



Digital Assistant for Pharmacists Using Indonesian Language Based on Rules and Artificial Intelligence

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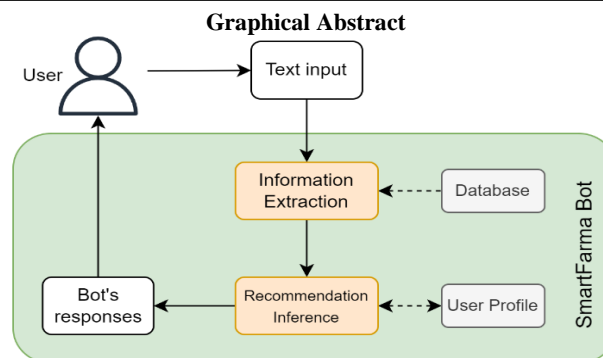
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ABSTRACT

The widespread availability of large language models (LLMs) has encouraged many individuals to explore chatbot development for their business needs. However, creating chatbots for handling sensitive information, like in healthcare, can be challenging. Mistakes made by these bots when extracting information or providing health recommendations can have serious consequences. When developing a chatbot for pharmacy recommendations, it is essential for the bot to effectively extract symptom-related information and other relevant patient data and then offer recommendations for actions or medications based on that information. In this study, we proposed a straightforward and effective approach that combines regular expression templates for information extraction with forward chaining for inference to create a pharmacy recommendation chatbot called SmartFarma. In scenarios like pharmacy recommendations, we will demonstrate that the use of regular expression templates is sufficient and produces better results than some machine learning methods. Additionally, by using regular expressions, SmartFarma can be developed with transparent data handling, allowing experts to trace, monitor, and evaluate its recommendations. This research primarily focuses on the extraction of patient information. Our model, as proposed, achieved an impressive score of 81.54%, outperforming both the Biomedical Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-Trained Transformer (GPT) models.

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1. INTRODUCTION

Pharmacists play a pivotal role in providing vital drug consultation services to patients, often serving as the initial point of reference for medical advice, especially in

regions burdened with high healthcare costs. However, the ability of pharmacists to respond comprehensively to patient inquiries and concerns is often limited, particularly in remote areas where access to specialized medical information can be challenging. In response to

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this critical gap in healthcare services, this study proposes the development of an innovative solution—an intelligent digital assistant (chatbot) designed to assist pharmacists in offering informed recommendations for patient complaints. Unlike static information resources, a chatbot offers dynamic and engaging interactions, creating a more effective platform for delivering valuable healthcare guidance. A chatbot can help pharmacists make recommendations by directing the conversation about what patients should know (1).

The availability of large language models (LLMs) such as ChatGPT has spurred interest in developing chatbots for various business purposes. However, creating chatbots capable of handling sensitive information, particularly in healthcare, presents unique challenges. Errors made by these bots when extracting information or providing health advice can lead to significant consequences (2). In developing a chatbot for pharmacy recommendations, it becomes crucial for the bot to proficiently extract symptom-related information and other pertinent patient data proficiently, subsequently offering tailored recommendations or medication suggestions based on this data.

In this study, we proposed the usage of regular expression matching (3, 4) to create an Indonesian chatbot for pharmacy recommendation, SmartFarma. Prior research shows that the regular expression matching method is more transparent and accurate than other machine learning algorithms (2, 5-7). This choice is rooted in the recognition that, especially within the healthcare domain, transparency in model results is of paramount importance (3, 4, 8).

Furthermore, the decision to employ regular expressions is underpinned by their ability to expedite the inference process, outperforming traditional machine learning models in terms of speed and accessibility. This agility ensures that our chatbot can be readily accessed by diverse users in various healthcare scenarios, thus promoting broader accessibility.

In the subsequent sections, we will delve into the technical details of our approach, present our evaluation results, and compare our regular expression-based methodology with machine learning models, particularly the Biomedical Bidirectional Encoder Representations from Transformers (BERT) model and GPT model (9). The primary objective of this chatbot is to empower pharmacists to diagnose and provide recommendations for common ailments frequently encountered by patients in Indonesia, including fever, diarrhea, cough, and runny nose or cold.

2. MATERIALS AND METHODS

In this section, we will describe methods used to develop a chatbot for Indonesian pharmacy recommendation,

SmartFarma. In the inference process, the SmartFarma chatbot is generally divided into two phases. The first one is extracting information from the user. We call this phase the Information Extraction phase. In this phase, the bot will gather information from the user until it is enough to create a recommendation. The bot will extract the information from the text given by the user and ask if it needs more information. The next stage is to process the given information to a recommendation; we call this phase the Recommendation Inference phase. Helped by some experts, we created an algorithm to determine the recommendation or response given the current patient's condition. The general process is shown in Figure 1.

During the information extraction phase, the system will use the previously created keywords database, which contains keywords and templates to detect existing symptom information. The user profile is temporary information that is used to record the symptoms experienced by the user.

2. 1. Regular Expression Templates Before we started the information extraction phase, we put together a database that contained specific patterns we could use to find and pull out important details from the text you provide. These patterns, known as regular expressions or regex, are like sets of special characters that help us find certain words or formats within a block of text. These patterns can be quite simple, like finding email addresses or phone numbers, or they can be more complex and look for patterns that depend on the context of the words around them.

The neat thing about regular expressions is that they work across different computer programming languages, so they can be used to find specific words or patterns in a sentence no matter what kind of computer program you're using. For instance, the regex pattern " $\d{3}-\d{2}-\d{4}$ " can be used to match and extract Social Security Numbers in the format XXX-XX-XXXX from a given text. In our case, using the pattern "de?ma?m" can match variations of writing the word "demam" (fever), such as "dmm," "demmm," and "dmam."

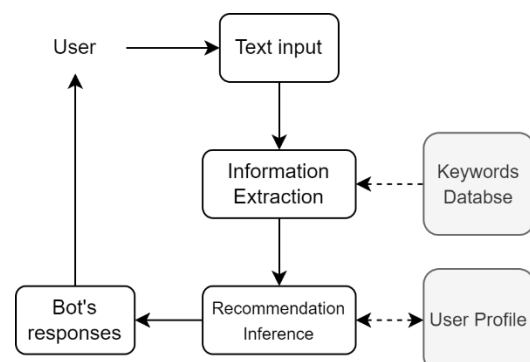


Figure 1. General process of SmartFarma chatbot

The initial stage in the development of this chatbot system is to build a database containing regular expression templates that will be used to extract information from the input text. An example of the template used in this study is shown in Table 1.

The database is stored and organized in JSON format with categories based on the patient's main symptoms. This structure will allow for a neater and more transparent data management process so experts can scale the system up and check easily if there is a doubt in the model's output. It's important to mention that when we created these regular expression templates, we did not look at the evaluation set, which we will talk about later. This was to make sure we did not accidentally use information from that set to create our templates. These templates were built following the guidance provided by the experts in the field based on Handbook of Nonprescription Drugs (10), making sure they were based on solid recommendations.

2. 2. Regular Expression Extraction Scheme At this stage, the system extracts the information entered by the user. The system will extract symptom information using the regular expression template that has been built and recorded. The information extraction process is shown in Figure 2.

There are two types of extraction processes performed. The first is information extraction without

context, and the other is information extraction with some context. Information without context is extracted throughout the dialogue to obtain information on patient symptoms directly from the text entered. It usually occurs at the first beginning of the conversation when the bot receives the first input from the user.

Information extraction with context is carried out in the middle of the conversation when the bot needs to know whether a symptom is present or not in the patient. In this case, user input will be assumed to respond to the bot question, which means the user answers in the context of the bot's previous response. Examples of differences in information extraction with and without context are shown below in Table 2.

In Table 2, the sample regex template on the first line will extract information on fever symptoms from the patient's input. On the other hand, in the second line, the regex is used to extract information about whether the patient agrees to something. This agreement will depend on the context of the conversation. For instance, when the bot wants to confirm if the patient is experiencing a symptom. A short answer "yes" from the user means the user is experiencing the respective symptom.

2. 2. 1. User Profile The result of this extraction process is stored in the form of a user profile. This profile contains patient information obtained in one conversation session. This information includes the symptoms that are present and the symptoms that are not present during the conversation. As well as other information needed in the inference stage later. Included among them is the conversation context needed for extraction, as shown in Figure 2. This user profile is stored in the database and created on each session.

Examples of stored user profiles are in Table 3. This user profile will be updated frequently as the user and bot conversation continue.

TABLE 1. Regular expression template samples

Symptoms	Regex template
Batuk berdahak (<i>Phlegm cough</i>)	((ba?tu?k(nya)?)(ber de?n?ga?n ?)(dahak))
Batuk kering (<i>Dry cough</i>)	((ba?tu?k(nya)?)(kering))
Demam (<i>Fever</i>)	(de?ma?m me?ri?a?ng pa?na?s palak)

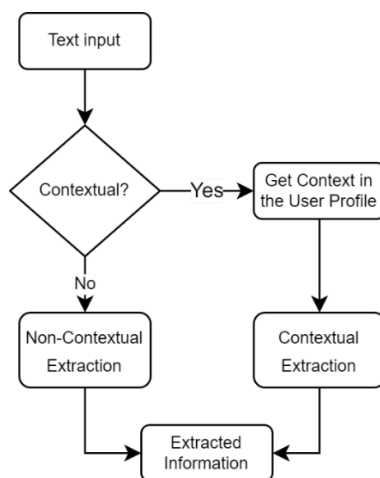


Figure 2. Context and Non-contextual Extraction

TABLE 2. Contextual and Non-contextual template samples

Regex templates	Type
(de?ma?m me?ri?a?ng pa?na?s palak)	Non-contextual
(ada) (i?ya) (be?na?r) (be?tu?l)	Contextual

TABLE 3. Example of Stored User Profile

Keys	Values
Existed Symptoms	Fever, Cough
Non-existed Symptoms	Headache
Age	12
Main Symptom	Fever
Current Context	Stomachache

2. 2. 2. Main Symptoms Extraction In Table 3, we can see there is a key called “Main Symptom”. In our system, we've identified a crucial element called the "Main Symptom." During the initial data extraction step, our primary goal is to identify the main symptoms reported by the user. After consulting with experts, we've determined that the main symptoms we focus on are fever, diarrhea, cough, and runny nose or cold.

The reason behind identifying these main symptoms is to streamline the decision-making process and mimic how a pharmacist would approach a real-life situation. When our system generates recommendations, it uses the main symptom as a key factor in determining the next response from the chatbot. This approach ensures that the bot prioritizes gathering information about the main symptom before seeking other details from the user. In our proposed method, the process to extract the main symptom information from the text is using regular expression.

2. 2. 3. Negative Phrase Extraction In order to accurately extract negative phrases in the Indonesian language, such as "Tidak Batuk" ("No Cough"), our system has implemented a method to handle these cases and ensure that symptoms are not falsely recorded as present. The system begins by detecting negative words, such as "Tidak" ("No"), using regular expressions. Prior to detecting symptoms, the system checks if negative words are present in the given text. If a symptom phrase follows the negative word, it is interpreted as the absence of the stated symptom. This approach effectively prevents the recording of symptoms that are negated by the presence of negative words, enhancing the accuracy of symptom extraction in our system.

2. 2. 4. Practical Consideration Regular expressions can be seen as a white-box approach, as opposed to the black-box nature of complex machine learning or deep learning models. Regular expressions provide explicit, rule-based patterns, acting like transparent rules that are easy to follow. In medicine suggestion cases, where clarity is crucial, this white-box approach ensures a clear understanding of how decisions are made. By defining specific patterns and rules supervised by the experts, we guarantee that essential factors in selecting the right medicine are not overlooked. We can see this process as a human-in-the-loop process, where any user feedbacks of current version can be used for future improvement, as illustrated in Figure 3. Unlike black-box machine learning models, regular expressions offer a more controlled and transparent process, particularly vital in healthcare contexts.

2. 3. Information Extraction using Bidirectional Encoder Representations from Transformers BERT is a method of encoding text data to become a

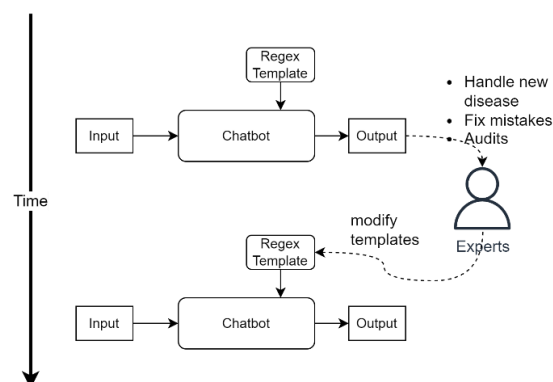


Figure 3. Regex template enables human-in-the-loop process to improve performance in the future

vector with a deep learning approach (7). BERT was developed using multi-layer transformer architectures that improve deep neural network models with Attention mechanisms (11). During pre-training, BERT learns contextual embeddings by predicting masked words in a sentence, capturing intricate linguistic relationships. It utilizes a massive corpus to establish a deep understanding of language structures and semantics, resulting in rich contextual representations (12). BERT encoding vectors can be used in various tasks, ranging from classification (13) to entity recognition in biomedical data (14).

BERT has spawned a diverse family of variations and adaptations, each designed to address specific NLP challenges and domains. These variants include models like RoBERTa (15), which optimizes pre-training techniques, and DistilBERT (16), which offers a more lightweight option. Additionally, models like BioBERT (17) and ClinicalBERT (18) cater to biomedical and clinical domains, respectively, by fine-tuning specialized datasets. In this study, we compared our method to one of a pre-trained BERT model that fits with our scheme and specializes in biomedical data, Biomedical NER.

2. 3. 1. Biomedical NER Biomedical NER (19) is a model that is built on top of the Distill BERT model (distilbert-base-uncased) and then trained on the Maccrobat dataset (20), which is biomedical text data. Biomedical BERT is intended to perform Named Entity Recognition (NER) on 84 entities from an English text.

In this study, we use the available API of Biomedical NER from the HuggingFace website. Visualization of the output of Biomedical NER in the HuggingFace website can be seen in Figure 4.

2. 4. Information Extraction Using Large-Language Model A large language model (LLM) is a class of deep learning models that are typically based on the transformer architecture and trained on a vast amount of text data to perform language-related tasks

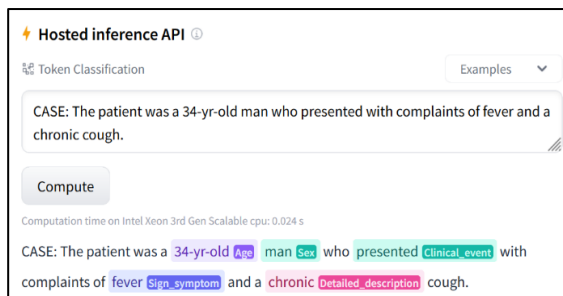


Figure 4. Biomedical NER model's result visualized in the HuggingFace website

(21). One of the models that is part of the LLM family is Generative Pre-Trained Transformer 3 (GPT-3), built by OpenAI (22).

GPT-3.5 is the latest iteration of the Generative Pre-trained Transformer model developed by OpenAI, which represents a significant breakthrough in natural language processing. GPT-3.5 is an evolved version of GPT-3 with additional fine-tuning and training. It is built upon the same transformer architecture and language understanding framework as GPT-3 but has a larger scale and improved performance. GPT-3.5 benefits from an expanded training dataset and more refined algorithms, enabling it to generate even more coherent and contextually relevant text. This language model has been trained on an extensive corpus of data, enabling it to perform a wide range of tasks, including machine translation, text completion, question answering, and text generation.

2. 5. Experiments Setup We built a dataset to evaluate the bot's extraction process. This dataset consists of 126 patient complaints that experts have annotated in Indonesian language. These complaints were obtained by randomly recording anonymous complaints expressed by patients who visited the pharmacy. An example dataset is shown in Table 4.

It is worth to note that, This dataset is used only for tsystem evaluation as the proposed scheme, and the other baseline does not require training data: Regex templates were designed based on expert reference, while Biomedical NER and GPT 3.5 API models used for comparison are pre-trained models. We use only 3 out of 126 data for a few-shot example, as shown in Table 5.

Biomedical NER and GPT 3.5 were used as a comparison with the regex method. As Biomedical NER was originally built for an English dataset, the text data used for evaluation were first translated using Google Translate from Indonesian before inputted into the Biomedical NER model.

For GPT 3.5, we use official OpenAI API and Langchain framework with no additional training or fine-tuning. Similar to Biomedical NER, we first translate the

TABLE 4. Example of Evaluation Set. The text in the parentheses is the English translation of the original complaint in Indonesian

Patient complaints	Annotated Symptoms
Seorang ibu mengeluhkan anaknya mengalami demam disertai dengan batuk. (A mother complained that her child had a fever accompanied by a cough)	Demam, Batuk (Fever, Cough)
Dewasa, batuk dan demam, belum diberi obat hanya diberi suplemen stimuno (Adults, cough and fever, have not been given medication, only given stimuno supplements)	Demam, Batuk (Fever, Cough)
Seorang pria datang dengan keluhan demam (A man came with complaints of fever)	Demam (Fever)
Pasien 13 tahun mengalami diare 2 kali sehari disertai mual muntah tanpa demam. Sudah mengonsumsi Mylanta (A 13-year-old patient experienced diarrhea 2 times a day accompanied by nausea and vomiting without fever. Already taking Mylanta)	Diare (Diarrhea)

data to English using Google Translate. Then, we create a prompt to extract the symptoms from the given text with a few-shot example, as shown in Table 5. These examples that randomly picked from dataset are added to give the context and example input-output format. We replace the {human_input} with the text that will be extracted and use parameter temperature sampling 0.9 in the GPT-3.5 API.

2. 6. Evaluation Scheme We employ the Jaccard Index to assess the model's performance. This choice is

TABLE 5. Prompt used to extract symptoms in GPT 3.5

```
Extract the list of symptoms given the text.
Return only symptoms separated by commas.
Examples:
Human: "cough and fever, no cold for their child, and have not used medicine before"
AI: "Fever, Cough"
Human: "A 13-year-old patient experienced diarrhea 2 times a day accompanied by nausea and vomiting without fever. Already taking mylanta"
AI: "Diare"
Human: "Patient aged 10 months, had a fever, 37.5 degrees,"
AI: "Fever"
Let's start!
Human: {human_input}
AI:
```

predicated upon during the extraction procedure from a given text, we can obtain more than a single symptom information. Consequently, we utilize a set-based evaluation methodology deemed to be better suited to the circumstances. The Jaccard Index is calculated using Equation 1.

$$J(A, B) = \frac{A \cap B}{A \cup B} \quad (1)$$

In this study, A is the set of information extracted by the model, and B is the set of information that should be extracted (ground truth). When A is equal to B, then the Jaccard Index value will be 1, otherwise when there is no same value between set A and B, the equation will return 0.

2. 7. Recommendation Inference During the inference stage, the information acquired from the extraction process is utilized to determine the recommendations to be provided. The method used at this stage is forward chaining (23, 24). It involves the system attempting to offer recommendations based on the available information. The bot will follow pre-defined rules that provided by experts based on current user information. In case where the information is insufficient, the system will prompt the user through a bot dialog to provide more information.

To enhance the dialogue's dynamism, we have developed a response pool consisting of a comprehensive collection of all possible questions, recommendations, and bot responses, along with their variations. The inclusion of variations ensures that the bot's dialogue appears more dynamic. Random selection is made from this response pool to determine the bot's response.

3. RESULTS AND DISCUSSIONS

In this section, we present the results and discussions of our study. We analyze the performance of various methods, including the proposed approach, machine learning methods, Biomedical Named Entity Recognition (NER), and GPT-3.5, in the context of pharmacy recommendation.

3. 1. Recommendation Inference In Table 6, It seems that the performance of the proposed method is much better than the machine learning method, Biomedical NER, and GPT-3.5. This happens because the characteristics of the data used in the Pharmacy Recommendation case are much simpler. In Table 5, we can see that pharmacists tend to have standard writing and are not too wordy. This makes it easy for a regular expression to extract the information.

From the table, we can see Biomedical NER and GPT-3.5 have problems extracting information from the given input. Through examining the evaluation set, we

TABLE 6. Evaluation of Extraction Result

Model	Jaccard Similarity
Biomedical NER	51.48%
GPT-3.5	74.01%
Regular Expression (ours)	81.54%

can analyze the specific errors made by each model. In the case of Biomedical NER, it faces limitations in handling negative phrases, which is shown in Table 7. Biomedical NER model incorrectly identifies certain symptoms and categorizes them as existing, even when they do not exist in the user.

GPT-3.5 on the other hand successfully handle the negative phrase better than Biomedical NER. However, as GPT-3.5 is a general model that design for various natural language tasks. GPT-3.5 often failed to detect symptoms in the text. We can see some examples in Table 8.

Although the regex model shows the highest Jaccard similarity, its performance can still be enhanced by examining factors that may improve it. The performance of the regex model is generally lower due to the detection of information that experts consider less significant (False positive). For example, Table 9 illustrates some instances where the regex model captures "teething" information based on the guidelines employed, while the expert who annotated the evaluation data does not consider it important to capture. Variations in information perception among experts are common, yet they affect the calculation of Jaccard Similarity.

TABLE 7. Incorrect Extraction by Biomedical NER. Words in red should not exist due to the negative phrase

Patient complaints	Groundtruth	Extracted
diare, mual dan muntah, usia 13 tahun, tidak disertai demam.	Diare, Mual Muntah	Diare, Mual Muntah, Demam
<i>(diarrhea, nausea and vomiting, age 13 years, not accompanied by fever)</i>	<i>(diarrhea, nausea and vomiting)</i>	<i>(diarrhea, nausea and vomiting, fever)</i>
anak berusia 8 tahun mengeluhkn pilek sejak tadi pagi, pilek terkadang meler terkadang mampet, tanpa batuk dan demam.	Pilek (Runny nose)	Pilek, Batuk (Runny nose, cough)
<i>(an 8 year old child has had a runny nose since this morning, the runny nose is sometimes runny sometimes clogged, without cough and fever.)</i>		
Batuk berdahak untuk dewasa, tidak pilek.	Batuk berdahak (Cough with phlegm)	Batuk berdahak, Pilek (Cough with phlegm, runny nose)
<i>(Cough with phlegm for adults, not colds)</i>		

3.2. Chatbot Performance Evaluation The chatbot was created using Python as the primary programming language and the Flask framework to support its backend functionality. Additionally, for the user interface display, we harnessed the capabilities of Flutter technology. This decision to employ Flutter was made with an eye toward the future, as it enables streamline and efficient development for both Android and iOS platforms. By using Flutter, we aimed to ensure that our chatbot could offer a consistent and user-friendly experience on a wide range of mobile devices.

TABLE 8. Incorrect Extraction by GPT-3.5

Patient complaints	Groundtruth	Extracted
Pasien anak demam, meminta sediaan tablet (<i>Pediatric patients with fever, ask for tablet supplies</i>)	Demam (<i>fever</i>)	Sediaan tablet (<i>Tablet supplies</i>)
demam, sedang menyusui. (<i>Fever, currently breastfeeding</i>)	Demam (<i>fever</i>)	Demam, Menyusui (<i>Fever, Breastfeeding</i>)
batuk berdahak, pilek, usia 10 tahun, berat badan 60 kg, tidak demam. (<i>cough with phlegm, runny nose, age 10 years, weight 60 kg, no fever</i>)	Batuk berdahak, pilek (<i>cough with phlegm, runny nose</i>)	Batuk berdahak, pilek, berat badan 60 kg (<i>cough with phlegm, runny nose, weight 60 kg</i>)

TABLE 1. Example Different Evaluation Raised False Positive

Patient complaints	Groundtruth	Extracted
pasien bayi demam, tumbuh gigi, baru 1 hari, tidak disertai kejang, RR normal, BAK lancar, tidak diare. (<i>baby patient has fever, teething, only 1 day, not accompanied by seizures, normal RR, smooth urination, no diarrhea.</i>)	Demam (<i>Fever</i>)	Demam, Tumbuh Gigi (<i>Fever, Teething</i>)
anak usia 10 bulan, demam suhu 37,5C sejak tadi malam, setelah kehujanan, tidak kejang, sudah menggunakan bye bye fever. napas biasa dan tanpa keluhan lain. Kemungkinan gigi akan tumbuh, serta ingin obat dengan sediaan drop. (<i>10-month-old child, fever 37.5C since last night, after being caught in the rain, no seizures, already using bye-bye fever. Normal breathing and no other complaints. It is possible that the teeth will grow, and you want medicine with drop preparations</i>)	Demam (<i>Fever</i>)	Demam, Tumbuh Gigi (<i>Fever, Teething</i>)

To illustrate how the chatbot operates within the Smartfarma, we can refer to specific dialog examples depicted in Figures 5 and 6. In Figure 5, the conversation sequence demonstrates the chatbot's ability to inquire about specific information from the user before providing a recommendation. What's noteworthy here is that our chatbot can adeptly handle user inputs that may include non-standard words or abbreviations in the Indonesian language, denoted by the text in red. This flexibility in understanding and processing diverse forms of user input is a testament to the robustness of our chatbot's design.

Conversely, in Figure 6, we observe a scenario where the chatbot has gathered adequate information, thus obviating the need to seek additional data. This streamline process allows the chatbot to move from information collection to the recommendation phase, improving the user experience by minimizing unnecessary interactions and wait times.

4. FUTURE WORK

One of the advantages of using a regex template as the main extraction scheme is its transparency and modularity. In the future, adding, removing, or modifying diseases' knowledge can be seamlessly executed by modifying the rules stored in the system. This approach also facilitates easy tracking and

User: Pasien berumur 70 tahun terkena diare
(*A 70 year old patient has diarrhea*)

Bot: Apakah pelanggan terkena gejala gawat ABCD?
(*Does the customer have ABCD emergency symptoms?*)

User: engga, tapi pasien sakit perut hbt
(*no, but the patient has a bad stomach ache*)

Bot: Apakah diare berlangsung >14 hari?
(*Does the diarrhea last >14 days?*)

User: ga
(*no*)

Bot: Terdapat peluang adanya penyakit kronis/inflamasi. Apoteker sebaiknya menyarankan pelanggan untuk segera berkonsultasi ke dokter untuk pemeriksaan yang lebih dalam.

(*There is a chance of chronic/inflammatory disease. Pharmacists should advise customers to immediately consult a doctor for a deeper examination*)

Figure 5. Dialog sample between user and chatbot

User: Seorang remaja mengalami diare yang disertai dengan tanda abcd

(*A teenager has diarrhea accompanied by the abcd sign*)

Bot: Segera bawa pelanggan ke IGD

(*Immediately take the customer to the ER*)

Figure 6. Short dialog sample between user and chatbot

correction of wrong extractions, contributing to the continuous improvement of the chatbot's performance, especially for handling more complex diseases in the future.

We can also easily further enhance the current scheme by integrating other methods, such as fuzzy logic, to address the uncertainty inherent in a patient's input. By incorporating fuzzy logic, we can introduce a more nuanced understanding of symptoms, allowing the chatbot to interpret and respond to ambiguous or imprecise information with greater accuracy. However, in the context of our current study, the referenced rule predominantly addresses symptoms using binary answer (exist/unexist). In future scenarios involving uncertainty and imprecision, fuzzy logic could undoubtedly be employed to improve effectiveness. Additionally, adding Language Model Models (LLM) for only the text generation step could enable the chatbot to generate more contextually appropriate responses, contributing to an improved user experience and overall effectiveness in medical conversations, without reducing its performance.

5. CONCLUSION

In this study, we developed a bot that can make it easier for pharmacists to provide recommendations to patients. The developed bot is made using a regular expression template as a method of extracting information from input. As for the inference process, or determining the dialog the bot speaks, we used the forward chaining method to complete information and provide recommendations. At the extraction stage, we compared the method we proposed with the use of the Biomedical NER, a BERT-based NER model, and GPT-3.5, an LLM model. The method we proposed outperformed both model in performance with a Jaccard similarity value of 81.54%.

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Persian Abstract

چکیده

در دسترس بودن گسترده مدل‌های زبان بزرگ (LLM) بسیاری از افراد را تشویق کرده است تا توسعه ربات‌های چت را برای نیازهای تجاری خود کشف کنند. با این حال، ایجاد ربات‌های چت برای مدیریت اطلاعات حساس، مانند مراقبت‌های بهداشتی، می‌تواند چالش برانگیز باشد. اشتباهاتی که این ربات‌ها هنگام استخراج اطلاعات یا ارائه توصیه‌های بهداشتی مرتکب می‌شوند می‌تواند عواقب جدی داشته باشد. هنگام توسعه یک ربات چت برای توصیه‌های داروخانه، برای ربات ضروری است که به طور موثر اطلاعات مربوط به علائم و سایر داده‌های مربوط به بیمار را استخراج کند و سپس توصیه‌هایی را برای اقدامات یا داروها بر اساس آن اطلاعات ارائه دهد. در این مطالعه، ما یک رویکرد ساده و مؤثر پیشنهاد کردیم که الگوهای بیان منظم را برای استخراج اطلاعات با زنجیره‌سازی رو به جلو برای استنتاج ترکیب می‌کند تا یک ربات چت توصیه داروخانه به نام SmartFarma ایجاد کند. در سناریوهایی مانند توصیه‌های داروخانه، نشان خواهیم داد که استفاده از قالب‌های بیان منظم کافی است و نتایج بهتری نسبت به برخی روش‌های یادگیری ماشین ایجاد می‌کند. علاوه بر این، با استفاده از عبارات منظم، SmartFarma را می‌توان با مدیریت شفاف داده توسعه داد و به کارشناسان اجازه می‌دهد تا توصیه‌های آن را ردیابی، نظارت و ارزیابی کنند. این تحقیق در درجه اول بر استخراج اطلاعات بیمار متمرکز است. مدل ما، همانطور که پیشنهاد شد، به امتیاز چشمگیر ۸۱.۵۴٪ دست یافت که از هر دو مدل رمزگذار دو جهته زیست پزشکی از ترانسفورماتورها (BERT) و ترانسفورماتورهای از پیش آموزش دیده (GPT) بهتر عمل کرد.