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Conceiving and Creating a Diagnosis Chatbot to Back Up Primary Health Services

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ABSTRACT

The use of technology in the medical field is rapidly expanding. The delivery of healthcare and the nature of the patient-doctor relationship have both been revolutionized by technological advancements. Both patients and physicians have benefited from the revolutionary effects of artificial intelligence and chatbots in the medical field. An interactive diagnostic tool is needed to improve the healthcare system. Chabot is built on top of the newest machine learning technologies, including the decision tree algorithm, to aid users in self-diagnosis. The system will be trained to interpret user queries about different ailments through natural language processing and provide accurate answers. Like Siri, Alexa, etc., the system may be utilized for efficient information extraction, but its focus will be narrowed to illness diagnosis.

Keywords: Chatbots, Health care, Natural Language Processing, Machine Learning, Diagnostic bot.

INTRODUCTION

Presumably, the doctor-patient dynamic hasn't changed much over the years. When ill, the patient consults a physician. The doctor takes the patient's history, considers the patient's symptoms, and then makes a diagnosis. An expert system that can comprehend the patient's human language and is given the facts that physicians already know may assist with primary diagnostic questions. Besides saving money, this is also a handy option. Chatbots, also known as chatter-bots, are artificially intelligent programs designed to carry on conversations with human beings. Both spoken and written communication are acceptable. In this way, ChatBots may be tailored to serve certain purposes; for instance, a health-related ChatBot would only be able to answer questions on that topic. The Turing test is a good litmus test for the intelligence of such a system. To pass the Turing test, A must dialogue with X. A has no idea if X is an intelligent machine or a human being. Application fields of chatbots include statistics, marketing, customer service, education, amusement, and economics, while consumer applications include the food and gaming industries, the health and retail sectors, the social media and travel industries, and the utility sector.

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Machine learning is the study of mathematical models and computational methods that enable a machine to acquire knowledge about its environment and perform a job without being explicitly programmed to do so. It may be broken down into two major categories: supervised learning and unsupervised learning. The suggested system employs a kind of supervised learning. Directed instruction is the data used to train the machine, which is essentially the same thing. To rephrase, It signifies that we have data labeled with the right solution. The computer learns to map inputs to outputs by analyzing this training data. For instance, the collection includes information on a wide range of disorders. The first stage is to teach the system how to handle various ailments properly. It will be classified as a case of the flu if the patient has a temperature and a headache but as a cold otherwise. Conjunctivitis is the name given to a condition in which the eyes become red and irritated. Thanks to the dataset's training, the system will correctly identify conjunctivitis when a user reports redness and itching in one or both eyes. Given that the outcome variable is a categorical label like "conjunctivitis" or "cold/flu" rather than a continuous score, classification is used. We require a set of tools to handle the text produced by the voice recognition system, which takes the user's spoken input and turns it into text. In order to extract the semantic meaning of the user input, certain toolkits assist in partitioning sentences into words and executing tasks like stemming and tagging different elements of speech. The Natural Language ToolKit (NLTK) is a python package that serves as one such toolkit. Widespread use in python programs, especially those dealing with language processing, etc.

Open source NLTK includes a wide variety of libraries, tutorials, and hands-on activities. When NLTK was developed in 2001, it was at Penn. By labeling words with their places and roles in a phrase, NLTK can parse text strings into their component pieces. Then, the succeeding labeled words are processed to identify their relative importance and provide an output.

Background Study

Reference [1] presents the results of research on Chatbot architecture, including comparing nine carefully selected publications' varied plan systems in light of their basic methodologies. There have been significant improvements to ChatBots in the last decade, and these publications serve as examples. The author discusses the similarities and differences in approach and examines the Chatbots that won the Loebner award in detail. Human-Computer Speech Interaction, the Natural Language Toolkit (NLTK), and the isolation of its three main components—the Responder, Classifier, and Graphmaster—form the basis of these methods [1]. Parsing, AIML scripting, pattern matching, and the use of SQL and relational databases are only some of the key bot implementation strategies the author highlights. The Turing Test and the Loebner Prize are also explained in detail. The "imitation game," as proposed by Turing. It's a test to see whether a computer is as intelligent as a human being by simulating human thought processes. The Loebner Prize is awarded annually to the winner of a contest in which contestants must determine whether or not they are communicating with a computer. The primary goal is to see whether the chatbot seems human-like in conversation. It also sheds information on the process of voice recognition used by chatbots. The procedure uses digital signal processing to transform an audio file into a readable text file[1].

The authors suggest a counselling bot in [2], which uses deep learning techniques such as convolution neural networks to offer a conversational service for mental health treatment. Training

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data might be in any format, from images and videos to audio and text. The app employs sophisticated natural language processing (NLP) and natural language generation (NLG) techniques to interpret user input and provide appropriate responses. Similarly, the system makes use of a kind of emotional intelligence since it is crucial to the medical chatbot's operation. In order to properly analyze the patient's situation and provide a suitable response, it must consider emotional factors in addition to the language. Sentence entailment is only one example of the many facets of NLU that need collecting as many relevant corpora of the target language as possible. The system will also include Continuous Emotional Monitoring of the patient to detect any emotional changes over time [2], in addition to multimodal emotion identification and NLP. The author references prevalent AI trends and practices while offering suggestions on how to enhance state of the art. Basic AI architecture and operation are the main points of discussion. Chatbots (or chatterbots) framework is created. The author argues that the present approach to artificial intelligence is inadequate and proposes an alternative theory based on the concept of machine insight for the ultimate destiny of such frameworks.

The authors of [3] compare and contrast two different chatbots: SARANG, built using AIML, and FUTURE, built in C++. Specifically, it demonstrates the advantages of utilizing the AIML markup language. The ALICE (Artificial Linguistic Internet Computer Entity) bot, currently available in AIML, has roughly 50,000 answers. When given 1500 questions, the SARANG chatbot provided answers to 1200 (or 80%) of them. In this work, we explore the issues with the Turing Test, including its inability to generalize, narrow scope, and lack of forwarding momentum. The model [3] identifies a set of five core competencies shared by all expert machines: mathematics, comparability, reasoning, and logic learning, strategies and memories, perceptions, observation, and awareness. If a system can only meet some of the aforementioned capabilities, we call it "partial intelligence," whereas full intelligence requires that all of these capabilities be met. However, today's machines cannot match all of these capabilities [4, 5]. In particular, several goals may coexist inside a single discourse, and they need not all be offered at the same time.

The examples provided in reference [6] demonstrate how easily interactive technologies may be integrated into a person's routine. Increases in chatbot development have occurred, although the reasons for this are still unclear for the most part. This cutting-edge technology allows for the possibility of meaningful interactions between humans and machines. Over the course of two weeks, 54 participants in India and the United States shared their subjective impressions. How these initiatives are received and what requirements exist among people may help us identify potential gateways for chatterbots. The goals of the investigation include gaining an awareness of what follows: One) Hopes Regarding Chatbots, the kind of inputs most often favored three) potential applications of chatbots derived from user requirements [6]. It's common to practice developing a slew of conversational agents (CAs) to handle a certain topic and field of inquiry. Consistent use of CAs may improve user experience in ways that go beyond functional needs. The areas of interest to the customer are suggested as a means of enhancing customer engagement, as suggested in reference [7].

From the data analysis perspective, they also include rich flags in conversational exchanges aimed at eliciting client satisfaction via successful use of the agent's tools and a pleasant overall experience.

Agents that dynamically improve their effectiveness and teamwork might be built using these signals. Distinguishing between these indications allows us to better understand the evolving components of conversational partnerships. The CA structure recommendations and directions for developing adaptable agents based on customers' conversational linguistic habits are explored. In a nutshell, the author proposes enhancing natural language classifiers to allow them to respond with sarcasm and humor, like real people. According to the suggested framework, the chatbot should dynamically adjust to the preferences of the human they are interacting with. Feedback provision, lighthearted chitchat, systemic inquiry, and ongoing public statements are important conversation terrains. They highlight rich signals in dialogue connections for collecting customer satisfaction, which may be employed to develop controllers that can change computational exhibits and collaboration styles[7]. This is all accomplished via a focus on quantifiable exhibiting.

Paradigms for intelligent bots that can communicate with humans use Natural Language. Current chatbots are rule-based and hence unable to solve complex, real-world issues. The chatbot architecture, which uses deep learning algorithms to have all conversations ready from the conversations themselves, avoids these difficulties [8]. We show that chatbot frameworks may be used in real-world applications, and we cite a paper that suggests using a deep learning technique based on gated, end-to-end memory systems. This model is discovered in a no-supervision model that spans the whole process from beginning to end. The system is built in a medical clinic and can generate and regulate language to properly lead conversations, issue API calls, and obtain responses depending on those API calls [9]. It dissects the problems with the current rule-based approach and suggests fixes for the new dataset, including data from medical facilities, to improve the reactions [10]. Current systems, such as ELIZA, Siri, and ALICE, are shown to affect the proposed system in [11]. The classic chatbot ELIZA helped illustrate how rephrasing questions may lead to more natural conversations. Incorporating AIML into our framework was made easier thanks to ALICE. The customer will be encouraged to ask a question that is associated with sports; Siri finally helped us understand the limits of language processing in voice-to-speech bots [12]. The user interacts with the software by speaking their question into their phone. In order to create an AI for games, we will be encoding a wide variety of questions and answers in AIML and storing them in a database. When a client submits a query, it is cross-referenced against the many instances in the database, and the format most similar to that instance is presented in the form of discussion to the user[13].

Two approaches to using decision trees are shown in reference [14]. The first approach follows the standard practice already present in commercial video games to program the game's artificial intelligence, which entails physically programming the system in line with the AI software engineer's participation to increase user satisfaction. The second strategy is based on iterative programming practices, and its ultimate aim is to construct an AI for fun and games. The two methodologies are shown to have certain commonalities [14]. Doctors can keep tabs on their patients' health thanks to cloud-based control technologies [15].

Proposed Approach

The proposed system will function as an application in the medical field. The user has the option of creating an account on the site, in addition to engaging in live chat with a medical professional. A preliminary diagnostic chatbot is included on the site in case the attending physician is unavailable.

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The user can use either text or voice to enter their symptoms. The chatbot will use NLP in order to comprehend the user's inquiry. After the bot has gained an understanding of the primary symptoms, it will proceed to inquire more questions of the user and attempt to formulate a diagnosis based on their responses. In order to assist in the formation of an appropriate diagnosis, the system uses a decision tree algorithm and takes a top-down approach. The first symptom that is given will serve as the basis for the decision tree's root. If the bot detects that you're experiencing symptoms that match those of another ailment, it'll ask you some more questions to narrow down the list of potential diagnoses. After the user has been questioned using an approach based on a questionnaire provided by the system, the decision tree is then navigated appropriately until a leaf node is encountered. The diagnosis that has been generated will be included in the leaf node. Figure 1 depicts the proposed system architecture.

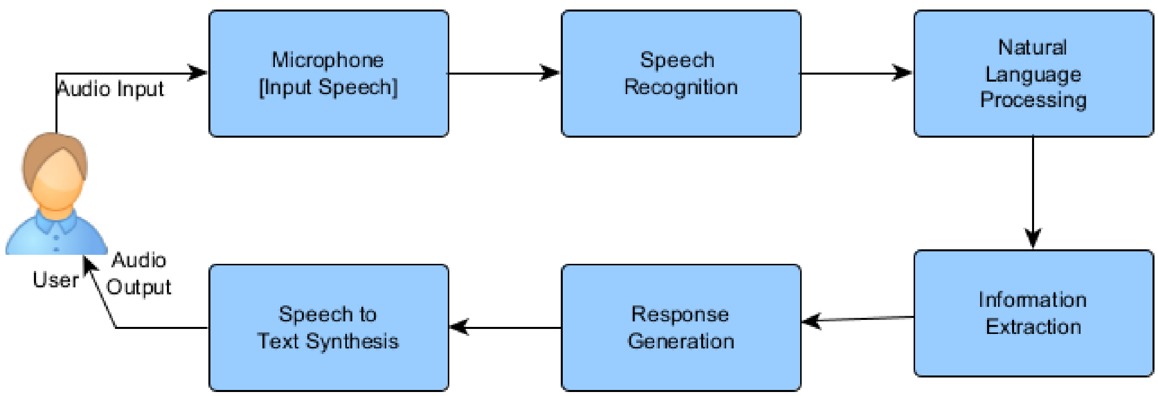

Figure 1: Proposed Architecture

The system will contain a variety of modules. However, the following descriptions cover the three most important components:

- The analysis of the entered answer using NLP in order to comprehend user intent
- The formation of a decision tree and the traversal of it until a leaf node is reached
- The translation of user queries from voice to text and from text to speech for the outcome.

Not only are they easy to comprehend, but they also have the potential to be very effective, which is why they are the method of choice when it comes to both prediction and categorization. The term "decision tree" comes from the fact that its structure is similar to that of a tree, with nodes representing a test or, in our instance, a symptom, and branches representing the result of the test (whether the individual has that symptom or not), and leaf nodes containing potential diagnoses. In our approach, the chatbot is required to reach a conclusion depending on each user's input. For instance, if a user inputs that they have a temperature, the chatbot has to determine how it should react. How will the patient be probed in the other direction, and how will we conclude with a prognosis? We are able to carry out this function with the assistance of the decision tree algorithm. The most important module of our system is the one that handles decision-making. Both the smooth operation of the system and the reliability of the findings are directly tied to the quality of the decisions that are made. The system will depend on the input provided by the user at each stage and

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will be perception-based. By comparing the information provided by the user to the symptoms at each successive level, the decision tree algorithm will assist us in navigating our way to a solution. If there is no match, the system will continue to iterate through the loop until either the top of the tree or a leaf node is reached. Because a decision tree is a supervised learning method, the goal is to first build a training model that can be used to forecast the value of a target (in this example, a prospective sickness) via the process of learning decision rules using data that has previously been input into the system (training data).

The information that was utilized is presented in a tabular style and lists around 55 illnesses along with the symptoms that are associated with them. It was difficult to track down a precise clinical dataset; hence, the dataset was filtered to guarantee that only common illnesses and their symptoms were included. This was done to maximize the effectiveness with which disease diagnosis could be performed.

Result and Discussion

The proposed methodology is a working version that identifies around 200 symptoms and 55 illnesses. It conducts diagnoses at many levels of the decision tree utilizing the information provided by those levels. After compiling a list of possible symptoms into a decision tree, the algorithm utilizes the information to conduct a series of follow-up questions with the user.

Round Trip Time: It was discovered that the system's reaction time ranged from 20ms to 30ms, which depended on the symptoms count.

Accuracy: The approach that was developed provided 85 right responses out of every 100 questions that were asked about prevalent illnesses. It was determined that the accuracy was 85%. The outcome of the proposed system was checked with a physician to evaluate the model's performance. The bot identified the common disease terms as much as a physician did but failed to identify the uncommon disease terms, leading to decreased accuracy of the model. We plan to fine-tune the bot by increasing the training set and to improvise the performance accuracy. Table 1 lists the accuracy percentage of the bot with that of a physician in identifying the common and uncommon disease terms, and its visual representation is given in Figure 2.

Table 1: Performance Measure

Terms	***Accuracy (%)***	
	Physician	**Bot**
Common Disease Terms	100	85
Uncommon Disease Terms	100	57

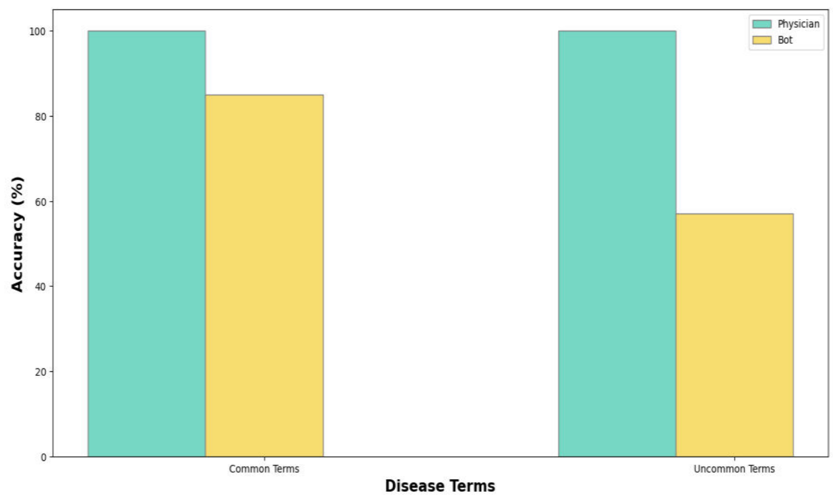

Figure 2: Performance Accuracy

Conclusion

The current landscape of healthcare has been significantly reshaped by artificial intelligence. The suggested approach has the intention of reducing the distance that exists between patients and the medical platform. In order to construct a productive diagnostic chatbot, AI techniques such as decision trees and natural language processing (NLP) are employed to retrieve information from a medical database that contains around 150 different disorders. The chatbot will pose questions to the user in a manner that is meant to simulate a conversation between a physician and a patient. The questions are derived from the previous input provided by the user, and the information gleaned from their responses is used to formulate a potential diagnosis. The diagnostic form is exploratory in nature and is intended to assist the user in making decisions on further steps. In the future, the software will need to expand its database and enhance the machine learning component to provide a more accurate diagnosis.

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