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Enhancing Medical–Bot Using Natural Language Processing

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***Abstract*:** Automated medical chatbots are designed to have technology-driven discussions with the goal of lowering healthcare expenses and enhancing access to health-care services and information. These chatbots interact with patients and offer individualised diagnosis based on their concerns and characteristics. By a conversational method, the system can reliably recognise symptoms and forecast a patient's issue. This suggests that by employing natural language processing, a successful oral language medical chatbot may be attainable (NLP).

Index Terms **- Natural Language Processing(NLP), Conversational approach, Diagnosed symptoms, predicts problem.**

I. INTRODUCTION

An computerized diagnostic chatbots is a software application that communicates with patients and provides medical support using natural language. It is able to process massive volumes of data from the internet in order to produce reliable & methodical data based just on user's requirements. Chatbots are utilized in a variety of applications, such as customer service, virtual help, online bookings, and online training.

Workload of healthcare providers can sometimes make it difficult to provide the best service to their patients. To solve this issue, medical offices can employ a chatbot to provide 24-hour availability and answer regular enquiries. The chatbot can diagnose patients and detect their diseases or illnesses based on the symptoms provided by the individual. This not only improves access to medical services but can also reduce healthcare costs.

By communicating with users in a human-like manner, a medical chatbot can enhance the work of healthcare professionals and improve their performance. Conversational data offered by the user during interaction serves as the foundation of the system, which focuses on potential problems and early signs. The chatbot moves the conversation forward by asking questions and reviewing diseases based on the user's input data.When an illness is found, the chatbot analyses its severity and respond promptly by proposing treatments and prevention remedies or may recommends to consult doctor. The medical knowledge base used by the chatbot is created, validated, and maintained in accordance with strict guidelines, and automated regression testing can be used to ensure consistency.

Medical questions are often verbose and contain specialized medical concepts that require language resources for effective processing. This makes language resources crucial for effective medical chatbots. By leveraging these resources and machine learning techniques, chatbots can provide accurate and efficient medical assistance to patients, improving access to healthcare services and reducing healthcare costs.

Chatbots have been more popular in a variety of areas, including healthcare, in recent years. Chatbots are computer programmes that replicate human-to-human interaction. They have the potential to cut healthcare expenses while also improving access to medical care and information. Chatbots may engage patients in chats about their medical questions and concerns through natural language processing (NLP) and ml algorithms, and present them with tailored clinical grounds upon individual symptoms and profile.

Chatbots can be very effective in supporting healthcare practitioners who confront enormous workload and limited resources in the medical industry.By providing 24/7 availability, chatbots can deal with routine inquiries, provide preliminary diagnoses, and even connect patients with healthcare professionals if necessary. With so much available information on the web, chatbots can provide precise and systematic data according on a user's demand and requirement.

This technology has the potential to revolutionize healthcare by providing patients with accessible and personalized medical care, while also easing the burden on healthcare providers. However, it is important to ensure that chatbots are developed and implemented with strict guidelines and testing procedures to ensure their effectiveness and reliability.

Chatbots in healthcare have the potential to provide many benefits beyond reducing the workload on healthcare providers. For example, they can improve access to medical information and services for people in remote or underserved areas. They can also help patients save time and money by providing quick and accurate diagnoses without the need for an in-person visit to a healthcare provider. In addition, chatbots can offer a level of anonymity and confidentiality that some patients may prefer.

To develop an effective medical chatbot, it is crucial to use a conversational approach that can accurately identify symptoms and understand the nuances of human language. This requires a sophisticated NLP system that can process complex medical terminology and understand the context and intent behind patient queries. Furthermore, the chatbot must be trained on a vast amount of medical data to ensure its accuracy and reliability.

This includes developing a robust knowledge base of medical information, as well as incorporating real-world patient data to improve the chatbot's ability to diagnose and treat illnesses. Despite the potential advantages of chatbot in healthcare, they should not be viewed as a replacement for real healthcare personnel. Chatbots can offer preliminary diagnostics as well as basic medical advice,but they cannot replace the expertise and personalized care of a trained healthcare professional. However, chatbots can be a valuable tool in improving access to medical care and assisting healthcare providers in delivering more efficient and effective care to their patients.The main pros of medical chatbots is their capability to provide personalized and individualized care to patients. By engaging in conversation with patients and asking targeted questions, chatbots can gather important information about a patient's symptoms, medical history, and lifestyle factors. This information can then be used to provide tailored recommendations for treatment and follow-up care.

Medical chatbots can also play a role in promoting public health by providing educational resources and encouraging healthy behaviors. For example, a chatbot could provide information on preventive measures such as vaccines, healthy diet and exercise habits, and regular health screenings. By engaging patients in conversation and providing targeted recommendations, chatbots can help patients make more informed decisions about their health. Another benefit of medical chatbots is their potential to reduce healthcare costs. By providing preliminary diagnoses and advice, chatbots can help patients avoid unnecessary visits to emergency rooms or urgent care centers. This can result in significant cost savings for patients and healthcare providers alike. However, it is important to note that medical chatbots must be designed and implemented carefully to ensure their effectiveness and safety. They must be trained on accurate and reliable medical information, and must be regularly updated to reflect new research and changes in medical best practices. In addition, chatbots must be designed to handle sensitive medical information with strict privacy and security protocols. Overall, medical chatbots have the potential to revolutionize healthcare by improving access to medical information and services, providing personalized care to patients, promoting healthy behaviours, and reducing healthcare costs. As technology continues to advance and NLP systems become more sophisticated, the potential for chatbots in healthcare is only set to grow.

II. Related Work

To handle medical inquiries, medical information retrieving (MIR) systems have traditionally depended on natural language (NLP) approaches and healthcare lexical resources [13], [11], [12]. Zhu and Carterette presented a query kits approach to select cohorts required for clinical studies [14]. This method weights medical phrases in particular searches based on factors such as query duration, frequency of ideas, and wide vs narrow concepts.

The authors utilised his technique [15] to identify medical ideas. The National Library of Medicine (NLM) created this medical NLP tool that maps biology texts to the concepts of the Unified Medical Language System UMLS) Metacisaurus. Cross-validation shows that the authors' weighting technique beats the fixed weighted approach for various rating metrics. The improvement, however, was not statically important. Martinez and co. They presented a strategy for automatically extending medical searches based on UMLS ideas and linkages [16].The authors used the TREC Medical File Track to illustrate the usefulness of the suggested technique and found that it exceeded the benchmarking method both on 2011 and 2012 dataset. Proven. I believe, however, that depending simply on the UMLS body of knowledge is insufficient [17]. The authors of a recent paper developed an intelligent medical query expansion approach that begins with the identification of key terms utilised in matched and retrieval procedures [12].

Nevertheless, this strategy overlooks synonyms and lexically related phrases for each key term and fails to evaluate the semantic links between key terms. Stanton and co. We presented machine learning with supervision as a method for associating query terms with relevant medical ideas [18]. Nevertheless, their suggested search strategy excluded all non-medical query words, and the medical training resources employed did not enable the user to explore the concepts indicated in his inquiry due to worries regarding insufficient coverage in the subject. Several of the Chung and Chun presented a basic principle query expansion model based on certain query notions [19].

Unfortunately, the proposed approach only significantly improved results quality. This is due to the authors' disregard for stopwords and complex words in medical papers and query strings, as well as their restriction of the extension's scope to dumping lookup records for summary reports. Those named Goriot et al. We concentrated on employing resources for query rebuilding and employed a proto resources and utilize [20].

III. RESEARCH METHODOLOGY

We have developed a user-friendly method for effectively interacting with medical chatbots through straightforward English conversations. Our approach involves utilizing Natural Language Processing (NLP) to collect user input by conversing about symptoms and their duration. For predicting illnesses, we have implemented both Decision Tree Classifier and SVM models. The SVM model works based on the Structural Risk Minimization Principle and is particularly well-suited for handling text data and chatbots due to its ability to handle high-dimensional input spaces, linearly separable data, and sparse matrices. It is widely used for text classification. To evaluate the accuracy of the model, we employ cross-validation, which assesses the efficiency of the model that focuses on test and training data. Furthermore, accuracy and recall measurements are utilised to assess the model's efficacy.

3.1Data Collection and Preprocessing

The first step in building a medical chatbot will be to collect a large dataset of various attributes relevant to our desired outcomes and answers related to medical conditions, symptoms, treatments, and general health information. This data will then be pre-processed in order to eliminate irrelevant information, rectify any mistakes, and convert it to Csv file format for train machine learning algorithms.

3.2 Data and Sources of Data

For this study primary and secondary data has been collected, From the website of Kaggle Datasets for the the disease corresponding to its symptoms and another dataset containing the precautions related to disease and an another dataset related to description of the diseases.

3.3 Training Machine Learning Algorithms

Once the dataset has been pre-processed, the Decision Tree Classifier and SVM algorithms will be trained on the data.
The Decision Tree Classifier will be trained to classify questions into different categories such as symptoms, treatments, and general health information, while the SVM algorithm will be used to provide accurate answers to the questions.

3.4 Integration of NLP Modules models

In order to enhance the conversation with the medical chatbot, NLP modules Named Entity Recognition, Sentiment Analysis, and Part-of-Speech tagging will be integrated into the system. These modules will help the chatbot to understand the context of the conversation and respond accordingly.
Name Entity Extraction (NER): NER is a technique for identifying and extracting medical-related items from text, such as illnesses, symptoms, and therapies.
Portion Segmentation (POS): POS aids in determining the function of the each word in a phrase, including a word, verb, adjective, and so on. That data can be utilized to determine the sort of inquiry getting asked and to respond appropriately.
Sentiment Classification: Sentiment analysis is used to determine if the emotional tone of a text is positive, negative, or neutral. This allows our medical chatbots to identify when a user is anxious or frustrated and respond accordingly. NLP is critical in deciding how the chatbot will recognize and comprehend user input for this medical chatbot. Engagement and feedback analysis, Turing test variants, and purposefully difficult input can all be used to evaluate the NLP system's efficiency.

IV. RESULTS AND DISCUSSION

4.1 Testing and Evaluation

This medical chatbot will be tested and evaluated on a separate dataset to measure its accuracy and effectiveness in providing accurate answers to medical-related questions. The performance of the chatbot will be evaluated based on metrics as precision is 96%, recall of 97% , and F1 score of 97.

Figures

Performance Score :

The performance of the chatbot will be evaluated based on metrics such as precision , recall, and F1 score.

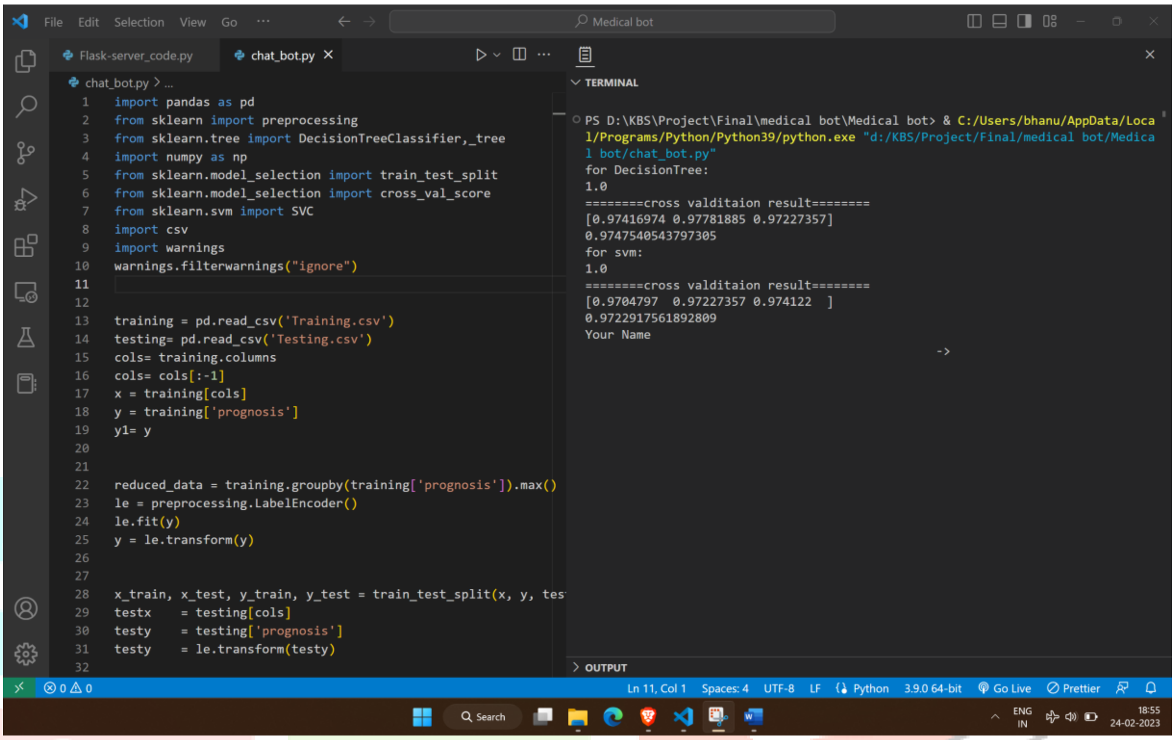

Fig 1 Medical chat-bot performance scores

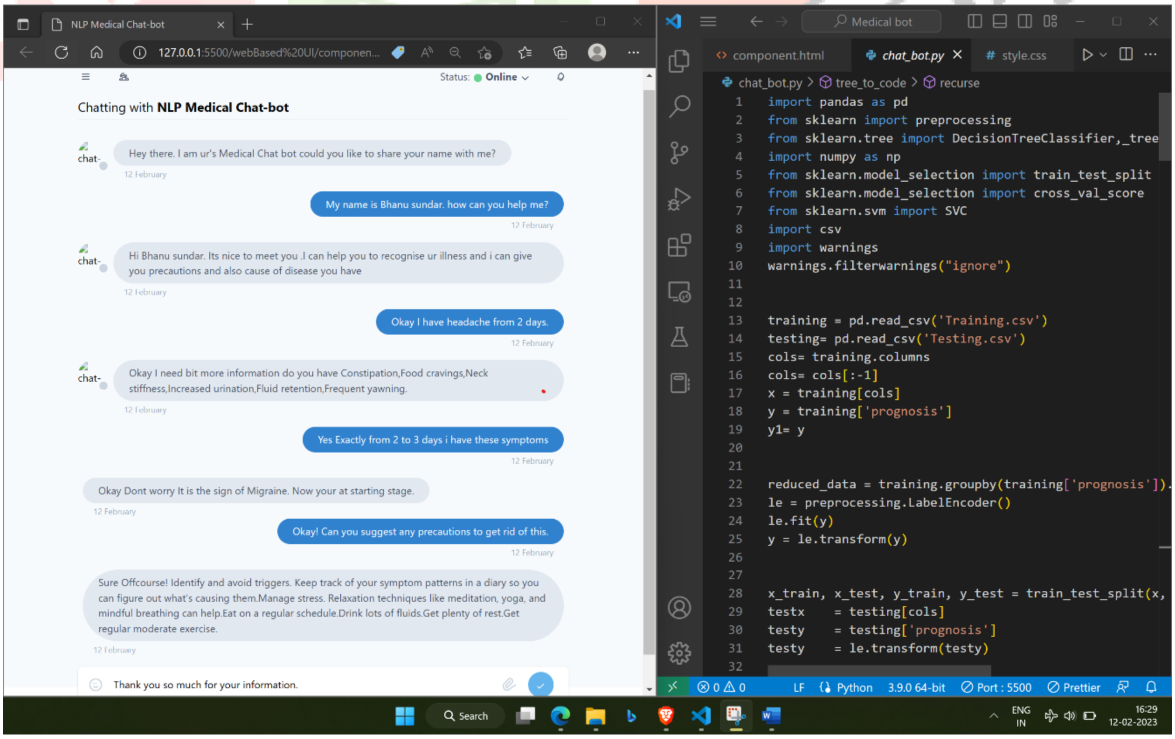

Fig 1 Medical chat-bot User Interface

V. CONCLUSION & FUTURSCOPE

In the current work, we have provided a novel approach for an efficient Medical Chat bot with proposed methodology. In conclusion, medical chatbots are becoming increasingly popular in the healthcare industry as they provide patients with an easy and convenient way to access medical information and receive health advice. With the use of NLP techniques and ML models, these chatbots are capable of detecting symptoms and providing potential diagnoses, making it a valuable tool for triaging patients and reducing the burden on healthcare systems. It is crucial to highlight, however, that these chatbot should not be utilized in place of expert health assistance and consultations, but rather as a complement. Even farther development and research is required to increase their accuracy and dependability.

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