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Sentiment analysis of consultation answers on Alodokter using Support Vector Machine (SVM)

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ABSTRACT

In the medical field, fast and accurate access to information is crucial for diagnosis, treatment, and research. Medical information retrieval systems play an essential role in facilitating this access. Despite the abundance of online medical resources, users often face challenges in processing and interpreting information efficiently. Question Answering (QA) systems aim to provide accurate and relevant responses to user queries, making them integral to platforms such as Alodokter, one of the most popular health websites in Indonesia. Alodokter offers vast medical content and allows direct interactions between users and certified medical professionals, making it a rich source of reliable and contextually relevant data. This study explores the implementation of the Support Vector Machine (SVM) method to classify and analyze sentiment in responses found on Alodokter. SVM is a supervised machine learning algorithm known for its high performance in classification tasks, particularly with non-linearly separable data. Its strong generalization capabilities make it well-suited for complex QA data involving diverse linguistic structures and varying medical contexts. Using Alodokter data, this research evaluates SVM performance across different training-testing ratios to identify the most effective configuration. The experimental results demonstrate that the best classification performance was achieved with a 60:40 training-testing ratio, yielding an accuracy of 70%. At this ratio, negative questions achieved 68% precision, 78% recall, and an F1-score of 73%, while positive questions yielded 74% precision, 62% recall, and F1-score of 67%. Conversely, the 50:50 ratio resulted in the lowest accuracy of 59%, with notable imbalances in recall values, particularly for negative questions. In conclusion, SVM proves to be an effective tool for sentiment-based QA analysis on Alodokter, offering valuable insights to improve online health services and enhance user experience in digital healthcare platforms.

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1. INTRODUCTION

In the medical field, fast and accurate access to information is crucial for diagnosis, treatment, and research. Medical information retrieval systems serve as essential tools to facilitate such access (Zhang et al., 2018). However, despite the abundance of online medical resources, retrieving medical

information often requires significant time and effort, especially when users must process and interpret data from various sources.

Alodokter is a website that provides information about health, diseases, medications, and other medical services to the general public (Murti Ali Lingga, 2019). It is one of the most popular online health platforms in Indonesia, with millions of users. The platform offers a wide range of health-related content and enables interactions between patients and medical professionals. Alodokter contains a vast and diverse dataset, including user-submitted questions and responses from doctors. This large volume of data allows for more comprehensive and representative analysis. Since the answers are typically provided by licensed doctors, the information is generally reliable and accurate—an important factor in ensuring valid analytical results. Furthermore, because Alodokter focuses on health issues relevant to Indonesia, the analysis results can offer valuable insights into the health needs and concerns of the local population (Murti Ali Lingga, 2019).

Support Vector Machines (SVM) are machine learning algorithms that utilize supervised learning models to recognize patterns. SVMs are widely used for classification and regression tasks (Rama et al., 2023). They are known for their high performance in classification, especially when dealing with non-linearly separable data. This capability is critical to ensure accurate results in analysis. SVMs also have strong generalization capabilities, meaning they perform well on previously unseen data—as demonstrated in a study by Tri Putri Lestari, where SVM achieved an accuracy of 86.6%, with positive precision at 86%, neutral at 1.00%, and negative at 87%; positive recall at 90%, neutral at 87%, and negative at 26%; and F1-scores of 88% (positive), 42% (neutral), and 86% (negative) (Lestari, 2022).

Given the variability of questions and contexts in a question answering (QA) environment, implementing the SVM algorithm for sentiment analysis on consultation responses from Alodokter is a strong choice. The combination of high-quality data and SVM's capability to handle complex classification tasks is expected to produce valuable analytical results. This can help improve understanding and enhance the quality of online healthcare services in Indonesia. Through continued technological innovation and multidisciplinary collaboration, the implementation of SVM-based sentiment analysis on Alodokter's QA data can contribute to advancements in diagnosis, treatment, disease management, and the overall quality and safety of healthcare services.

2. METHOD

The system development stages for this research began with data collection. The next step involved classifying the data into positive (a combination of questions categorized as correct) and negative (a combination of questions categorized as incorrect). This was followed by preprocessing, which consisted of four processes: case folding, punctuation removal, stopwords removal, and stemming. After preprocessing, term weighting was carried out using the TF-IDF (Term Frequency–Inverse Document Frequency) method. Subsequently, the selected model was evaluated using the Support Vector Machine (SVM) algorithm. The overall system development workflow is illustrated in Figure 1.

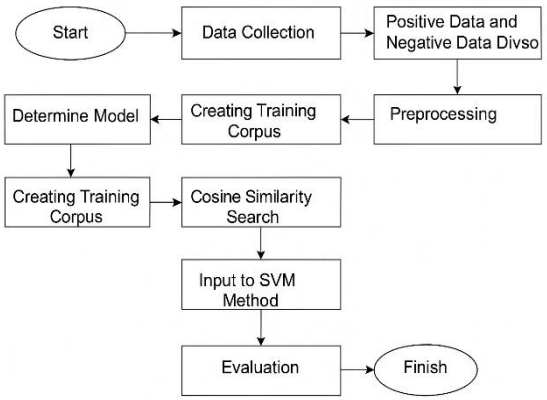

Figure 1. System Development Stages

3. RESULTS AND DISCUSSION

3.1 Data Collection

The data used in this research was obtained from the Alodokter website, which consists of 300 entries containing questions, answers, and categories. The table below presents a sample of the data retrieved from the Alodokter platform.

Table 1. Question Dataset

No	Questions	Categoris	Labels
1	Saya dari tadi perut terasa penuh kaya banyak angin. tenggorokan juga dok gak enak. kaya mau sendawa tapi susah keluarnya. dok minta sarannya dong dokter bagaimana cara agar bisa bersendawa?	Penyakit dan Pengobatan	positif
2	Perkenalkan dok saya perempuan 30 th sudah menikah dan punya anak 1. sudah hampir 2 minggu saya keputihan saya berwarna hijau kekuningan kental seperti ingus dan baunya tidak sedap biasanya gatal kalau keluar keputihan warna hijau.. dan tidak setiap hari saya mengalami keputihan berwarna hijau kekuningan. Menurut dokter sebaiknya bagaimna ?	Penyakit dan Pengobatan	positif
3	Alodokter, Dok sebagai seorang penderita asam lambung apa diperbolehkan untuk diet? Bagaimana cara menurunkan berat badan jika menderita asam lambung? kira-kira menu yang sehat untuk penderita aslam apa dokter?	Penyakit dan Pengobatan	positif
4	Alodokter, Begini dok, 2 hari lalu saya mengalami sakit telinga sebelah kiri setelah flu, sakit telinga tersebut kadang terjadi saat menelan dan menguap dibarengi dengan suara seperti gemericik dan rasa sakit. Hari ini telinga saya terasa seperti agak budek yang kanan aman2 saja dokter. Apa yang harus saya lakukan dok?	Penyakit dan Pengobatan	positif
.....	.....	.....	.....
299	Bangun tidur tadi pagi jari manis tangan kanan saya tiba2 nyeri, sakit saat di tekuk, kaku dan kesemutan. Apakah ini gara2 setiap saya kerja dan bawa motor? itu kenapa yah ? Dan obat tradisional apa untuk mengobati nya dok? Terimankasih	Penyakit dan Pengobatan	positif
300	Bangun tidur 2 jari saya sakit sekali buat di tekuk, dan di gerakkan posisi menggenggam aja gak kuat nekuk dok. Kata mama saya ini saya kena tigger finger. tapi saya takut dok, klo ini berlangsung lama. Mau saya periksakan ke RS. tapi kata mama trigger finger bisa sembuh sendiri. apakah benar dokter?	Penyakit dan Pengobatan	positif

3.2 Data Processing

In this research, we conducted data preprocessing to make the data more suitable for processing by the Question Entailment algorithm. Since the data used is in text form, Text Preprocessing (Rajpurkar et al., 2016) was utilized, which includes Case folding, Punctuation Removal, Stopwords Removal, and Stemming.

3.2.1 Case Folding

Case folding is one of the processes in text preprocessing that is performed to standardize characters in the data by converting all letters to lowercase (Jumeilah, 2017). In this study, the case folding process is carried out to make all letters in the 'Question' and 'Category' data lowercase.

```
df['pertanyaan'] = df['pertanyaan'].str.lower()
df.head(10)
```

No	questions	categories	labels
1	saya dari tadi perut terasa penuh kaya banyak ...	Penyakit dan Pengobatan	positif
2	perkenalkan dok saya perempuan th sudah menika...	Penyakit dan Pengobatan	positif
3	alodokter dok sebagai seorang penderita asam l...	Penyakit dan Pengobatan	positif
4	alodokter begini dok hari lalu saya mengalami ...	Penyakit dan Pengobatan	positif
5	dok minggu yang lalu saya operasi wasir dok ca...	Penyakit dan Pengobatan	negatif
6	tadi saya bersihkan kotoran telinga menggunaka...	Penyakit dan Pengobatan	negatif
7	om saya usia tahun rambutnya mulai rontok dan ...	Penyakit dan Pengobatan	negatif
8	selamat pagi dokter mau bertanya saya laki lak...	Penyakit dan Pengobatan	negatif
9	dok jerawat di dagu saya on off dok dan ga per...	Penyakit dan Pengobatan	negatif
10	dok hari kemaren saya emg flu hidung tersumbat...	Penyakit dan Pengobatan	positif

Figure 2. Script and Result of Case Folding

3.2.2 Punctuation Removal

Punctuation Removal is one of the processes in Text Preprocessing aimed at eliminating punctuation marks such as commas, periods, and others. In this study, the Punctuation Removal process is carried out to remove punctuation and numbers from the 'Questions' data (Siringoringo & Jamaludin, 2019).

```
import re
df['pertanyaan'] = df['pertanyaan'].apply(lambda x: re.sub(r'http\S+|www\S+|https\S+', '', x, flags=re.MULTILINE))
df['pertanyaan'] = df['pertanyaan'].apply(lambda x: re.sub(r'#\w+', '', x))
df['pertanyaan'] = df['pertanyaan'].apply(lambda x: re.sub(r'@\w+', '', x))
df['pertanyaan'] = df['pertanyaan'].apply(lambda x: re.sub(r'[^\w\s]', '', x))
df['pertanyaan'] = df['pertanyaan'].apply(lambda x: re.sub(r'\d+', '', x))
df['pertanyaan'] = df['pertanyaan'].apply(lambda x: re.sub(r'\s+', ' ', x))
df['pertanyaan'] = df['pertanyaan'].str.replace('?', '')
df.head(10)
```

No	questions	categories	labels
1	Saya dari tadi perut terasa penuh kaya banyak ...	Penyakit dan Pengobatan	positif
2	Perkenalkan dok saya perempuan th sudah menika...	Penyakit dan Pengobatan	positif
3	Alodokter Dok sebagai seorang penderita asam l...	Penyakit dan Pengobatan	positif
4	Alodokter Begini dok hari lalu saya mengalami ...	Penyakit dan Pengobatan	positif
5	dok minggu yang lalu saya operasi wasir dok ca...	Penyakit dan Pengobatan	negatif
6	Tadi saya bersihkan kotoran telinga menggunaka...	Penyakit dan Pengobatan	negatif
7	Om saya usia tahun rambutnya mulai rontok dan ...	Penyakit dan Pengobatan	negatif
8	selamat pagi dokter mau bertanya saya laki lak...	Penyakit dan Pengobatan	negatif
9	dok jerawat di dagu saya on off dok dan ga per...	Penyakit dan Pengobatan	negatif
10	dok hari kemaren saya emg flu hidung tersumbat...	Penyakit dan Pengobatan	positif

Figure 3. Script and Result of Punctuation Removal

3.2.3 Stopword removal

Stopword removal is the process of removing words that are considered to have no significant meaning in text analysis. These words are usually common words such as 'and', 'in', 'that', 'from', and 'for' in Indonesian (Rama et al., 2023). The aim of stopword removal is to reduce noise in the data and focus on more significant words for analysis.

```
import nltk
nltk.download('stopwords') #mengunduh package stopword

from nltk.corpus import stopwords #mengimport stopword

# membuat daftar stopword dalam bahasa indonesia
stopwords = nltk.corpus.stopwords.words("indonesian")

# Remove stopwords
df['text_token'] = df['text_token'].apply(lambda x: [item for item in x if item not in stopwords])
df.head(10)
```

No	questions	categories	labels	text_token
1	saya dari tadi perut terasa penuh kaya banyak ...	Penyakit dan Pengobatan	positif	[perut, penuh, kaya, angin, tenggorokan, dok, ...
2	perkenalkan dok saya perempuan th sudah menika...	Penyakit dan Pengobatan	positif	[perkenalkan, dok, perempuan, th, menikah, ana...
3	alodokter dok sebagai seorang penderita asam l...	Penyakit dan Pengobatan	positif	[alodokter, dok, penderita, asam, lambung, dip...
4	alodokter begini dok hari lalu saya mengalami ...	Penyakit dan Pengobatan	positif	[alodokter, dok, mengalami, sakit, telinga, se...
5	dok minggu yang lalu saya operasi wasir dok ca...	Penyakit dan Pengobatan	negatif	[dok, minggu, operasi, wasir, dok, cepat, meng...
6	tadi saya bersihkan kotoran telinga menggunaka...	Penyakit dan Pengobatan	negatif	[bersihkan, kotoran, telinga, cutton, bud, tel...
7	om saya usia tahun rambutnya mulai rontok dan ...	Penyakit dan Pengobatan	negatif	[om, usia, rambutnya, rontok, depannya, botak,...
8	selamat pagi dokter mau bertanya saya laki lak...	Penyakit dan Pengobatan	negatif	[selamat, pagi, dokter, laki, laki, usia, ramb...
9	dok jerawat di dagu saya on off dok dan ga per...	Penyakit dan Pengobatan	negatif	[dok, jerawat, dagu, on, off, dok, ga, tuntas,...
10	dok hari kemaren saya emg flu hidung tersumbat...	Penyakit dan Pengobatan	positif	[dok, kemaren, emg, flu, hidung, tersumbat, me...

Figure 4. Script and Result of Stopword removal

3.2.4 Stemming

Stemming is one of the processes in Text Preprocessing that removes words with affixes and returns them to their root form (Siringoringo & Jamaludin, 2019). In this study, the stemming process involves removing words with affixes and reverting them to their root form in the 'Questions' data. Since the data used is in the Indonesian language, the Sastrawi library is employed for the Stemming process.

```
!pip install Sastrawi #instal modul sastrawi

# import Sastrawi package
from Sastrawi.Stemmer.StemmerFactory import StemmerFactory

# create stemmer
factory = StemmerFactory()
stemmer = factory.create_stemmer()

df['stemmed'] = df['text_token'].apply(lambda x: [stemmer.stem(y) for y in x]) #proses stemming setiap kata.

df.head(10)
```

no	questions	categories	labels	text_token	stemmed
1	saya dari tadi perut terasa penuh kaya banyak ...	Penyakit dan Pengobatan	positif	[perut, penuh, kaya, angin, tenggorokan, dok, ...	[perut, penuh, kaya, angin, tenggorok, dok, ga...
2	perkenalkan dok saya perempuan th sudah menika...	Penyakit dan Pengobatan	positif	[perkenalkan, dok, perempuan, th, menikah, ana...	[kenal, dok, perempuan, th, meni, anak, minggu...
3	alodokter dok sebagai seorang penderita asam l...	Penyakit dan Pengobatan	positif	[alodokter, dok, penderita, asam, lambung, dip...	[alodokter, dok, derita, asam, lambung, boleh,...
4	alodokter begini dok hari lalu saya mengalami ...	Penyakit dan Pengobatan	positif	[alodokter, dok, mengalami, sakit, telinga, se...	[alodokter, dok, alami, sakit, telinga, belah,...
5	dok minggu yang lalu saya operasi wasir dok ca...	Penyakit dan Pengobatan	negatif	[dok, minggu, operasi, wasir, dok, cepat, meng...	[dok, minggu, operasi, wasir, dok, cepat, atas...
6	tadi saya bersihkan kotoran telinga menggunaka...	Penyakit dan Pengobatan	negatif	[bersihkan, kotoran, telinga, cutton, bud, tel...	[sih, kotor, telinga, cutton, bud, telinga, ki...
7	om saya usia tahun rambutnya mulai rontok dan ...	Penyakit dan Pengobatan	negatif	[om, usia, rambutnya, rontok, depannya, botak,...	[om, usia, rambut, rontok, depan, botak, gonta...
8	selamat pagi dokter mau bertanya saya laki lak...	Penyakit dan Pengobatan	negatif	[selamat, pagi, dokter, laki, laki, usia, ramb...	[selamat, pagi, dokter, laki, laki, usia, ramb...
9	dok jerawat di dagu saya on off dok dan ga per...	Penyakit dan Pengobatan	negatif	[dok, jerawat, dagu, on, off, dok, ga, tuntas,...	[dok, jerawat, dagu, on, off, dok, ga, tuntas,...
10	dok hari kemaren saya emg flu hidung tersumbat...	Penyakit dan Pengobatan	positif	[dok, kemaren, emg, flu, hidung, tersumbat, me...	[dok, kemaren, emg, flu, hidung, sumbat, cium,...

Figure 5. Script and Result of Stemming

3.2.5 TF-IDF

In this research, we performed data preprocessing to make the data more suitable for processing by the Question Entailment algorithm. Since the data used is in text form, Text Preprocessing (Hanami, 2023) was utilized, which includes Case folding, Punctuation Removal, Stopwords Removal, and Stemming.

a. Term Frequency (TF):

TF is the frequency of a word in a specific document.

Formula: $TF_{i,j}=\frac{\text{The number of occurrences of term i in the document j}}{\text{The number of occurrences of the term in the document } j}$ (1)

```
print("\nTerm Frequency (TF):")
tf = X_final.toarray()
print(tf)
```

```
Term Frequency (TF):
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
```

Figure 6. Script and Result of TF

b. Inverse Document Frequency (IDF):

IDF is a measure of how common or rare a term is across all documents.

Rumus: $IDF_i = log \frac{Total\ number\ of\ documents}{The\ number\ of\ documents\ that\ contain\ term\ i}$ (2)

```
print("\nInverse Document Frequency (IDF):")
idf = tfid.idf_
print(idf)
```

```
Inverse Document Frequency (IDF):
[6.01396308 5.3208159  6.01396308 ... 6.01396308 6.01396308 5.09767235]
```

Figure 7. Script and Result of IDF

c. TF-IDF

TF-IDF is the product of TF and IDF.

Formula: $TF\text{-}IDF_{i,j} = TF_{i,j} \times IDF_i$

```
"""# TF IDF"""

tfid = TfidfVectorizer()
X_final =  tfid.fit_transform(X)
feature_names = tfid.get_feature_names_out()

print("TF-IDF Matrix:")
print(X_final.toarray())
```

```
TF-IDF Matrix:
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
```

Figure 8. Script and Result of TF-IDF

3.2.6 Test Results

The test results in this study use 300 question data that serve as test and training data. The selected question data was then manually labeled with the help of a validator, producing two labels: positive (appropriate questions) and negative (inappropriate questions). The number of positive class is 141 questions and the number of negative class is 153 questions. Below are the graphs and visual representations of the positive and negative questions.

Figure 9. Visualization of Positive Questions

From the visualization image above, we can conclude that the words that often appear are those that are visually printed large, such as 'doc.'

Figure 10. Visualization of Negative Questions

4. CONCLUSION

Based on the experimental results using various data split ratios (90:10, 80:20, 70:30, 60:40, and 50:50), the highest accuracy was achieved with the 60:40 ratio, reaching an accuracy of 70%. At this ratio, for negative questions, the precision was 68%, recall was 78%, and the F1-score was 73%. Meanwhile, for positive questions, the precision reached 74%, recall was 62%, and the F1-score was 67%. Conversely, the 50:50 ratio produced the lowest accuracy at 59%, showing an imbalance particularly in precision and recall values for negative questions (precision was 79%, but recall was only 32%), resulting in an F1-score of 45%.

REFERENCES

Abdillah, A.F., Putra, C.B.P., Apriantoni, A., Juanita, S. dan Purwitasari, D., (2022). Ensemble-based Methods for Multi-label Classification on Biomedical Question-Answer Data. Journal of Information Systems Engineering and Business Intelligence, 8(1), pp.42–50

Aruda, S. A. Q. (2022). *Klasifikasi Pertanyaan Berbahasa Indonesia Menggunakan Algoritma Support Vector Machine*. *14*(2), 44–52.

Fikri, M. I., Sabrila, T. S., & Azhar, Y. (2020). Perbandingan Metode Naïve Bayes dan Support Vector Machine pada Analisis Sentimen Twitter. *Smatika Jurnal*, *10*(02), 71–76. https://doi.org/10.32664/smatika.v10i02.455

Hanami, A. (2023). Term Frequency Inverse Document Frequency (TF-IDF). *Visitor Analytics*, *December*. https://www.visitor-analytics.io/es/glosario/t/term-frequency-inverse-document-frequency-tf-idf

Jumeilah, F. S. (2017). Penerapan Support Vector Machine (SVM) untuk Pengkategorian Penelitian. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *1*(1), 19–25. https://doi.org/10.29207/resti.v1i1.11

Lestari, T. P. (2022). Analisis Text Mining pada Sosial Media Twitter Menggunakan Metode Support Vector Machine (SVM) dan Social Network Analysis (SNA). *Jurnal Informatika Ekonomi Bisnis*, *4*(3), 65–71. https://doi.org/10.37034/infeb.v4i3.146

Murti Ali Lingga, E. D. (2019). *Alodokter, Konsultasi Kesehatan Via Online*. https://money.kompas.com/read/2019/04/25/204700726/alodokter-konsultasi-kesehatan-via-online?page=all

Rajpurkar, P., Zhang, J., Lopyrev, K., & Liang, P. (2016). SQuad: 100,000+ questions for machine comprehension of text. *EMNLP 2016 - Conference on Empirical Methods in Natural Language Processing, Proceedings*, *ii*, 2383–2392. https://doi.org/10.18653/v1/d16-1264

Rama, P., Putra, B., & Perdana, R. S. (2023). Klasifikasi Judul Berita Online menggunakan Metode Support Vector Machine (SVM) dengan Seleksi Fitur Chi-square. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *7*(5), 2132–2141.

Siringoringo, R., & Jamaludin, J. (2019). Text Mining dan Klasterisasi Sentimen Pada Ulasan Produk Toko Online. *Jurnal Teknologi Dan Ilmu Komputer Prima (JUTIKOMP)*, *2*(1), 41–48. https://doi.org/10.34012/jutikomp.v2i1.456.

Satria, G. J., Adikara, P. P., & Wihandika, R. C. (2022). Klasifikasi Pertanyaan COVID-19 Bahasa Indonesia menggunakan Naive Bayes. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *6*(1), 148–153. https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/10382

Sudin, S., Junaedi, H., & Santosa, J. (2019). Analisis Jenis Pertanyaan Berbahasa Indonesia pada Question and Answering System Menggunakan Metode Support Vector Machine(SVM). *Dintek*, *12*(1), 72–80.

Winiarti, S., Widayanti, D., & Ahdiani. (2022). Klasifikasi Jenis Buku Berdasarkan Cover dan Judul Buku Menggunakan Metode Support Vector Machine dan Cosine Similarity. *Sainteks*, *19*(1), 53.

https://doi.org/10.30595/sainteks.v19i1.13423
Yasni, L., Subroto, I. M. I., & Haviana, S. F. C. (2018). Implementasi Cosine Similarity Matching Dalam Penentuan Dosen Pembimbing Tugas Akhir. *Transmisi*, *20*(1), 22. https://doi.org/10.14710/transmisi.20.1.22-28
Zhang, X., Wu, J., He, Z., Liu, X., & Su, Y. (2018). Medical exam question answering with large-scale reading comprehension. *32nd AAAI Conference on Artificial Intelligence, AAAI 2018*, 5706–5713. https://doi.org/10.1609/aaai.v32i1.11970