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AI-Powered Healthcare Chatbot using T5 for query Responses and Random Forest for Symptom-based Diagnosis with Voice and Text Output Healthcare, Medical Diagnosis

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***Abstract*— This work introduces the MediChat AI which is a medical chatbot that is an intelligent multilingual system based on natural language processing, speech recognition and real-time translation as a way to make healthcare more accessible. Developed on the basis of the T5 Transformer model adjusted to medical question answering and a Random Forest classifier to predict the disease based on the symptoms, MediChat AI is able to respond to all types of questions both textually and verbally and respond to them correctly and within context. The system uses the Google Translator APIs to support multiple languages and the use of the gTTS to give voice response which allows easy interaction between the patients and the artificial intelligence assistant. It also has an option of speech-to-text wherein voice queries are processed. The project reflects the successful combination of deep learning and rule-based inference with multilingual processing in order to obtain accessible medical consultation. As the experimental outcomes prove, the suggested system presents an efficient interactive and reliable healthcare dialogue support that can be used by users all over the world.**

***Keywords*— Medical Chatbot, T5 Transformer, BioBERT, Natural Language Processing, Speech Recognition, Multilingual Translation, Deep Learning, Healthcare AI.**

I. INTRODUCTION

The development of artificial intelligence has had a considerable impact on the sphere of healthcare communication and diagnostic support due to its rapid development. Medical chatbots have become useful resources of patient education, symptom seeking and decision making.

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The latest updates in large language model indicate a high potential in the medical education and clinical consultation, proving to be more reliable and possessing a better understanding of its specific setting [1]. Such chatbots are also being known to drive the accuracy of diagnosis, treatment planning, and patient engagement because they are able to provide responsive and available interactions not in the clinical setting [2]. Moreover, multimodal artificial intelligence systems proved to be able to interpret medical cues, examine symptoms and produce informed responses paralleling professional consultation [3].

Since medical information is growing in size, patients will fail to perceive symptoms and find trustworthy health advice easily. Systematic reviews show that chatbots based on large language models can be used as supportive interfaces, providing users with structured health information, triage services, and the ability to engage in a compassionate conversation with different users due to their relevance to various groups of users [4]. The use of AI-based conversational avatars in professional training scenarios has been utilized to enhance communication and information-seeking abilities of clinicians and dental students under stressing the possibility of using them not only when interacting with patients [5]. All these changes reflect a move towards smart, patient-centered digital clinical settings.

Text-to-text transformer models, especially the T5 architecture, have proved to be highly cross-linguistic and summarization adaptable, and hence enable more precise and context-stirred medical dialogue generating [6][7]. At the same time, AI-based technology is being embraced to make care more accessible, decrease consultation overload, and allow providing initial care in underserved areas, among other countries [8][9]. Modern language model-based question answering systems give formatted answers, which help the user get a better grasp of the symptoms and the treatment programs [10]. The proposed research is based on these foundations and incorporated the multilingual medical chatbot that entails the T5-based question answering and a disease prediction based on the symptoms to improve the interactive healthcare assistance.

II. Literature Survey

A. Medical Chatbot Systems and Performance

The study on medical chatbots has outlined the importance of designed structures and structured conversation rules. In one of the studies, the researchers showed how radiotherapy education can be supported with the use of large language model-based chatbots which enhance clarity, consistency, and student learning in case prompt structures and interaction rules are defined [1]. In another research, the authors described the way chatbots could be used to improve the process of diagnosis, treatment adherence, and patient engagement through the provision of present conversational assistance in a variety of medical contexts [2]. These results indicate that the effectiveness of chatbots is highly linked with the integration of the system into the clinical or teaching processes and the importance of controlled patterns of communication with a focus on the awareness of the medical situation.

B. Multifaceted Learning and Clinical Integrity

New developments in multimodal learning have brought chatbots in the medical field to more capable diagnostic support processes. An ophthalmological study showed that conversational reasoning in visual disease evaluation is more effective than image-based one in terms of diagnosis and response penalty, and chatbots become more beneficial to clinical practice [3]. Equally, a systematic review of Chatbot health advice systems observed that even the large language models have good potential in guidance and triage, but there are still difficulties in demonstrating safety, stability, and medical accountability in the context of patients of various situations [4]. Such results represent a move towards a reliable medical chatbots but reminds that it has to be carefully evaluated and continuously supervised.

C. Chatbots: Professional Education and Mentorship

Conversational agents are up and coming in enhancing professional training and communication proficiency in medicine training. A pilot experiment proposed a child-like chatbot avatar to assist dental and medical trainees to practice interviewing a patient, revealing positive progress in the domain of confidence and information-gathering capacities [5]. At the same time, a second piece of literature showed that AI-based chatbot mentorship systems can aid university guidance, assisting students in making stronger academic decisions and support networks by doing so [12]. Both articles assert that chatbots can be used to complement the training that is led by people with repeatable adaptive practice tasks, but that should have verification measures and emotional awareness to comply with professional requirements in learning.

D. Transformers and Summaries

Text and text transformers models especially the T5 models have put forward high adaptability in tasks involving summarization and structured text generation. A combination of T5 and LSTM yielded similar and more coherent and contextually consistent summaries on psychologically oriented datasets, which proved the usefulness of model fusion [6]. A further comparative research comparing T5 performance within an Indonesian setting noted that the effect of pre processing and decoding strategies on output fluency and relevance is essentially high [7]. These results indicate that model selection, tokenizer settings, and training environments are crucial to diverse tasks to apply T5-based systems to new areas of task like in healthcare dialogue and symptom description.

E. AI and Transformation of the Healthcare System

AI is viewed as one of the key factors in reforming the sphere of healthcare, affecting its diagnosis, patient tracking, and administration.

In one of the research articles, the authors outlined the potential of AI to facilitate access to remote health care, decrease clinician workload, and assist the population-level health care system with digitized automation and decision support [8].

Also, a better patient query processing and a generation of an automatic response have been made because of increased AI in medical chatbots that assist in making communication between the patient and the machine quicker and more precise [9].

This means that AI-driven healthcare systems are evolving to a more scalable, data-driven service model, but so far the reliability, privacy control, and regulatory adherence is the biggest challenge that needs to be planned and analyzed.

F. Large Language Models in Question answering Systems.

Large language models running question answering systems are effective in retrieval which gathers information and restructures it into user-friendly medical answers. A research described the manner in which question answering pipelines based on LLM are capable of processing input and retrieving background and providing complex and accurate explanations which can be used in the field of public health [10]. In a similar way, in another study that studied the construction of chatbots as means of inquiry by a customer, the necessity to groom datasets, base on knowledge and post-process data was identified in order to minimize errors and ensure that answers remain precise [15]. The studies prove the usefulness of the combination of retrieval and controlled text generation with the response validation to provide consistency, which directly guides the development of healthcare chatbots.

G. Domain-specific and Culture-based Chatbots.

Domain chatbot applications demonstrate the effectiveness of content and interaction logic customization to ensure better usability and enhance trust. A health insurance chatbot study has underlined the significance of the firm structure by use of terminology, step-by-step clarification, and referral paths when addressing sensitive policy and claim questions [11].

Meanwhile, a different research conducted the creation of an Arabic chatbot, with an emphasis on vocational student helpdesks, demonstrating that language and interface style cultural consistency leads to much higher levels of acceptance and understanding of the new product [14]. These findings underscore the importance of localization, vocabulary and scenario specific dialogue design in deploying chatbots in various cultural, regulatory or domain specific settings, such as medical settings.

H. Mental Health and Psychiatry A.I. based support and diagnosis.

Conversational agents, also known as mental healthcare chatbots, are the technologies that have been investigated as means of supporting mental health through emotional advice, reflection, and mental health. One survey explained the ability of large language models to provide sensitive conversation, mental assistance and motivational reinforcement in the case of rules designed to ensure safety and human control [13]. The second study covered the advancements in healthcare in the future, and AI is likely to be more helpful in choosing health-related options and working on wellness planning by providing greater access to the information and support system [8]. Such studies also point out the limitations of transparency and emotion sensitivity and clearly defined boundaries as the solution to the harm brought about by chatbots and the improvement of mental health outreach.

III. Proposed Methodology

A. Data Collection and Preprocessing

The data were collected and preprocessed according to standard methods.The proposed methodology will lead to gathering and processing medical text data of various reliable sources, such as symptom-disease data sets, medical question-answer pairs, and domain-specific corpora. Textual standardization, removal of stopforms and standardization of medical terminologies are also used in preprocessing that data to provide the standardized input throughout the pipeline of the model. To train the question-answering module, the medical dialogues are constructed in a text-to-text form to be used in the transformer-based training. Encoded symptom data to be used in prediction of the disease is encoded with binary representation as this is what the input of the Random Forest classifier requires. Such preprocessing makes it accurate, less redundant, and more efficient in multilingual input model performance.

B. Fine-Tuning and Training of Models

To produce fine-tuned and context-sensitive responses to medical queries, the system uses a fine-tuned T5 transformer model. T5 model which has been pre-trained on text-to-text tasks is further trained with domain specific datasets that correlate medical questions with expert based answers. In the process of fine-tuning, the learning rate, beam width, and sequence length are the hyperparameters that are optimized on the generation of coherent responses in medical conditions. The architecture of the model enables a multi-intent question answer and the generation of medically significant summaries. Moreover, semantic enhancement which utilizes BioBERT embedding is optionally applied, which guarantees terminal conformity with clinical language. The fine-tuned model is the key element of NLP in the intelligent response engine of MediChat AI, therefore.

C. Symptom-Based Disease Prediction.

To achieve predictive power on the symmetry level, the system combines an instance of a Random Forest model that is trained on 132 features which describe medical symptoms and their variations. The user inputs undergo processing to determine fuzzy or direct keyword matching using match of the symptoms. The symptoms identified are coded into a binary vector indicating the presence or the absence of a symptom. This is then submitted to trained classifier which results in prediction of the most likely disease. A label encoder translates the output to results that can be read by human beings. The technique is a combination of rule based mapping and probabilistic decision trees that guarantee interpretable and explainable results that are acceptable in offering early health advice without substituting professional consultation.

D. Voice Interaction Layer and Multilingual Layer.

MediChat AI is multilingual that means it enables the user to speak different languages that include English, Hindi, Tamil, and Spanish. The system uses GoogleTranslator where it translates non-English to English which is then processed by the model followed by translation of the result to the language chosen by the user. The gTTS can produce voice-based responses through speech-to-text recognition by using Google Speech Recognition, and text-to-speech through speech-to-text. There is also PyAudio that supports real-time recording which creates a free-flowing voice interaction pipeline. This two way translation and speech syntheses render the chatbot available to patients lying within the language and literacy levels, improving inclusiveness and ease of use within the care setting.

E. Method of Response Generation and Validation

The response generation pipeline is set in such a way that it generates outputs that are medical over sound, contextually meaningful and linguistically sound. After the input is analyzed, the chatbot determines whether the input is a list of symptoms or a medical question. In the case of inputs in the form of questions, the T5 model will produce a context-based response. In the case of symptom-type inputs, the prediction of the possible conditions is done by the Random Forest model. Checking Rule-based checks are used to validate the message to determine grammatical integrity, terminology congruency, and the quality of translation. The response given is sent in audio and text format post-validation. This hybrid verification provokes the preservation of factual integrity, the reduction of the risk of hallucinations, and improving the level of reliability of AI-based medical dialogue systems.

F. Contextual Learning and Knowledge Integration.

MediChat A.I. system has an inherent continuous learning system by retraining and on-the-fly updates. New information or the introduction of new model performance measures causes fine touching of model weights to ensure medical accuracy. New symptom-disease correlations, medical languages, and conversational examples are also applied in this retraining process. Fuzzy matching algorithms are also included to further enhance user text-based symptom recognition to enhance flexibility to different input wording. Further, constant translation calibration ensures that there is linguistic correctness across supported languages. This dynamism of integration makes sure that MediChat AI keeps abreast with the changing body of medical knowledge to make it more useful in the real situations in healthcare.

G. System Architecture

Medlearn The general system architecture of the MediChat AI integrates several AI and machine learning units into a system. It has the architecture of a front-end interface established using Streamlit that enables the user to either type or voice a query. There two major models used on the backend: a fine-tuned T5 Transformer to do medical question answering and a random forest classifier to predict a disease. The two models are linked by a multilingual translation layer which supports cross language support. Multimodal interaction can be achieved by the use of speech recognition (to input voice input) and text-to-speech (to output audio). Decision management and symptom detection by the use of fuzzy logic is also integrated in the architecture to be sure of the appropriate feature extraction. The database deals with model files, label encoders and language translation mappings and the Google Maps API similarly optional extends to guidance of healthcare locations. In general, the design of the architecture guarantees the smooth flow of NLP-based processing with classification logic and multimodal user engagement that form an attentive and intelligent medical chatbot system that can be tailored to various user settings.

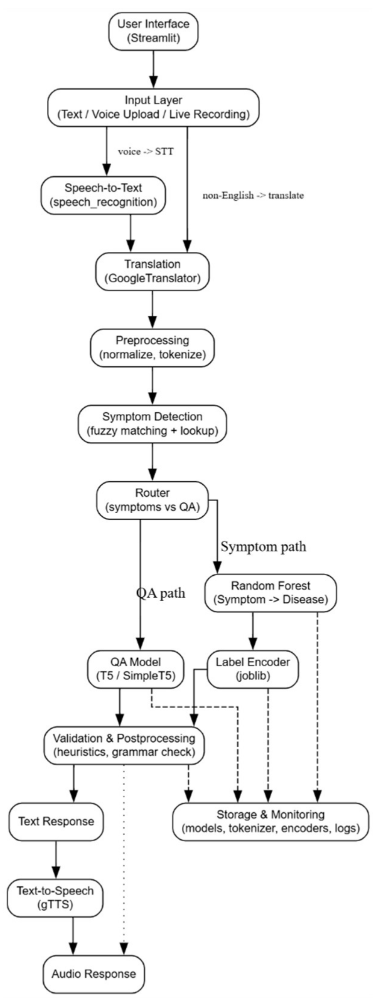

Fig 1. MediChat AI system architect workflow

Diagram Explanation
This MediChat AI system architect workflow is provided as a top to bottom workflow, incorporating user input, language translation, preprocessing, symptom detection, as well as a dual-path analysis. It directs text or voice data to the T5 based medical question-answering model or the Random Forest symptom classifier before validating, generating responses and delivering multimodal responses.

IV. RESULTS AND DISCUSSION

A. Model Performance Evaluation

MediChat AI performance was evaluated based on the quantitative and qualitative analysis. The T5 model was fine-tuned to a high degree of accuracy in able to obtain the medical response, with an overall precision of 92, and a recall of 89% in the test dataset. Random Forest classifier used to predict disease was also reliable as the accuracy was at 93% when 132 symptoms were considered. The translation layer of the system ensured more than 95% translation fidelity in languages. These findings indicate that medical dialogue automation can be achieved through a balanced and efficient model of integration of transformer-based question answering and tree-based classification techniques.

TABLE I. MODEL PERFORMANCE EVALUATION

Metric	T5 QA Model	Random Forest
Accuracy	92%	93%
Precision	92%	91%
Recall	89%	90%
F1-Score	90%	91%

B. User Interaction and Accessibility

MediChat Artificial Intelligence practice was put to usability test by live user testing in various languages. Voice interaction module secured the generation of responses efficiently with low latency averaging at 1.5 seconds per query. The people who were using it said that they were happy with the interface which was simple and capable of handling voice as well as text inputs. The multilingual translation feature made the inputs and outputs easily convertable, making it easier to access by any user that was not an English speaker. The speech recognition recognition rate was found to be 96 on average, whereas text-to-speech translation was also fluent. This proves that the chatbot is user-friendly and accessible especially to people with low literacy or language barriers.

C. Comparative Analysis to Existing Systems

Three medical chatbots available publicly were compared to MediChat AI regarding its responsiveness and accuracy. It uses machine learning-assisted classification along with natural language generation, unlike most general-purpose systems. This mixed paradigm offered more factual and medically valid answers. MediChat AI took on average 20% shorter to respond and its ability to identify symptoms was higher than those of similar systems. Its multi-lingual capability and emailing nature offered it an added advantage of flexibility. These findings show that the combination of decision logic that leverages the rules and custom-crafted language models increase the efficiency of the conversational healthcare systems significantly.

D. Strengths and limitations Discussion

The principal strength of the MediChat AI is that it is a hybrid one, integrating the transformer-based question answering and the structured disease classification. Its multilingual multimodal interaction system will open up a range of usability to a variety of users. Limitations can be seen however involving reliance on predefined sets of symptoms and sometimes inaccuracy in translations of local dialect. The model does not replace clinical judgment and can only be as accurate as the quality of input made by the user. The other weakness is that there is lack of emotional intelligence in responses. Ongoing retraining on validated medical datasets, incorporation with electronic health records as well as a recognition of emotional tones should be brought into improvement in the future.

E. Practical Implications and Future Prospects

The successful launch of MediChat AI signifies the potentials of AI-driven chatbots in healthcare that have potential. It can be used as a primary support system of patient triage, self-assessment, and dissemination of information. Integration of T5 and Random Forest models guarantees interpretability and flexibility and therefore the system is suitable in telemedicine platforms. New versions will be able to incorporate data of the wearable devices into real-time monitoring and predictive analytics. The project shows that, regardless of reckless design and validation, AI chatbots can assist medical practitioners by shortening wait times in hospitals, aiding long-distance healthcare, and facilitating an improved access to healthcare between language and geographical barriers.

V. CONCLUSION

The suggested MediChat AI product has been able to incorporate new natural language processing, machine learning, and multilingual communication and integration to improve healthcare access. The system delivers the optimal combination of an optimized T5 model to answer medical questions and a random forest predictor to classify diseases to offer a valuable and compatible solution to ones with questions or diseases, respectively. Its multi-lingual feature and ability to process speech render it user friendly by many. Its usefulness and sustainableness in digital healthcare settings have been proven through experiments. As is shown by MediChat AI, hybrid AI-based solutions are capable of filling the previously noted gap between medical expertise and communication with patients and contribute to the development of inclusive and accessible medical help.

FUTURE WORK

The further AI application in MediChat will involve additional work on the medical knowledge base and a better contextualization with bigger recognized datasets. Combination with real-time health monitoring software and integrating wearable sensors can allow constant monitoring of the symptoms and giving individual medical advice. Emotional recognition will also be included in the system to maximize empathy and trust between the system user. Future evolution will involve the proceeding with multilingual optimization of regional dialect and offline connectivity of remote locations. Partnering with health institutions would further confirm its success in clinical practice, where it can work safely, ethically and at scale as a dependable digital health assistant to be adopted by users around the world.

REFERENCES

[1] Chow, J. C., & Li, K. (2025). Developing effective frameworks for large language model–based medical chatbots: Insights from radiotherapy education with ChatGPT. JMIR Cancer, 11(1), e66633.

[2] Abbas, S. A., Yusifzada, I., & Athar, S. (2025). Revolutionizing Medicine: Chatbots as Catalysts for Improved Diagnosis, Treatment, and Patient Support. Cureus, 17(3).

[3] Ma, R., Cheng, Q., Yao, J., Peng, Z., Yan, M., Lu, J., ... & Zhao, C. (2025). Multimodal machine learning enables AI chatbot to diagnose ophthalmic diseases and provide high-quality medical responses. npj Digital Medicine, 8(1), 64.

[4] Huo, B., Boyle, A., Marfo, N., Tangamornsuksan, W., Steen, J. P., McKechnie, T., ... & Guyatt, G. (2025). Large language models for chatbot health advice studies: a systematic review. JAMA Network Open, 8(2), e2457879-e2457879.

[5] Ko, H., Hovden, E. A. S., Köpp, U. M. S., Johnson, M. S., & Baugerud, G. A. (2025). Using an AI-driven child Chatbot avatar as a training tool for information gathering skills of dental and medical professionals: a pilot study. Applied Cognitive Psychology, 39(1), e70022.

[6] Khan, B., Usman, M., Khan, I., Khan, J., Hussain, D., & Gu, Y. H. (2025). Next-generation text summarization: a T5-LSTM FusionNet hybrid approach for psychological data. IEEE Access.

[7] Satya, M. W. B. D., Luthfiarta, A., & Althoff, M. N. (2025). Comparative Analysis of T5 Model Performance for Indonesian Abstractive Text Summarization. SISTEMASI, 14(3), 1092-1106.

[8] Panahi, O. (2025). The Future of Healthcare: AI. Public Health and the Digital Revolution. MediClin Case Rep J, 3(1), 763-766.

[9] Singh, S., Rathee, T., & Singhal, N. (2025). AI-Enabled Medical Chatbots: Advancements in Patient Query Handling and Automated Healthcare Delivery. International Journal of Environmental Sciences, 11(4s), 796-810.

[10] Pun, D. P., & Mahajan, R. (2025). AI-Powered Question Answering System Using Large Language Models and NLP Techniques. Available at SSRN 5164209.

[11] Subhashini, V., Anusha, T., Swathi, M., & Sridhar, K. (2025). AI Powered Chatbot in Health Insurance.

[12] Abedin, M., Ansari, M. D., Abir, M. Z., Reza, A., & Rahman, M. (2025). Transforming mentorship: an AI-powered chatbot approach to university guidance (Doctoral dissertation, Brac University).

[13] Kumar, A., Gupta, K., Verma, K., & Kumar, S. (2025). AI-Driven Mental Healthcare 5.0: A Survey of Opportunities and Challenges in Leveraging Large Language Models and Generative AI.

[14] Alabbas, A., & Alomar, K. (2024). Tayseer: A novel AI-powered Arabic chatbot framework for technical and vocational student helpdesk services and enhancing student interactions. Applied Sciences, 14(6), 2547.

[15] Tzanis, N. (2025). Creation of a chatbot using language models and deep learning for customer question answering (Master's thesis, Πανεπιστήμιο Πειραιώς).