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Automated Conversation Chatbot for Multiple Languages for Hospitals

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Abstract: *Chatbots replicate human speech to provide applications a more user-friendly user interface or simply for fun. Artificial intelligence (AI) and natural language processing (NLP) are two cutting-edge technologies that may be used to enhance chatbots' ability to imitate more organic and genuine communication. As more and more mobile device users switch to a larger usage of texts and messaging, chatbots may be used to provide clients with multilingual advice and services. While some chatbots have been constructed in other languages, the majority only speak English these days, and very few are able to. If configured appropriately, multilingual chatbots may provide a digital communication alternative that transcends linguistic borders.*

Keywords: Chatbot, Artificial Intelligence ,AIML, NLP, DJANGO

I. INTRODUCTION

One of the main focal areas in the globe nowadays is the healthcare industry. People are becoming more and more vulnerable to lifestyle diseases. In this context, early disease diagnosis and treatment become crucial. Rural healthcare presents a significant challenge to the Indian healthcare system. This is a major impediment that faces the Government of India. According to the 2011 census, 68.8% of Indians reside in rural areas with few healthcare facilities and high rates of disease-related mortality. Rural residents of many Indian States must travel great distances in order to receive appropriate medical diagnosis and treatment.

It can be difficult to find professional consultation, especially in rural areas. Rural residents are also concerned about affordability. As a result, many people put off seeking medical attention, which causes even treatable diseases and ailments to become life-threatening and raises mortality rates. Adopting healthcare chatbots is the solution. They provide initial assistance more affordably and on demand than one-on-one conversations. Doctors can use the healthcare chatbots to monitor their patients. The computer age is the age of artificial intelligence. Modern technologies are being developed to help people. Artificial intelligence-based chatbots are one example of these advancements (AI). An AI-based chatbot is a piece of software that primarily serves the purposes of simulating human communication and responding to user questions. The use of chatbots in consumers' daily lives is growing quickly as new businesses thrive using cutting-edge technology. They can be used for many things, including information retrieval, request routing, and customer service. The use of chatbots in the healthcare industry is one such example. The significance of chatbots in the healthcare industry has been covered by the paper's author. They have mentioned the fact that healthcare chatbots can be used for a variety of tasks, such as scheduling appointments, setting reminders, and taking medications.

According to the survey, research on healthcare chatbots has primarily focused on English or another specific language. In addition to English, the suggested solution supports several Indian languages. Along with disease prediction, the solution can respond to user queries using sentence similarity. It is unrealistic to expect a chatbot to provide a formal diagnosis. If the symptoms are given, it can be used to provide useful information. A predictive diagnosis can be made by the chatbot. This can aid in giving the initial response and in directing the person to a qualified healthcare professional. Doctors and patients can both use healthcare chatbots as their personal assistants. The answer is to adopt healthcare chatbots. People are increasingly using chatbots (also known as bots, smart bots, talk bots, interactive agents, conversational agents, or conversational entities) as a natural way to communicate for both practical (such as information gathering) and amusement reasons.

They affordably and promptly provide initial assistance through one-on-one conversations. Doctors can use the healthcare chatbots to keep an eye on their patients. The computer age is the age of artificial intelligence. Modern technologies are being created to benefit people. Artificial intelligence-based chatbots are one example of these developments (AI). An AI-based chatbot is a software application that is prima primarily used to simulate human conversations and provide answers to user-provided questions. With the use of cutting-edge technology, new businesses are thriving, and there are many healthcare facilities and high disease-related mortality rates. Rural residents of various Indian States must travel great distances in order to get appropriate medical diagnosis and treatment. There is a severe shortage of medical professionals in the healthcare sector. Physical consultations with medical specialists are time- and money-consuming.

According to the report, research on healthcare chatbots has been focused on English or another specific language. In addition to English, the suggested method covers other Indian languages. Along with illness prediction, the solution may respond to user inquiries using phrase similarity. It is unrealistic to expect a chatbot to provide a professional diagnosis. If the symptoms are given, it may be utilised to offer important information. A predicted diagnosis may be made by the chatbot. This may aid in giving the first answer and in directing the person to a qualified healthcare expert. Doctors and patients may both employ healthcare chatbots as their personal assistants.

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II. EXISTING ALGORITHM

Cross-lingual Cross-lingual adaptation teaches the relationships between languages and gets beyond the need for a lot of training data in the target languages (Wisniewski et al.,2014; Zhang et al., 2016). Many NLP tasks, including entity identification (Ni et al., 2017), conversation state monitoring (Chen et al., 2018), part-of-speech tagging (Wisniewski et al., 2014; Zhang et al., 2016; Kim et al., 2017), and dependency parsing, have been subjected to cross-lingual transfer learning techniques (Ahmad et al., 2019). In contrast, pre-trained cross-lingual language models to align various language representations were suggested by Lample and Conneau (2019) and Conneau et al. (2019), producing state-of-the-art outcomes in numerous cross-lingual classification tasks. The aforementioned tasks were primarily concerned with classification and sequence labelling; however, Chi et al. (2019) suggested pre-training an XNLG's encoder and decoder in order to perform cross-lingual generation tasks including question creation and abstractive summarization. Since it focuses on language generation, the latter is the most relevant to our objective; yet, cross-lingual conversation generation has not yet been examined. The aforementioned tasks mostly included classifying and labelling sequences, however Chi et al. (2019) suggested pre-training. Specifically, question generation and abstract summarization are cross-lingual generation tasks that need both the encoder and decoder of a sequence-to-sequencemodel (XNLG). In the current system, if a user types in one language, the translator translates it and provides results in that language, making it impossible for the person who requested the information to understand it.

III. PROPOSEDALGORITHM

The suggested system has an easy-to-use chat interface that allows users to connect with it. The user has the option of entering symptoms he is now experiencing or health-related questions. The Chabot will forecast a sickness or answer pertinent questions based on the user's input.

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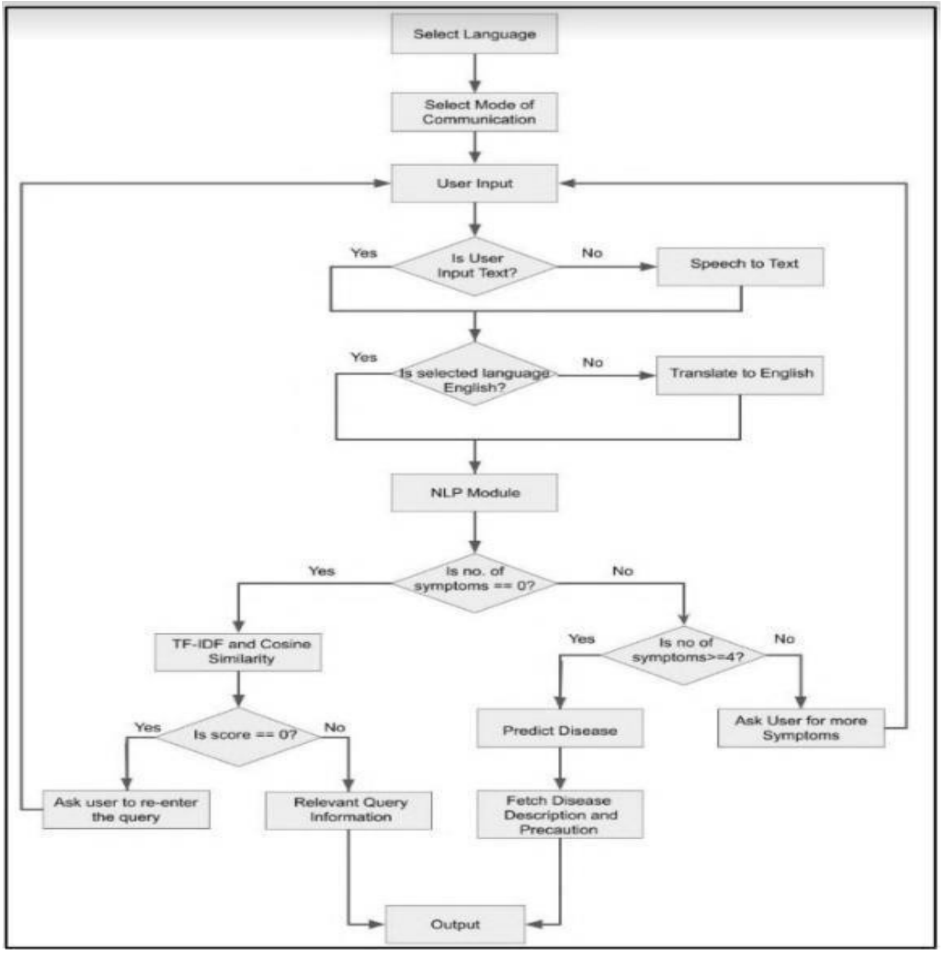

Figure 1 : Flow diagram for the proposed system

Advantages of proposed system

1. Increase customer engagement
2. Improve lead generation.
3. Reduce customer service costs
4. Meet customer expectations

IV. IMPLEMENTATION

The persona-chat dataset is extended by the planned Automated Conversation Chatbot for Multiple Languages for Hospitals dataset (Zhang et al., 2018; Dinan et al., 2019a). We specifically include Telugu, Tamil, English, Kannada, Malayalam, and Hindi to ConvAI2 (Dinan et al., 2019a). We divided the first validation set into a new validation set and test sets since the ConvAI2 test set is concealed. The training, validation, and test sets are first automatically translated utilising APIs (PapaGofor Korean, Google Translate for other languages). The machine-translated conversations and personal phrases in the validation set and test set were revised by native speaker annotators with at least a bachelor's degree and fluency in English for each language. Despite the cultural differences across languages, the primary objective of human annotation is to guarantee that the edited dialogues are coherent and fluent in the target language. Because of this, annotators are not limited to the conversations. Additionally, they are free to add their own language and personal lines. The annotated conversations might stray from the original translation while maintaining the continuity of the character and discussion.

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Figure 2: different languages in chat bot

The user's preferred language of communication must first be chosen. The system now supports three of the following languages: English, Hindi, Tamil, Telugu, and Malayalam. If the user is conversing by voice, the system will first translate the user's input into text. The speech-to-text translation was carried out using the Python-based Speech Recognition module.

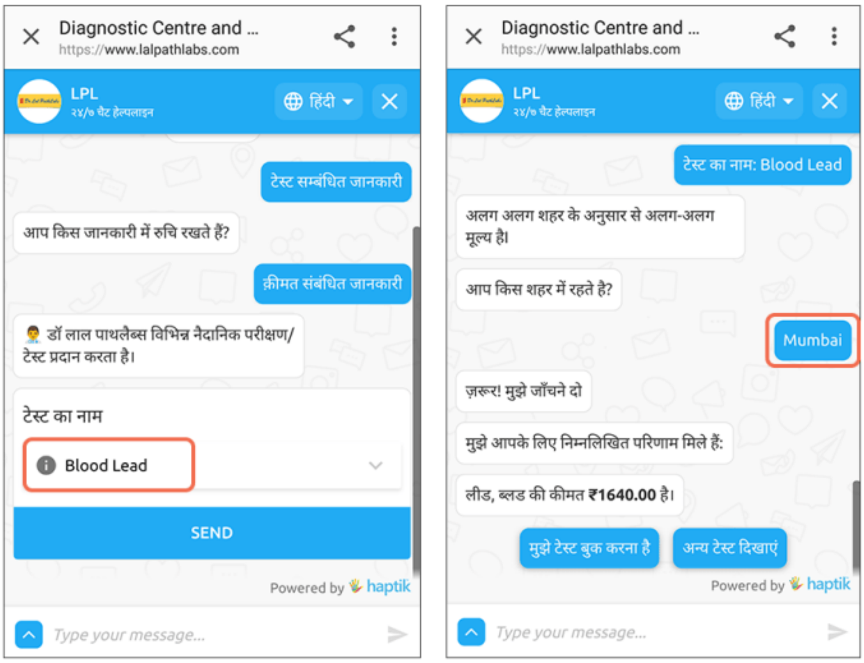

Figure 3: chat bot in Hindi language

Using translation APIs to human-annotate the conversations offers many benefits above just gathering fresh personal words and dialogues in each language. It does this in two ways. First, it makes data distribution across languages more similar (Conneau et al., 2018), making it easier to assess how well the system works across different languages. Second, improving the data construction efficiency by revising the machine-translated dialogues based on the original English dialogue. Third, it uses the carefully crafted English persona conversations as a model to ensure dialogue quality without the need to train a new pool of workers to produce fresh samples (Conneau et al., 2018). However, it is expensive to translate the entire training set—130Kutterances—by hand into six different languages. So as to enhance the quality of the automatically translated training set, we suggest an iterative approach. We first choose 200 dialogues (roughly 2600 utterances) from the training set in each language, and we assign human annotators to list any common translation errors. For instance, common English slang words like "cool," "I see," and "lol" are typically translated literally. Then, using the simplest ring matching, we revise all of the incorrect translations in the training set, returning a revision log that contains all of the revised utterances. Installing a Python module is necessary in order to create the chatbot's virtual environment. Oncethishasbeendone,youcanproceedwithcreatingthestructureforthechatbot. Start by outlining the data pipeline through which intent classification and entity extraction will take place. Rasare suggests using the supervised embeddings pipeline, but there are several others that can be used as well.

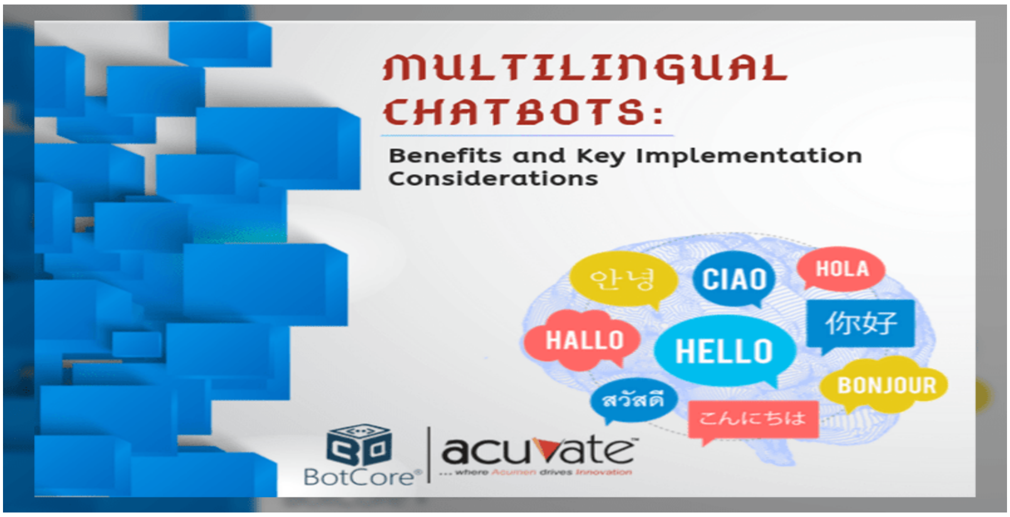

Figure 4: multilingual chatbot

We use a transfer learning strategy by initialising our models using the weights of the massive, multilingual pretrained model M-Bert (Wolf et al., 2019). (Pires et al., 2019). To convert the M-Bert encoder to the causal decoder, we apply the causal mask to the self-attention layer. We randomly initialise the cross encoder decoder attention for the encoder-decoder model (Rothe et al., 2019). The two models are then trained using cross-entropy loss on the combined training set in all seven languages. The model is trained on English conversational samples (the source language) and assessed on data from the other 6 languages in this context. We align the embedded representations of several languages into the same embedding space by using cross-lingual pre-training to the encoder-decoder model, as suggested by Chi et al. (2019). Pre-training the encoder and the decoder separately using masked language modelling, as in Lample and Conneau (2019); together pre-training the encoder and the decoder using two objective functions: Cross-Lingual Auto-Encoding (XAE) and Denoising Auto-Encoding (DAE) (Chi et al., 2019). While XAE employs parallel translation data to pre-train both the encoder and decoder with machine translation goals, DAE perturbs the encoder's input phrase and attempts to reconstruct the original sentence using the decoder. The language IDs are provided into the decoder, much as in the multilingual models, to regulate the language of produced sentences. Parallel and non-parallel data in the target language are needed for both pre-training phases.

The model is fine-tuned using just the source language data (i.e., English) after the two steps of pre-training, using the same cross-entropy loss as for the multilingual training. According to Chi et al. (2019), only the encoder parameters are changed via back-propagation, whereas the word embedding layer and the decoder both stay frozen. As a result, the decoders may continue to provide multilingual output while continuing to allow users to learn new activities using just the target language.

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V. RESULTS

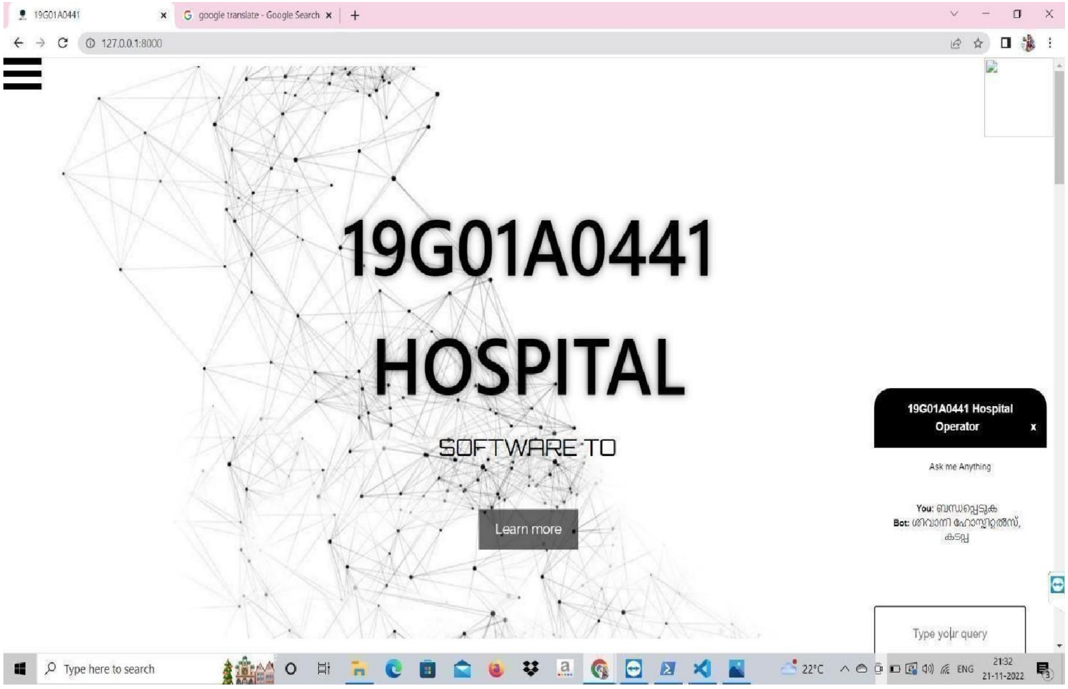

Figure 5: chatbot in Malayalam language

This automated conversation chatbot for Malayalam language for hospitals demonstrates the implementation of a multilingual healthcare chatbot system.

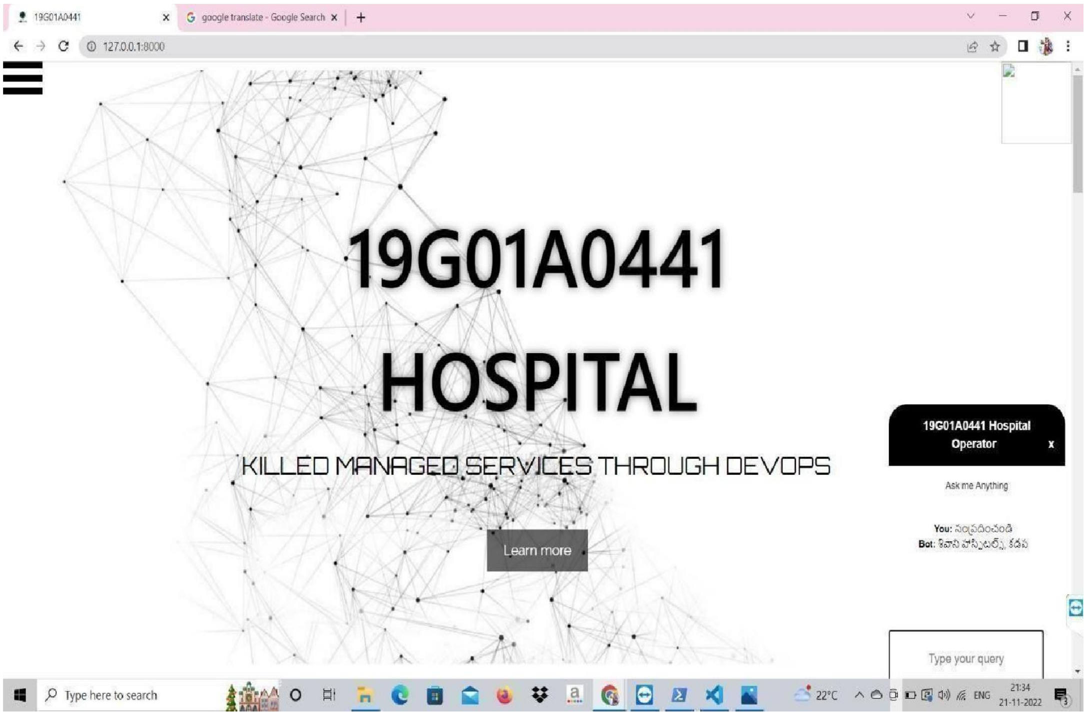

Figure 6:chatbotin Telugu language

This automated conversation chatbot for Telugu language for hospitals demonstrates the implementation of a multilingual healthcare chatbot system.

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Figure 7: chatbot in Tamil language

This automated conversation chatbot for Tamil language for hospitals demonstrates the implementation of a multilingual healthcare chatbot system.

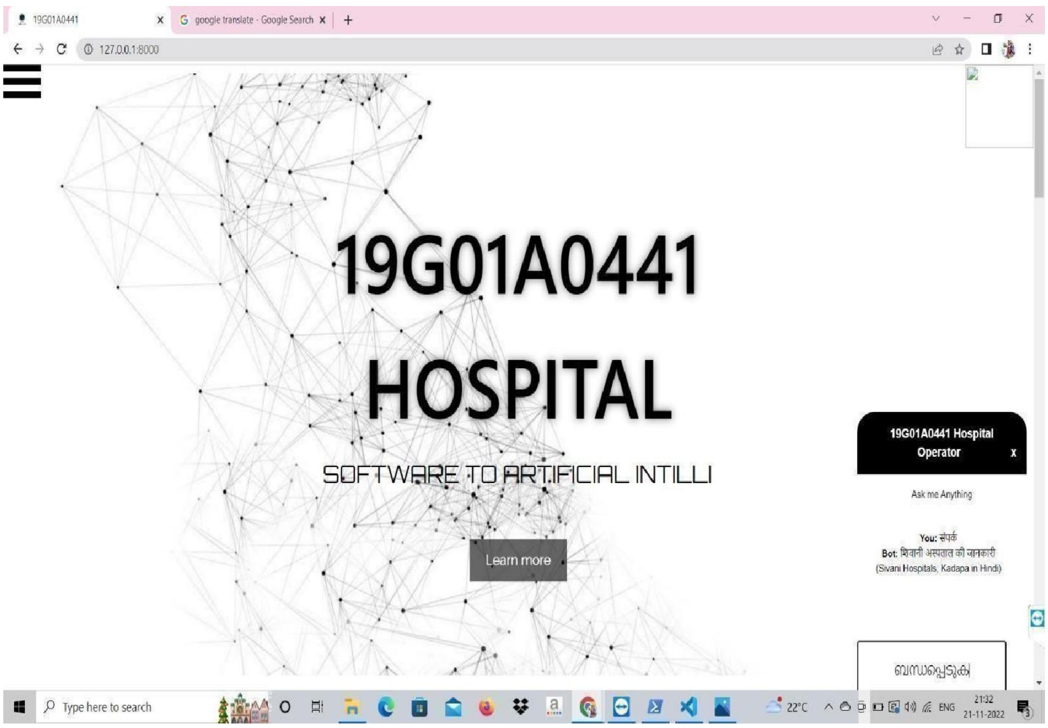

Figure 8: Chatbot in Hindi language

This automated conversation chatbot for Hindi language for hospitals demonstrates the implementation of a multilingual healthcare chatbot system.

VI. CONCLUSION

A multilingual healthcare chatbot system is implemented in this Automated Conversation Chatbot for Multiple Languages for Hospitals. The chatbot system supports many languages for text and voice, making it especially beneficial for India's rural residents who speak regional languages. The system can answer users' health-related questions in addition to performing its primary task of diagnosing diseases based on user symptoms. Along with the illness diagnosis, the system also gives the user information on the disease description and any necessary precautions. The Random Forest Classifier has the greatest accuracy of 98.43% among the five Machine Learning Classification methods examined by the Automated Conversation Chatbot for Multiple Languages for Hospitals. To choose which answer to the user inquiry is the most suitable, the suggested system uses TFIDF and Cosine Similarity. The lack of data is one of this multilingual chatbot system's drawbacks. To get better results, the system might be trained using a bigger, more thorough data set…

REFERENCES

[1]. https://censusindia.gov.in/2011-provresults/paper2/data_files/india/Rural_urban_2011.pdf

[2]. M. M. Rahman, R. Amin, M. N. Khan Liton and N. Hossain, "Disha: An Implementation ofMachine Learning Based Bangla Healthcare Chatbot," 2019 22nd International Conference on Computer and Information Technology(ICCIT),Dhaka,Bangladesh,2019,pp.1-6,doi:10.1109/ICCIT48885.2019.9038579.

[3]. R. B. Mathew, S. Varghese, S. E. Joy and S. S. Alex, "Chatbot for Disease Prediction andTreatment Recommendation using Machine Learning," 2019 3rd International Conference on Trends in Electronics and Informatics(ICOEI),Tirunelveli,India,2019,pp.851-856,doi:10.1109/ICOEI.2019.8862707.

[4]. P. Srivastava and N. Singh, "Automatized Medical Chatbot (Medibot)," 2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control(PARC),Mathura,India,2020, pp.351-354, doi:10.1109/PARC49193.2020.236624.

[5]. Mrs. Rashmi Dharwadkar, Dr.Mrs. Neeta A. Deshpande "A Medical ChatBot". InternationalJournalofComputerTrendsandTechnology(IJCTT)V60(1):41-45June2018.ISSN:2231-2803.

[6]. L. Hidayatin and F. Rahutomo, "Query Expansion Evaluation for Chatbot Application," 2018International Conference on Applied Information Technology and Innovation (ICAITI), Padang,Indonesia,2018, pp. 92-95, doi: 10.1109/ICAITI.2018.8686762.

[7]. U. Bharti, D. Bajaj, H. Batra, S. Lalit, S. Lalit and A. Gangwani, "Medbot: ConversationalArtificial Intelligence Powered Chatbot for Delivering Tele-Health after COVID-19," 2020 5thInternational

[8]. Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp.870-875,doi: 10.1109/ICCES48766.2020.9137944.

[9]. L. Athota, V. K. Shukla, N. Pandey and A. Rana, "Chatbot for Healthcare System UsingArtificial Intelligence," 2020 8th International Conference on Reliability, Infocom TechnologiesandOptimization(TrendsandFutureDirections)(ICRITO),Noida,India,2020,pp.619-622,doi:10.1109/ICRITO48877.2020.9197833.

[10]. S.Kannadhasan and R.Nagarajan, Design and Development of Environmentally W-Shaped Structure Antenna for Wireless Applications, International Web Conference on Smart Engineering Technologies(IWCSET 2020), 26-27 June 2020, Ramco Institute of Technology, Rajapalayam, ISBN:978-93-5407-648-0, Published in Journal of Green Engineering, Volume 10, Issue 9, September 2020.

[11]. S.Kannadhasan, M.Shanmuganantham, R.Nagarajan, and S.Deepa, Future Progress in Artifical Intelligence: Process and its Applications, Virtual International Conference on Metamorphosis of Modern Management and Research, 13 August 2020, Bannari Amman Institute of Technology, Sathyamangalam, Published for International Journal of Innovative Research in Computer and Communication Engineering, e-ISSN: 2320-9801, p-ISSN: 2320-9798, Volume 8, Issue 12, December 2020, DOI: 10.15680/IJIRCCE.2020.0812007, Impact Factor: 7.488

[12]. Gokula Chandar ,Leeban MosesM; T. Perarasi M; Rajkumar; "Joint Energy and QoS-Aware Cross-layer Uplink resource allocation for M2M data aggregation over LTE-A Networks", IEEE explore, doi:10.1109/ICAIS53314.2022.9742763.

[13]. Dhuddu Haripriya, Venkatakiran S, Gokulachandar A, "UWB-Mimo antenna of high isolation two elements with wlan single band-notched behavior using roger material",Vol 62, Part 4, 2022, Pg 1717-1721, https://doi.org/10.1016/j.matpr.2021.12.203

[14]. Gokula Chandar A, Vijayabhasker R., and Palaniswami S, "MAMRN – MIMO antenna magnetic field", Journal of Electrical Engineering, vol.19, 2019.

[15]. Rukkumani V , Moorthy V, Karthik M , Gokulachandar A, Saravanakumar M, Ananthi P, "Depiction of Structural Properties of Chromium Doped SnO2 Nano Particles for sram Cell Applications", Journal of Materials Today: Proceedings, vol.45, pp.3483-3487, 2021. https://doi.org/10.1016/j.matpr.2020.12.944

[16]. G.Srividhya, R.Nagarajan and S.Kannadhasan, Enhancement of Clustering Techniques Efficiency for WSN Using LEACH Algorithm, International Conference on Advances in Smart Sensor, Signal Processing, and Communication Technology (ICASSCT 2021), Goa University, Goa, 19-20 March 2021, Published for IOP Journal of Physics: Conference Series, Vol No: 1921, 2021, doi:10.1088/1742-6596/1921/1/012013

[17]. S.Kannadhasan, M.Shanmuganantham and R.Nagarajan, System Model of VANET Using Optimization-Based Efficient Routing Algorithm, International Conference on Advances in Material Science, Communication and Microelectronics (ICAMCM-2021), Jaipur Engineering College and Research Centre, Jaipur, 19-20 February 2021. Published for IOP Conference Series: Materials Science and Engineering, Vol No: 1119, 2021, doi:10.1088/1757-899X/1119/1/012021

[18]. Kannadhasan S & R. Nagarajan (2022): Performance improvement of antenna array element for mobile communication, Waves in Random and Complex Media, DOI: 10.1080/17455030.2022.2036867,

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