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Towards Building a Chatbot-Based First Aid Service in Arabic Language

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ABSTRACT

In this paper, we introduce a modern standard Arabic (MSA) conversational AI in the field of first aid to assist anyone facing an emergency case. The proposed chatbot - based model not only provide adequate medical assistance, but also engage in empathetic interactions with users. Due to the lack of a reliable dataset that fits our purpose, we collect and construct a dataset of 374 records covering 55 first aid topic. Our chatbot architecture relies fine tuning pretrained language models in its intent classification and employs textual similarity to match user queries to records from the dataset. We evaluate the proposed model based using both a quantitative approach, through performance metrics of different modules, and a qualitative approach using a questionnaire.

1. Introduction

Conversational AI has emerged as a critical technology in the healthcare industry, revolutionizing how patients interact with medical services and empowering healthcare providers to deliver personalized and accessible care. By integrating natural language processing (NLP) and machine learning techniques, conversational AI enables healthcare chatbots and virtual assistants to engage in human-like conversations with users, efficiently addressing their medical inquiries, providing relevant health information, and even offering mental health support. Conversational AI holds the potential to extend medical services to remote or underserved populations, improve patient adherence to treatment plans, and assist in early detection and management of health conditions [1,2].

In the modern digital era, a first aid chatbot is an invaluable resource because it plays a significant part in providing prompt and accurate information during emergency medical situations. This ground-breaking technology combines the accessibility and convenience of chat-based interfaces with in-depth medical expertise, enabling users to get help immediately when dealing with accidents or other health-related occurrences [3]. A first aid chatbot that can provide instructions for fundamental life-saving measures enables people to act right now while waiting for expert medical assistance. These chatbots can also provide assurance, address frequent worries, and lessen panic or

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anxiety in tense circumstances [4]. It was reported that more than 50% of the injuries leading to death could have been prevented if there had been an immediate medical intervention. First-aid chatbots have the ability to save lives and improve the general safety of those in need by offering trustworthy information and help [5].

On the other hand, medical emergencies are often distressing and emotionally challenging experiences for patients and their loved ones. Empathy support, delivered by first responders or even through chatbots and virtual assistants, offers an understanding response to patients' emotional needs during critical situations. Empathetic interactions during medical emergencies not only provide emotional comfort but also contribute to more accurate information gathering, as patients are more likely to share critical details about their condition when they feel heard and supported. Research has shown that empathetic care positively impacts patient satisfaction, adherence to treatment, and overall recovery rates as it helps alleviate patients' anxiety, fear, and stress [6]. While many medical chatbots focus on providing accurate healthcare support, we believe that integrating empathy support as a part of emergency medical care can significantly improve patient experiences.

This paper proposes a first-aid chatbot system; our primary objective was to create a versatile and reliable tool capable of providing users with first aid and medical information in the Arabic language, especially during emergencies. We aspired to establish a comprehensive knowledge base that users could access whenever they needed urgent medical support. Moreover, we set out to craft a chatbot that delivered accurate information and exhibited a human-like conversational style. We aimed to imbue the chatbot with empathetic behaviour, ensuring that it interacted with users in a compassionate and understanding manner, be it during casual chit-chat or standard conversations. By fostering a friendly interaction atmosphere, we sought to make users feel comfortable seeking assistance from the chatbot. Building such a chatbot demanded a multidisciplinary approach involving multiple NLP techniques. We embarked on endeavours ranging from developing our corpus to finetuning user inputs using state-of-the-art language models. This comprehensive exploration of NLP domains significantly contributed to the chatbot's efficacy and versatility, allowing it to meet the diverse needs of users seeking prompt medical guidance.

The remainder of the paper is organized as follows: First, we review the related works regarding medical chatbots. Next, we explain our approach for creating the dataset and the underlying NLP pipeline. Then, we evaluate our work and demonstrate our results. Finally, in 5, we summarise our research and give some future research directions.

2. Literature Survey

Recent years have seen an increase in the development of chatbots with the advances in smartphone capabilities, machine learning, and natural language processing. The same applies to chatbots in the healthcare domain due to the increasing demand for accessible and personalized healthcare services. Among the oldest and most popular healthcare chatbots is Eliza [7], a bot built for the mental health domain that simulates a psychotherapist's conversation.

In the context of first aid, few research has exploited the use of chatbots to manage or assist users during an emergency. Ouerhani *et al.,* [8] introduced SPeCECA, an intelligent pervasive chatbot for emergency case assistance based on cloud computing. Their model uses conditional random field (CRF) to extract entities from user input using word embeddings and employs a Support Vector Machines (SVM) classifier to classify intents. The chatbot has access to a manually constructed knowledge base with pre-defined emergency case scenarios.

With the outbreak of COVID-19, there was a rise in the development of chatbots that support patients during the pandemic. Many chatbots were developed questions related to the COVID-19 emergencies. Most of them operated by recognizing keywords, patterns, and question-answer pairs and collected data from renowned available resources such as WHO or CDC [9-11]. Moreover, some developed bots gathered user information, such as medical history and demographics, to better assess their infection severity [12,13]. In [14], the authors not only provide physical assistance in emergency COVID-19 but also employ NLP to give psychological assistance through sentiment analysis systems. In 2022, Rodriguez *et al.,* [15] conducted a qualitative analysis among nursing students using SafeBot, a decision tree-based conversational agent. The chatbot was designed as a web chat that provided a poisoning emergency scenario for students where they had to offer in-depth responses about the topic, and the bot compared them to gold standard answers from its knowledge base.

Few research has been conducted on conversational AI in the Arabic language in the healthcare domain. Wael *et al.,* built [16] an application that serves as an Arabic healthcare assistant in the field of paediatrics that supports various Arabic dialects, including Egyptian. The user employed different models such as logistic regression TF-IDF, Doc2vec, and Bert bidirectional transformers (BERT) models. Their model consisted of four main steps: data collection, data preprocessing, data extraction, and training. Their findings show that the BERT model outperforms other approaches with a clear margin.

Similarly, Fadhil *et al.,* introduced OlloBot, an Arabic conversational agent that supports patients with the care process [17]. It helps the doctors monitor their patients by tracking their physical activities, logging daily meals, giving medical tips, and offering mental support to patients. OlloBot's infrastructure is based on IBM Watson Conversation cloud service as it supports the Arabic language. The bot highlights patterns in user input and matches them with the pre-defined intents. The system is implemented with a Node.js backend. The authors use qualitative analysis to evaluate their proposed system by formulating a questionnaire and measuring users' ratings on their perception of the usefulness and ease of use of OlloBot.

3. Methodology

3.1 Dataset

The Arabic language faces many limitations compared to other languages, such as English, in developing conversational artificial intelligence (AI) systems due to the lack of task-oriented dialogue datasets [18]. Arabic poses unique challenges due to the language's characteristics and complexities, such as morphology, orthographic variations, ambiguity, and multiple dialects, which make it a more challenging language for chatbot development [19].

Among the few available Arabic datasets for medical conversational AI is the dataset provided by the SemEval-2016 [20] competition, precisely the Community Question Answering task, which aimed to develop systems capable of answering new questions in a community forum. While the English subtasks focused on measuring question similarity and external source analysis, the Arabic sub-task involved reranking correct answers for new questions. The Arabic dataset used in SemEval-2016 was sourced from three popular Arabic medical websites: WebTeb, Al-Tibbi, and the medical corner of Islamweb. The dataset, CQA-MD, consisted of 1,531 question-answer (QA) pairs.

We performed an in-depth examination of the CQA-MD corpus and found that the dataset was deemed unsuitable for our chatbot. This was due to many reasons; firstly, since the questions and answers were user-generated, they contained unfiltered content commonly found in online Arabic posts. This included the customary practice of users starting their posts with greetings or salutations, which is a common way for Arabic speakers to establish a friendly tone in their communication. While this may be appropriate for online forums, it posed difficulties regarding data cleaning and standardization for our chatbot model. Additionally, the most repeated words in the dataset primarily related to pregnancy, headaches, and pre-birth topics, which deviated significantly from our focus on first aid and emergency questions. Moreover, the questions were highly specific and lengthy, and the answers provided by doctors exhibited similar characteristics. Another limitation was the lack of tags or topics associated with each record, making it challenging to determine the specific focus of each question-answer pair.

The above reasons lead us to construct our dataset for the medical chatbot; such an approach can be valuable to ensure relevance and accuracy in the emergency context. A critical factor in creating the dataset was finding reliable and trusted sources such as medical literature, medical websites, or expert opinions and ensuring that the data covers a wide range of first aid conditions, symptoms, and treatments. The source also needed to be secure and adhere to ethical guidelines when collecting and handling medical data, such as anonymizing and de-identifying sensitive or personally identifiable information. Another critical factor was the data format and labels; the collected data had to provide context categorization, including intents, entities, labels, and appropriate responses.

We scrapped first aid information from Mayo Clinic's first aid [21] knowledge base. The Mayo Clinic is a renowned nonprofit medical practice and research group that employs a large team of medical experts, including physicians, nurses, and researchers. An advantage of using Mayo Clinic as a source is its rigorous review process. Medical experts regularly review and update their content to ensure accuracy and alignment with current medical guidelines. They have a long history of providing evidence-based and trustworthy medical information to the public. The webpage was divided into 55 topics, each addressing a specific emergency situation such as chest pain, choking, fainting, and more. We extracted questions and answers from the comprehensive descriptions provided for each topic. We translated the questions and answers to make the data usable for our chatbot model. The resulting dataset comprised 374 records, each consisting of a question, answer, and topic. Although the number of records in this dataset was limited, however to our knowledge, it is the first of its kind to specifically focus on first aid question-answer pairs for Arabic conversational AI. By employing this dataset, we ensured that our chatbot would possess a relevant and targeted knowledge base for assisting users in emergencies. The dataset collected is publicly available in the project GitHub repository (https://github.com/peternadykamal/mayoclinic-firstAid_QA-Dataset.git). Example records of the dataset are provided in Table 1.

3.2 Chatbot Model

Our chatbot is based on pre-trained language models trained on vast amounts of text data, including books, articles, websites, and other text-based materials. The training process involves learning the statistical patterns and linguistic structures present in the data. Language models play a crucial role in building medical chatbots by enabling natural language understanding and generation capabilities. One critical importance of language models in medical chatbot development is their ability to understand and interpret user queries, allowing the chatbot to accurately extract relevant information from user inputs. They employ techniques such as named entity recognition and intent classification to identify medical terms, symptoms, or specific requests to enable effective communication between users and chatbots [22,23]. We also considered the need for the proposed chatbot to be effective and respond in a timely manner, and hence, we focused on pre-trained models that were relatively small in size. This allowed us to achieve our desired functionality without compromising on performance.

Table 1
Sample of the collected dataset

Tag/Intent	Question	Answer
cardiopulmonary resuscitation	ما هو ترتيب الخطوات لتنفيذ الإنعاش القلبي الرئوي؟	تتستخدم جمعية القلب الأمريكية الحروف للمساعدة على تذكُّر ترتيب أداء خطوات الإنعاش القلبي الرئوي. C: يرمز إلى الضغطات A: يرمز إلى مجرى الهواء B: يرمز إلى التنفس.
	ماذا يجب أن تفعل بعد إعطاء أنفاس الإنقاذ أثناء الإنعاش القلبي الرئوي؟	استئناف ضغط الصدر لاستعادة تدفق الدم.
Choking	ما هي خطوات الإسعافات الأولية لشخص الاختناق؟	يوصي الصليب الأحمر الأمريكي بالخطوات التالية :1 (إعطاء خمس ضربات خلفية .2 (إعطاء خمسة دفعات البطن .3 (البديل بين خمس ضربات وخمسة دفعات حتى يتم خلع الانسداد.
	كيف تقوم بدفعات بطنية على شخص آخر؟	.لإعطاء دفعات البطن لشخص آخر ، والوقوف وراء الشخص للطفل ، اركع وراء .ضع قدمًا واحدة أمام الآخر قليلاً لتحقيق التوازن .لف ذراعيك حول الخصر .تلميح الشخص إلى الأمام قليلا. جعل قبضة بيد واحدة .ضعها فوق سرة الشخص مباشرة .امسك القبضة باليد الأخرى .اضغط على المعدة ، وتسمى أيضًا البطن ، مع قوة دفع سريعة تصاعدية - كما لو كنت تحاول رفع الشخص. كما لو كان الضغط مطلوبًا.

Our model relied on libraries like NumPy, TensorFlow, and PyTorch to reduce unnecessary dependencies and ensure more control over the implementation compared to large frameworks such as the Azure Bot Framework. Alongside the primary objective of providing first aid information, we recognized the importance of creating a friendly and human-like chatbot experience. We aimed to include chit-chat functionality to engage users and ensure empathetic interactions during conversations.

Our proposed NLP chatbot framework is illustrated in Figure 1 and consists of intent classification, similarity module, and conversational and empathy chatting module.

3.2.1 Intent classification

The main goal of this step is to identify the underlying intent or purpose that a user wants to convey based on their input and map it to one of the topics available in the collected dataset. This is a fundamental component in conversational agents, chatbots, or virtual assistants. Our intent classification relies on a transformer-based model, more specifically, a BERT family member that uses a bidirectional training approach, employing masked language modelling and next-sentence prediction objectives. We take advantage of the AraBERTv2 [24] model developed by the Arab NLP community, with the AUB (American University of Beirut) MindLab playing a significant role in its creation. AraBERTv2 has been released as an open-source model on the Hugging Face model hub, making it accessible in various Arabic NLP applications. AraBERTv2 is designed to comprehend and generate meaningful representations of the Arabic language. It has undergone pre-training on a large corpus of Arabic text, enabling it to capture the nuances and intricacies of the Arabic language. We further finetuned the model on our dataset, allowing the pre-trained AraBERT model to be tailored to the medical domain. The model can learn to better understand and generate relevant responses within the first aid context by training on the collected dataset, which contains domain-specific terminology and concepts. The output of intent classification is a class representing the predicted topic of the user input. The subsequent phase further uses this predicted intent to trigger the appropriate actions or responses within the classified intent.

3.2.2 Similarity module

The main idea behind this module is to compare the user input with stored records from the constructed dataset to identify and retrieve matching relevant information. To achieve this, we employ sentence embeddings which are numerical representations that capture the semantic meaning or contextual information of a sentence and relationships between words. Instead of relying on traditional embeddings, such as Word2Vec or GloVe, to represent individual words and combine these representations in a continuous vector space, we opted for a contextualized sentence embedding model that captures the sentence's overall semantic meaning and contextual information.

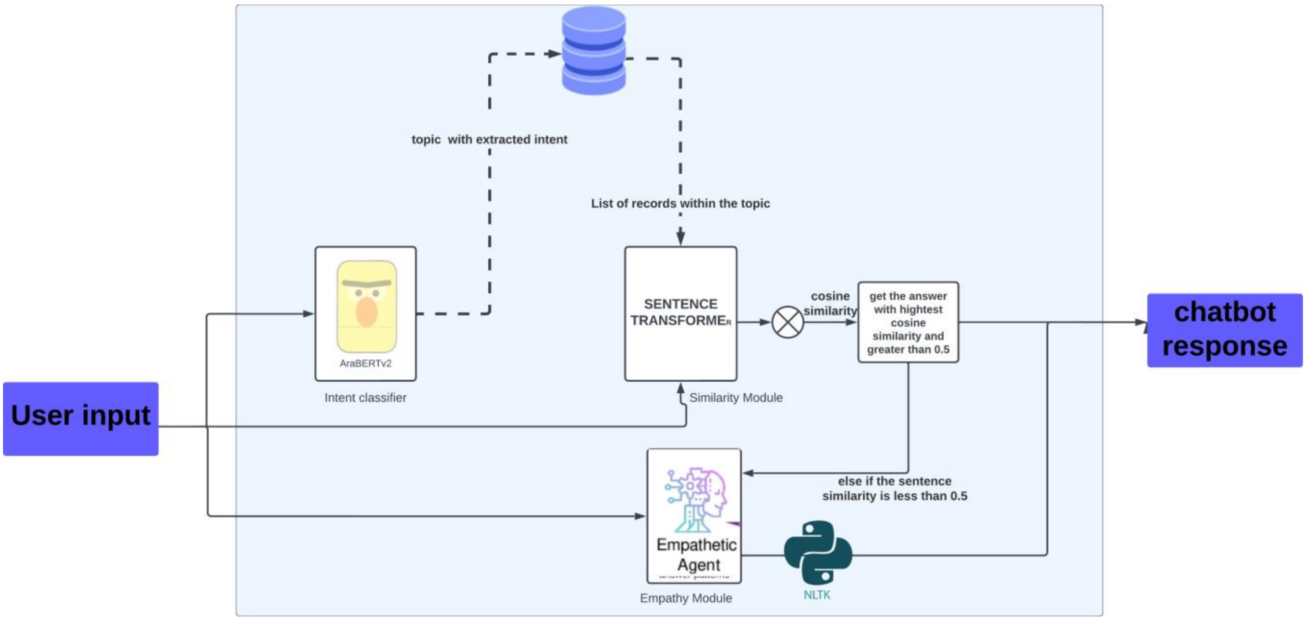

Fig. 1. Proposed chatbot architecture

The similarity module consists of the sn-xlm-roberta-base-snli-mnli-anli-xnli model, which is a similarity model designed for zero-shot and few-shot text classification. This model utilizes the xlm-roberta-base base model and is part of the sentence-transformers library. It has been trained on multiple datasets, including SNLI, MNLI, ANLI, and XNLI. The purpose of this model is to map sentences and paragraphs to a 768-dimensional dense vector space. The model is based on the xlm-roberta base model [25] designed explicitly for cross-lingual tasks. It has undergone pre-training on a large corpus of multilingual data, enabling it to handle multiple languages, including Arabic. The process of converting text to a sentence embedding involves several steps:

i. Tokenization: The input text is divided into individual tokens using AutoTokenizer provided by the transformer’s library. Tokens can represent words, sub words, or characters.
ii. Encoding: The tokens are encoded into numerical representations by mapping each token to its corresponding token ID and incorporating special tokens for classification or sentence pairing.
iii. Model Processing: The encoded inputs are fed into multiple transformer layers that apply self-attention mechanisms and feed-forward neural networks to capture dependencies and relationships between tokens.

iv. Pooling: To aggregate the hidden states of the model into a single fixed-length vector representation for a given input sequence. To obtain a sentence-level embedding, mean pooling calculates the average of all token representations within the sequence by summing up the individual token representations along the sequence dimension. Then it divides the sum by the total number of tokens.
v. Similarity Computation: Finally, sentence embeddings are used to compute the similarity between pairs of sentences. This is achieved using distance metrics like cosine similarity.

With the similarity module, we process the user input to obtain its vector representation and compare it with the vectorized values of the remaining questions within the selected intent category. The record with the highest similarity with the user input is chosen, and the corresponding answer for that question is returned as the response.

3.2.3 Empathy module

This module handles any user input that is not medically related; in other words, it offers a comforting message to the users in need. To be able to differentiate for the chit-chat and empathy aspect of our chatbot, we adopted an Arabic empathic language model trained on a large-scale modern standard Arabic empathy dataset that relies on a special encoder-decoder composed of a Long Short-Term Memory (LSTM) Sequence-to-Sequence (Seq2Seq) with Attention [26]. This language generation model is based on the BERT architecture and is specifically designed to generate empathetic responses in Modern Standard Arabic (MSA). By leveraging the power of BERT, this model can generate contextually appropriate and compassionate replies to user inputs, fostering a more engaging and supportive conversational experience.

During the pipeline's second phase, If the similarity score surpasses a specified threshold (0.5), we assume the user input was related to the context of first aid and hence return the corresponding answer from the dataset with the highest similarity score. Otherwise, if the similarity score is below the threshold, we generate a response using the chit-chat model. Additionally, we incorporated pre-defined answers using NLTK library, which enables us to tailor the chatbot's response for specific queries or statements (e.g., greetings or specifying the abilities of the first aid chatbot).

4. Results

In our research, we apply both quantitative and qualitative analyses, including evaluation metrics and user questionnaires, as a comprehensive approach to evaluate our proposed model. This combined approach allows us to assess the performance and user experience from different perspectives. In the quantitative analysis, we aim to measure the performance of both the intent classification and overall similarity modules. The validation loss for the intent classification was 1.5, while the accuracy reached 74.34% with learning rate 1e-5, batch size of 32 and 60 epochs. It is worth noting that for the similarity module, the test set was a subset of the original dataset encompassing different intents. When user queries were identical to records in the dataset, the cosine similarity was 1.0. It decreased when the question was paraphrasing one of the records with an average cosine similarity of 0.88.

Similar to [17], we follow the Technology Acceptance Model (TAM) developed by Fred Davis in 1989 and aims to explain and predict user acceptance and adoption of new technology. According to the TAM model, the behavioural intention to use technology is influenced by two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the extent to which a user believes using the technology will enhance their job performance or make their life easier.

Perceived ease of use refers to the user's perception of how easy it is to learn and use the technology. Our application of the TAM model was conducted through an online survey, as it allowed us to reach a wider audience and collect responses conveniently and efficiently. The users were provided with a link to the web app running our proposed chatbot, where users were freely engaging with the bot using modern standard Arabic. In total, we received 84 responses to the questionnaire; the gender distribution among participants was 46% females and 54% males. The participants were grouped according to age ranges: 18-24, 25-34, 35-44, and 45-54 and their distribution was 69%, 19%, 6%, and 6% respectively. Our overall analysis of the questionnaire led to the conclusion that users were satisfied with the performance of our chatbot. When answering the question "I am satisfied with the overall user experience", 85.6% responded with Strongly agree, 10.8% agreed, and 3.6% responded with disagree or strongly disagree. Almost 91.6% of the participants believed the chatbot would be useful for older people, while 3.6% were neutral and 4.8% disagreed. When asked about the helpfulness of first aid information provided by the chatbot, 81.9% and 12% strongly agreed and agreed that the information was helpful, while 3.6% were neutral and only 2.4 disagreed.

5. Conclusions

In this work we propose an Arabic -based chatbot that enables users to receive real-time first aid prompts and guidance and provides immediate assistance and support until professional responders arrive on the scene. The chatbot is equipped with a wealth of medical knowledge; it can provide step-by-step instructions for various emergencies, ensuring that users have access to potentially life-saving information at their fingertips. Moreover, our proposed model was able to effectively handle both medically related queries focused on first aid as well as engage in empathetic chit-chat interactions when the user's input was non-medical. Our chatbot provided users with accurate and contextually appropriate emergency responses by combining intent classification, similarity modelling, and empathy functionality. The proposed model shows the potential of conversational AI in the field of first aid for Arabic speaking populations, future work s would extend the current model to include more emergency topics and provide support for dialectal Arabic instead of modern standard Arabic. It is also recommended to explore more machine learning techniques for the similarity models to increase the similarity score.

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