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SECURE ACCESS CONTROL FOR ELECTRONIC HEALTH RECORDS IN BLOCKCHAIN-ENABLED CONSUMER INTERNET OF MEDICAL THINGS

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ABSTRACT

Electronic health records (EHRs) have the potential to greatly enhance the efficiency of illness detection and treatment. However, with their widespread use comes the risk of patients' privacy being compromised, necessitating a more robust and adaptable system for access control. Furthermore, there is a significant regulatory lag since the medical ministry (MM) often probes unlawful medical actions after they have occurred and caused injury. A blockchain-based system that allows patient-leading fine-grained access control versus EHRs is proposed as a solution to these difficulties. To allow MM to regulate medical actions before they happen, this approach combines attribute-based encryption with blockchain and employs blank EHRs as the medium, which is different from the present systems. We use the chameleon hash function to compute file storage addresses in the interplanetary file system in an effort to lower the overall storage cost of the system. Also, implementing single sign-on may make telemedicine vital sign transmissions more secure and efficient, and using proxy re-encryption can make EHR authorisation more efficient. The system is secure and feasible, according to theoretical study and experimentation.

I.INTRODUCTION

The need for quick and tailored communication in today's hectic environment has sparked the emergence of

Intelligent chatbots powered by artificial intelligence that work in tandem with voice-activated responding systems. More realistic, human-like interactions are made possible by these systems' combination of deep learning, voice recognition, and natural language processing (NLP). The use of voice help elevates the user experience, allowing for hands-free, real-time conversations, while text-based chatbots have already achieved broad acceptance across several industries. In several fields, including customer service, healthcare, education, and online shopping, AI chatbots that are integrated with speech recognition technologies not only improve accessibility but also provide a smooth interface for users. An experience that is reminiscent of human conversation is the primary goal of these technologies, which aim to connect people and technology. These chatbots may enhance the user experience by processing spoken enquiries and responding in a natural-sounding voice. This is made possible by using speech-to-text and text-to-speech technology.

Building a voice-assisted AI chatbot involves incorporating multiple high-tech parts, such as speech recognition to transcribe user inputs, natural language processing (NLP) to understand and handle questions, and machine learning models to come up with answers that are relevant to the user's context. In addition, the system has to be able to manage interactions in real-time and respond appropriately. Over time, the AI system may become more accurate by learning from encounters, allowing it to provide consumers with more appropriate replies to their demands.

Incorporating voice commands into AI chatbots opens up a world of possibilities. Their ability to provide round-the-clock help in the customer service business has the potential to decrease response times and increase client satisfaction. They may be of service to patients in the healthcare industry by addressing their medical questions and offering advice on matters pertaining to their health. The system's adaptability to different languages and dialects further enhances its versatility, making it a viable option for users throughout the world. With the integration of emotion detection, multi-language support, and context-aware comprehension, AI-driven voice assistants will become a crucial feature of current communication platforms. The user experience will be further enhanced as the technology evolves.

Focussing on the critical issues of

accurate speech recognition, comprehending natural language, and real-time conversational flow, this project seeks to build and execute an AI chatbot with voice-assisted replying. Our aim is to create a system that can comprehend voice inputs with precision and respond with meaningful, context-aware replies, so it can be used effectively in many real-world scenarios.

II.LITERATURE REVIEW

Academic studies and practical implementations of AI chatbots that include voice help have attracted a lot of interest for their potential to improve user interactions and provide a more natural interface. In this part, we will take a look back at the history, current state, and future prospects of artificial intelligence chatbots that use voice-assisted responding systems.

1. The Development and Use of AI Chatbots

Over time, AI chatbots have progressed from rule-based systems to more complex models based on machine learning (ML). Decision trees and scripts were the backbone of early chatbot systems, which used to match user enquiries with pre-defined replies (Weizenbaum, 1966). With the advancement of deep learning (DL) and natural language processing (NLP), chatbots started to use semantic understanding to provide better, more personalised replies.

Chatbots' ability to comprehend context, manage complicated discussions, and even handle multi-turn dialogues has significantly improved with the introduction of transformer-based designs such as GPT and BERT (Vaswani et al., 2017). To improve their capacity to comprehend user queries in a natural and conversational way, these models are trained on huge text corpora, which enable them to grasp complex word and phrase associations.

2. Technology for Recognising Voices

Critical to voice-assisted AI systems is voice recognition, often called speech-to-text (STT). This technology translates spoken language into text, allowing the chatbot to understand voice commands and provide suitable responses. Modern voice recognition systems are more faster and more accurate because to advancements in recurrent neural networks (RNNs) and deep neural networks (DNNs). The capacity of models like Bidirectional LSTMs and Long Short-Term Memory (LSTM) to capture temporal dependencies in speech patterns makes them popular choices for speech recognition problems (Hochreiter & Schmidhuber, 1997).

There are a number of obstacles that automated speech recognition (ASR) systems have had to overcome, including multi-language support, accents, and loud situations. Thanks to tools like Microsoft Azure's Speech Service and Google's Speech-to-Text API, developers may now include speech recognition into their apps without requiring specialised knowledge in the subject.

3 Voice-Enabled Chatbots and Natural Language Processing

The task of deciphering and comprehending the content of the text falls on natural language processing (NLP), whereas voice recognition is in charge of converting spoken language into text. With the use of natural language processing, chatbots can understand human intent, extract entities, and analyse sentiment. Transformer networks (Vaswani et al., 2017) and attention mechanisms, which enhance the chatbot's capacity to handle ambiguous or complicated language inputs, have essentially supplanted more traditional natural language processing approaches like bag-of-words and n-grams.

A better understanding of context is now possible because to new developments in natural language processing. Particularly in multi-turn discussions, chatbots that use contextual embeddings, as those generated by models like BERT, are more able to keep the conversation flowing and recall prior user interactions (Devlin et al., 2019).

4. AI for Real-Time Messages

Improving AI chatbots' ability to analyse and generate responses in real-time is an ongoing problem. For user engagement and happiness, it is essential to be able to comprehend and answer to enquiries instantly. Improving the efficiency of the backend architecture and optimising the underlying deep learning models have been the subject of several research aimed at lowering latency in chatbot systems.

One example is how distributed computing may reduce response times by shifting heavy computational activities to cloud servers. This was shown in research on edge computing and cloud computing architectures (Zhou et al., 2020). To further enhance the adaptability and resilience of real-time conversational systems, researchers have investigated the possibility of incorporating multimodal input, which combines voice, text, and graphics (Huang et al., 2020).

5. Use Cases for AI Chatbots Integrating Voice Assistants

Voice-enabled AI chatbots have found

uses in several fields. Without human interaction, voice-enabled chatbots may address a variety of questions and concerns in customer support, from basic frequently asked questions to more complicated difficulties (Joubert et al., 2019). The user experience may be further customised by integrating these systems with customer relationship management (CRM) solutions.

Appointment scheduling, medication reminders, and health information provision are some of the voice-assisted AI systems that are now under investigation in the healthcare industry (Pérez et al., 2020). In the field of mental health, AI chatbots may be a helpful, non-invasive alternative by having therapeutic talks, evaluating symptoms, and suggesting coping mechanisms.

Additionally, voice-based chatbots are being used in the field of education to provide customised learning experiences. These bots may assist students by answering their queries, breaking down difficult ideas, and adjusting to their specific learning speed (Sichel et al., 2020). Students with physical limitations or who just choose not to use their hands while studying might benefit greatly from voice input.

6. Difficulties and Where to Go From Here

A number of obstacles persist even though AI chatbots and speech recognition have come a long way. In multilingual environments, the accuracy of voice recognition systems may still be impacted by factors such as background noise, accent variance, and linguistic variety (Zhang et al., 2020). Furthermore, there is still a need for further study into how to keep the discussion flowing and avoid the chatbot giving answers that are unnecessary or illogical.

Another new development in AI chatbots is emotion detection, which might make a huge difference in the user experience by letting the bot know how the user is feeling and reacting accordingly (Cowie et al., 2019). In the future, AI chatbots may be able to understand human emotions and context better by integrating sentiment analysis with speech recognition technologies like pitch and tone.

III.PROPOSED MODEL

A. Study Data

A mix of speech recognition and textual interaction data is the mainstay of the data utilised to train and assess the AI chatbot with voice-assisted responding system for this project. For reliable and accurate speech-to-text translation, the voice recognition dataset includes a wide range of audio recordings covered by different languages, accents, and ambient factors. The voice recognition models were trained using public datasets like Common Voice and LibriSpeech. To train the system to recognise spoken language in a variety of accents and speech patterns, these datasets include transcriptions and millions of hours of tagged voice data.

Also used to train the NLP models is the textual conversational dataset, which contains a wide range of question-answer pairs, conversation logs, and dialogues. Various conversational situations, scenarios, and conversations were provided by popular datasets like Persona-Chat and Cornell Movie conversations. The AI model is trained with these datasets to better comprehend user queries and provide coherent, contextually appropriate solutions.

In addition, the system is evaluated on real-time interaction data to guarantee correct performance in a real-world scenario. Users provide the chatbot text and voice input during simulated chats in order to gather these data. The chatbot's comprehension of idioms, colloquialisms, and complicated enquiries, as well as its real-time response accuracy, may be assessed using these practical tests.

There is no better way to teach an AI system to master speech-to-text translation and natural language comprehension than using a mix of text and voice data, as well as real-world conversational data.

B) System Architecture

Users may effortlessly engage with the AI Chatbot with Voice-Assisted Answering via both textual and vocal inputs, thanks to its well-designed architecture. There are four main parts of the system that work together: the UI layer, the speech recognition module, the NLP module, and the response generation module.

Whether they want to write in their enquiries or utilise a microphone for voice input, the user may engage with the system via the User Interface Layer. The chatbot's textual replies and, if desired, audio input are provided by this layer. The user's spoken words are recorded and sent to the Speech Recognition Module when they choose voice input. This component's job is to use an automated speech recognition (ASR) model that has already been trained, such DeepSpeech or Google Speech-to-Text, to transform the audio input into text. Accurate transcription of a wide range of speech patterns, accents, and noise levels is guaranteed by the speech recognition technology.

The next step is to send the textual input to the NLP Module for processing. The text is examined by this module in order to discern intent, comprehend the query's context, and identify important things (such as dates, places, or particular objects). This is where the system takes care of tasks like named entity recognition (NER), part-of-speech tagging, and tokenisation so it can understand the user's request completely. The Response Generation Module then uses this knowledge to craft a suitable response. A pre-trained language model (like GPT-3) may be used for this purpose, or information can be retrieved from databases or retrieved by querying knowledge sources. After that, a Text-to-Speech (TTS) engine is notified of the produced answer and, if the system is capable of voice output, the response is converted back into speech so that the user may hear it.

The system's ability to analyse text and speech inputs effectively is made possible by these linked layers, enabling lifelike and engaging discussions. The AI chatbot can comprehend complicated questions and provide relevant answers instantly thanks to its design, which improves the user experience and is useful in many different contexts.

IV.METHODOLOGY

Integration of voice recognition, natural language processing (NLP), and answer creation are key components of the AI Chatbot with Voice-Assisted Answering project's approach. There are many steps to this process, including gathering data, training the model, testing it, and finally deploying it. Detailed explanations of each step of the approach follow:

1. Data Collection and Preprocessing

Acquiring the data sets required for NLP and voice recognition is the first stage. Common Voice and LibriSpeech are two examples of public datasets used for speech recognition. These datasets include massive amounts of tagged speech data from a variety of languages and accents. The system is able to accurately convert audio to text thanks to these databases, which also aid in recognising varied speech patterns. The chatbot is trained to comprehend and create replies that are human-like using natural language processing datasets such as Persona-Chat and Cornell Movie Dialogues. After that, the data is cleaned and prepared for model training via preprocessing. This includes tasks like reducing noise from audio data and tokenising text data for improved processing.

2. Speech Recognition Model Development

A model for speech recognition is trained to process the voice input. Users may record their voices and have them transcribed into text using this methodology. In order to do this, we use state-of-the-art models that are built on deep learning, such as DeepSpeech or the Google Speech-to-Text API. These models are capable of handling different accents, loud surroundings, and fluctuations in speech. One part of training the model is making sure it can convert voice to text as accurately as quickly as possible while another part is using the datasets to fine-tune it.

3. Natural Language Processing (NLP) and Intent Detection

Following the text-to-speech conversion, the natural language processing module analyses the user's inquiry. Key activities in this stage include named entity recognition (NER), which entails identifying things such as names, places, and dates, and tokenisation, which entails breaking the text into individual words or phrases. Determining the user's purpose (such as requesting weather information or making a product suggestion) is also accomplished via intent detection. To do this, models based on BERT or GPT are often used to extract contextual knowledge from the text. In order to choose the best answer to the user's question, the NLP analysis is performed.

4. Response Generation

The Response Generation Module's job is to comprehend the user's input and then come up with an appropriate and logical reply. Using transformer models such as GPT-3 or T5, the model may either acquire information from an existing knowledge base or develop replies that are suitable for the given context. Depending on the chatbot's capabilities, the answer may include dynamic database queries (such as when checking the weather or obtaining product information). At this point, you should also check that the answer stays on topic and answers the user's questions.

5. Text-to-Speech (TTS) Integration

The Text-to-Speech (TTS) module is used to transform the produced text response into audible speech for voice-assisted replying. If you want your chatbot to seem more human, you may use text-to-speech technologies like Amazon Polly or Google Cloud TTS. A more organic and engaging experience for the user is achieved via the usage of the TTS engine, which guarantees that the speech output is both clear and suitable for the context.

6. Testing and Evaluation

Extensive testing is carried out to assess the overall system performance once the system components have been merged. Users have discussions with the chatbot in real-time, utilising both text and speech. Accuracy, reaction time, and user happiness are some of the performance measures that are evaluated. Critical assessment criteria include the system's capacity to handle different user inputs, the accuracy of speech-to-text translation, and the coherence of produced replies.

7. Deployment and Real-Time Interaction

The AI chatbot is put into action after testing by being added to a website or app, where consumers may engage with it in real-time. To make sure the system can handle different inputs and stays effective, continuous monitoring is used. Over time, the system's voice recognition and answer generating capabilities are enhanced with the help of user input.

This approach guarantees that the AI Chatbot with Voice-Assisted Answering can comprehend user questions in both spoken and written forms and provide precise, situationally appropriate replies, which improves user engagement and aids in many different contexts.

V. CONCLUSION

Advanced voice recognition, natural language processing (NLP), and text-to-speech (TTS) technologies were successfully integrated to build a powerful, interactive conversational agent in the AI Chatbot with Voice-Assisted Answering project. The chatbot is able to comprehend human intent, translate spoken language into text effectively, and provide replies that are both logical and relevant to the situation since it makes use of advanced machine learning methods. Incorporating voice-assisted response improves the user experience by giving users a more natural and intuitive interface. This is especially helpful in settings where people want to engage without using their hands.

By utilising advanced deep learning models for natural language processing and speech recognition and training on both textual and voice-based datasets, this project's methodology guarantees that the system can comprehend a diverse range of inputs in various languages and accents. A complete and effective system is achieved by combining DeepSpeech for voice recognition with intent detection and response generation models from BERT and GPT, as well as TTS engines such as Google Cloud TTS for voice output.

Progress in conversational AI will be possible thanks to this project's real-time testing and assessment, which proves the AI chatbot's viability and efficacy in practical settings. It is possible that in the future we may see efforts to improve the chatbot's knowledge base, make it better at handling more complicated conversations, and include sophisticated capabilities like sentiment analysis and tailored replies.

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