covid-19"* has relationships *"MEMILIKI_KOMPLIKASI"* and *"STRATEGI_PEMERIKSAAN"* to indicate the complications and medical examinations of COVID-19, respectively. Therefore, the KG we formed is a heterogeneous graph.

To evaluate the KG, we conducted a series of query tests to retrieve some information from the graph. The queries were performed using Cypher, which is the standard query language for Neo4j. Table IV shows the results of the tests that we conducted.

We conducted 5 query tests on the KG (Table IV). In our tests, the KG can provide results that meet the expectations.

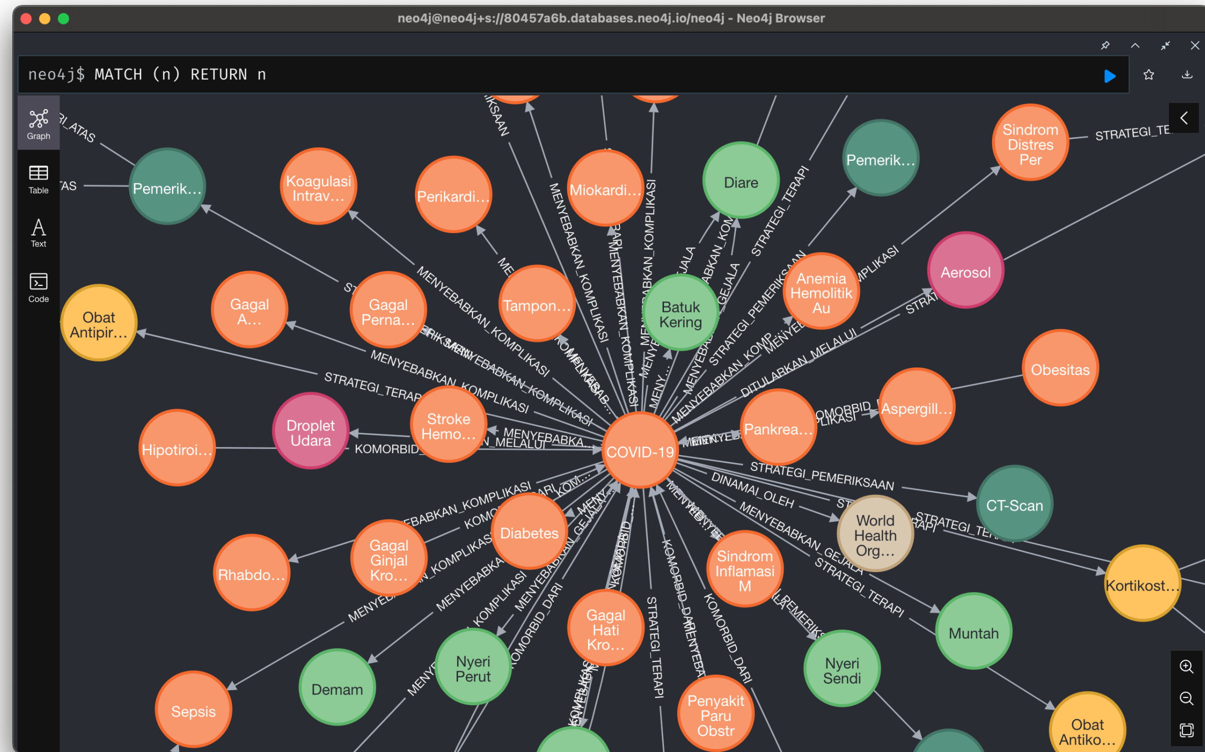

Fig. 3. Our COVID-19 KG

TABLE II
NODE LABELS

Node Label	Description	Examples	Count
Enzim	To describe the entity of enzyme molecules.	*angiotensin converting enzyme 2 (ace-2)*	1
Gejala	To describe entities such as conditions or events related to the symptoms of a disease.	*sesak napas, demam*	39
Hormon	To describe the entity of hormone molecules.	*endothelin-1 (et-1), angiotensin ii*	2
Jaringan	To describe the entity of tissues of a specific body organ or body part.	*mukosa hidung, mukosa mata*	9
Organ	To describe the entity of a specific body organ or body part.	*paru-paru, hidung*	9
Patofisiologi	To describe the entity such as conditions or events related to the physiological process of a disease.	*pyroptosis, badai sitokin*	22
Pemeriksaan	To describe the entity such as methods or modalities related to the medical examination of a disease.	*x-ray toraks, ct-scan*	21
Penyakit	To describe the entity of diseases.	*covid-19, sepsis*	34
Preventif	To describe the entity such as methods or protocols related to the prevention of a disease	*memakai masker, mencuci tangan*	15
SitokinProInflamasi	To describe the entity of inflammation molecules related to a inflammation process caused by a disease.	*interleukin 1 beta (il-1 beta), interleukin 6 (il-6)*	10
StrukturVirus	To describe the entity of proteins or parts related to the structure of a virus.	*protein membrane (m)*	4
Terapi	To describe the entity of methods, protocols, or things (such as drugs) related to the treatment of a disease.	*terapi oksigen, kortikosteroid*	51
Transmisi	To describe the entity of methods related the transmission of a disease.	*droplet udara, aerosol*	2
Vaksin	To describe the entity of specific vaccines of a disease.	*pfizer, moderna*	9
Virus	To describe the entity of viruses.	*delta, omicron*	12
Total			**240**

For example, in a query test for COVID-19 complications, the KG provides expected results such as sepsis, heart failure, and stroke. With the test results, we have successfully build a simple COVID-19 knowledge graph using Bahasa Indonesia. The Cypher feature of Neo4J also allows for an intuitive graph query process.

TABLE III
RELATIONSHIP LABELS

Relationship Label	Description	Count
BERIKATAN_DENGAN	To describe the relationship between a molecule (such as a hormone or enzyme) and a specific receptor, tissue, organ, or other body part entity. **Example:** {("protein spike (s)", "BERIKATAN_DENGAN", "angiotensin converting enzyme 2 (ace-2)")}	1
DITULARKAN_MELALUI	To describe the relationship between a disease and method related to transmission of a disease entity. **Example:** {("covid-19", "DITULARKAN_MELALUI", "droplet_udara")}	2
MEMILIKI_DIAGNOSIS_ DIFERENSIAL	To describe the relationship between one disease and another disease entities that represent a differential diagnosis of a disease. **Example:** {("covid-19", "MEMILIKI_DIAGNOSIS_DIFERENSIAL", "community acquired pneumonia")}	2
MEMILIKI_EFEK_SAMPING	To describe the relationship between the entity of a method, protocol, or thing related to the treatment of a disease and an event or condition entity that represents a side effect of the treatment of a disease. **Example:** {("azithromycin", "MEMILIKI_EFEK_SAMPING", "diare")}	35
MEMILIKI_KOMPLIKASI	To describe the relationship between a disease entity and an event, condition, or another disease that represents a complication caused by the disease. **Example:** {("covid-19", "MEMILIKI_KOMPLIKASI", "sindrom distres pernapasan akut")}	21
MENYEBABKAN	To describe a "cause" relationship between entities generally. **Example:** {("badan sitokin", "MENYEBABKAN", "tesis")}	19
MENYEBABKAN_GEJALA	To describe the relationship between a disease entity and an event or condition related to a symptom that represents a manifestation of the disease. **Example:** {("covid-19", "MENYEBABKAN_GEJALA", "batuk kering")}	39
MENYEBABKAN_ PENINGKATAN	To describe an "increase" relationship between entities. **Example:** {("severe acute respiratory syndrome coronavirus-2 (sars-cov-2)", "MENYEBABKAN_PENINGKATAN", "sitokin pro-inflamasi")}	8
PADA_SAMPEL	To describe the relationship between the entity related to medical examination and the entity of tissue, organ, or body part that represent the sample used to conduct a medical examination. **Example:** {("histopatologi", "PADA_SAMPEL", "ginjal")}	7
STRATEGI_PEMERIKSAAN	To describe the relationship between the disease entity and the entity of methods or protocols related to the medical examination that represent the medical examination of a disease. **Example:** {("covid-19", "STRATEGI_PEMERIKSAAN", "x-ray toraks")}	7
STRATEGI_PREVENTIF	To describe the relationship between the disease entity and the entity of methods or protocols related to the prevention strategy that represent the prevention of a disease. **Example:** {("covid-19", "STRATEGI_PREVENTIF", "isolasi")}	4
STRATEGI_TERAPI	To describe the relationship between a disease and the methods, protocols, or treatments entities associated with it. **Example:** {("covid-19", "STRATEGI_TERAPI", "terapi oksigen")}	11
TERDAPAT_DI	To describe a "can be found at/in/on" relationship between entities. **Example:** {("angiotensin converting enzyme 2 (ace-2)", "TERDAPAT_DI", "mukosa mulut")}	12
TERDIRI_ATAS	To describe a "consist of" relationship between entities. **Example:** {("obat antivirus", "TERDIRI_ATAS", "remdesivir")}	108
Total		**276**

TABLE IV
KNOWLEDGE GRAPH EVALUATION

Task	Cypher Query	Results
Show the symptoms of COVID-19 disease	MATCH(n:Penyakit{name: "covid-19"}) -[r:MENYEBABKAN_GEJALA]->(m) RETURN *	nyeri perut, diare, anosmia, nyeri otot, hidung tersumbat, nyeri tenggorokan, sesak napas, batuk kering, demam, muntah, malaise, nyeri sendi
Show the complications caused by the COVID-19 disease	MATCH(n:Penyakit{name: "covid-19"}) -[r:MEMILIKI_KOMPLIKASI]->(m) RETURN *	sepsis, aritmia, gagal jantung, stroke hemoragik, stroke iskemik, emboli paru, perikarditis, koagulasi intravaskular diseminata, pankreatitis, gagal hati akut, gagal ginjal akut, infark miokardia, sindrom inflamasi multisistem, gagal pernapasan akut, sindrom distres pernapasan akut, rhabdomyolysis, tamponade jantung, diabetes, miokarditis
Show the side effects of using dexamethasone as a COVID-19 treatment	MATCH(n:Terapi{name: "deksametason"}) -[r:MEMILIKI_EFEK_SAMPING]->(m) RETURN *	pusing, insomnia, depresi, jerawat, menstruasi, gangguan pencernaan, muntah, nyeri kepala
Show the examination strategy of COVID-19	MATCH (n:Penyakit{name: "covid-19"}) -[r:STRATEGI_PEMERIKSAAN]->(m) RETURN * LIMIT 5	x-ray toraks, ct-scan, pemeriksaan darah, pemeriksaan molekuler, pemeriksaan ekg
Show the therapy strategy of COVID-19	MATCH (n:Penyakit{name: "covid-19"}) -[r:STRATEGI_TERAPI]->(m) RETURN * LIMIT 5	terapi oksigen, vitamin, obat antikoagulasi, obat imunomodulatori, obat antivirus

Despite the limitations mentioned in the problem statement, our KG can still serve as a valuable foundation for further KG development, especially on promoting the use of Bahasa Indonesia in the KG development. An idea for future enhancement involves employing Natural Language Processing (NLP) techniques to extract information from various sources, facilitating the construction of a more extensive KG. Using NLP for the creation and comprehension of larger KGs offers substantial advantages over manually curated ones, primarily in terms of time-saving.

V. Conclusion

We have successfully demonstrated a simple COVID-19 KG using Bahasa Indonesia. Our COVID-19 KG aims to model information about COVID-19 in a comprehensive graph way. With the KG, we can obtain clearer and more understandable information, thus reducing the risk of information overload. However, since our study is a preliminary one, further research is needed to develop this KG into an even better.

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