An AI-NLP based Interactive Chatbot Model for Patient Prescreening at Doctor's Consultancy

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Abstract—Diabetes is a prevalent issue in Bangladesh, presenting significant challenges for healthcare systems. This project aims to develop an integrated health prescreening solution that combines an interactive chatbot with sensor modules for vital health data logging. Effective diabetes treatment requires comprehensive information from patients, including lifestyle, dietary habits, medications, and comorbidities, which typically consumes a lot of time during medical consultations. The proposed system streamlines this process by using dedicated sensors to collect essential health data, such as temperature, heart rate, and oxygen levels. Patients interact with a conversational chatbot to provide additional information, including symptoms and medical history. This data is then displayed on a screen at the end of the conversation for easy reference by healthcare professionals. The project progresses through four main stages: requirement analysis, system design, chatbot development, and sensor integration. While the sensor output may show slight fluctuations compared to medical-grade equipment, the chatbot achieves high accuracy (>90%) in conversation and information extraction. By integrating vital sign monitoring with an interactive chatbot, this project aims to reduce waiting times, enhance efficiency of medical checkups, and improve doctorpatient communication in a modern healthcare setting.

Keywords— Healthcare, Chatbot, Artificial Intelligence, Natural Language Processing, IoT, Medical diagnosis

I. INTRODUCTION

In healthcare industry, the process of gathering essential patient information and measurements before a doctor's visit often involves manual procedures that can be time-consuming and inefficient. Patients typically need to visit a healthcare facility, wait in lines, and have their vital signs and body measurements taken by healthcare staff. This traditional approach normally leads to long waiting time, delays in cares, and strain on healthcare resources. Moreover, taking a patient to a doctor causes a long queue of waiting patients, thus sometimes patients cannot get proper treatment.

Emerging technologies offer an opportunity to address the above issues. This study proposes developing a sensor integrated chatbot system for patient pre-screening. By combining Artificial Intelligence (AI), Natural language processing (NLP), and dedicated hardware, a comprehensive solution is presented that optimizes data collection and patient engagement. This research project mainly focuses on designing an interactive chatbot interface and a hardware module for gathering essential physical condition data. The chatbot utilizes advanced NLP techniques to intelligently gather medical information and provide appropriate responses, ensuring effective communication of patients' concerns and healthcare needs. Complemented by sensors in

the hardware module, real-time measurements such as temperature, heart rate, and oxygen levels are securely captured. This integration enhances chatbot functionality, enabling a holistic approach to patient pre-screening.

By minimizing physical visits and enabling remote engagement, the chatbot-hardware system aims to reduce waiting times, optimize resource allocation, and enhance the patient experience. Through seamless integration of technology and healthcare expertise, we can revolutionize patient pre-screening, improving efficiency, accessibility, and patient outcomes. This research contributes to a patient centric healthcare ecosystem that leverages advanced technologies to optimize pre-screening, leading to improved healthcare delivery and patient experiences.

II. LITERATURE STUDY

Recent advancements in chatbot technology offer exciting opportunities for pre-screening individuals at risk of chronic diseases, such as diabetes. While studies have explored the use of chatbots in healthcare for tasks like medication reminders and appointment scheduling, there is still limited research on their potential role in pre-screening for diabetes [1, 2]. This article contributes to the field by examining how interactive chatbots can be used to identify individuals who may benefit from further diabetes evaluation, thus enhancing early detection efforts.

Existing literature highlights several related systems that have addressed aspects of remote healthcare and medical assistance. One study by Harikrishnan and Stephen [3] describes the development of a hospital or home medical assistant robot, which utilizes surveillance and bystander modes to collect patient data and provide assistance. However, this system may face limitations in terms of its ability to effectively handle complex medical scenarios and communicate critical information to healthcare providers.

Another research by Stollnberger *et al.* [4] proposes a three-way teleconference system that enables remote consultations between doctors, patients, and assistants using a medical robot. While this system facilitates communication, it may have limitations in terms of its scalability and ease of use, potentially hindering its widespread adoption.

Moreover, the use of chatbots in medical diagnosis has gained attention. Srivastava and Singh [5] presented a diagnostic chatbot that engages patients in assisted and personalized disease diagnosis. However, its limitations may lie in its reliance on textual input, which may not fully capture nuanced symptoms or non-verbal cues from patients. In a similar vein, Divya *et al.* [6] introduced a self-diagnosis

medical chatbot driven by AI. This chatbot engages users in discussions about their health issues, extracts symptoms, and offers personalized disease diagnoses. It aims to improve accessibility to medical knowledge and empower users to understand their health before seeking professional medical advice.

Additionally, an AI-IoT based Healthcare Prognosis Interactive System developed by Reddy *et al.* [7] integrates a chatbot and an application interface to provide real-time medical diagnosis and support. However, this system may have limitations in terms of data security and privacy concerns related to collection and storage of sensitive patient information.

In this article, the proposed chatbot-hardware system offers a unique integration of AI-powered chatbot technology and physical sensor measurements. By efficiently collecting patient data and enabling effective communication with healthcare providers, the system aims to address the limitations of existing systems and revolutionize patient prescreening process, improving efficiency, accessibility, and patient outcomes.

III. DESIGN OF THE SYSTEM AND PROTOTYPE DEVELOPMENT

The Interactive Chatbot for Diabetes Patient Pre-screening system is an integrated chatbot solution for patient prescreening in hospitals and clinics. The system combines a chatbot interface with sensors to measure height, weight, heartbeat, oxygen saturation, and body temperature of patients. The system is modeled in multiple stages: Conceptual Design, Developing machine learning models, Interface Design, External Device integration, and Environment Design.

A. Conceptual Design

Conceptual design outlines flow diagram detailing various system functions. This section explains theoretical framework behind the system's design. Additionally, it covers dataset design for speech processing, design and development of chatbot, and integration of overall system with Raspberry Pi.

- 1) Dataset Design: Healthcare professionals and patients willing to provide informed consent are essential for this stage. Study objectives, data collection process (anonymized audio recordings), and potential risks and benefits are clearly described to the participants. Prioritizing privacy is ensured by using de-identified transcripts and maintaining robust data security throughout the process. Data pre-processing requires careful attention to de-identification, accurate transcription, relevant annotations (demographics, risk factors, and diagnoses), and ethical analysis. Data are collected, preprocessed through data management systems, and structured using JavaScript Object Notation (JSON) script with several lists of queries, corresponding responses, and individual tags [1, 8]. Basic structure of JESON structure for conversation dataset is shown in Fig. 1.
- 2) Chatbot Design: Python programming language is chosen to design and implement the chatbot because of its popularity and rich libraries. The JSON structured preprocessed dataset is used to train the designed Artificial Neural Network (ANN) [9-11]. A flowdiagram of focus position detection and tracking for the proposed chatbot is presented in Fig. 2.

3) Health Information Unit: A hardware system is developed by integrating various sensor modules and circuitry in a PVC-box. The hardware measures three parameters, body temperature, pulse rate, and oxygen level. For processing and storing data, Raspberry Pi is used. A DS18B20 temperature sensor is used to measure body temperature. The sensot has $\pm 0.5^{\circ}C$ accuracy renging from -10°C to +85°C. MAX30100 Pulse Oximeter Heart Rate Sensor module is for measuring pulse rate and oxygen level. This module is an optical sensor that derives its readings from emitting two wavelengths of light from two LEDs, a red and an infrared one. It measured the absorbance of pulsing blood through a photodetector. Figure 3 depicts overall process diagram of IoT part of the system. Necessary circuit diagram of the hardware prototype is illustrated in Fig 4. The overall process of the project is presented in Fig 5.

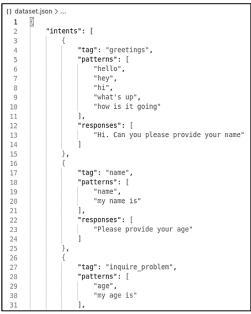


Fig. 1. Snip of the JSON structured dataset

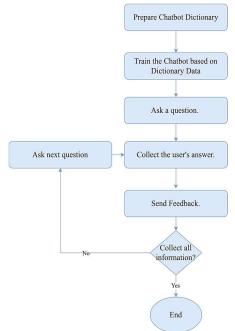


Fig. 2. Flowchart of the designed chatbot

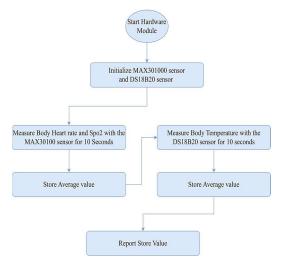


Fig. 3. Flowchart of collecting body health measurements

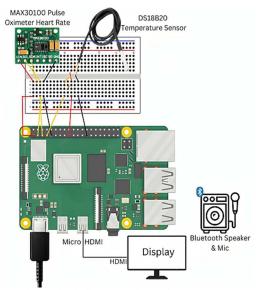


Fig. 4. Circuit diagram of the Hardware Prototype

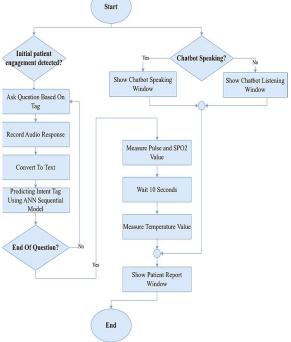


Fig. 5. Flowchart of overall process of the system

B. Interface Design

System interface is divided into three individual screens serving different purposes. Two screens are for user interaction with chatbot. Initial screen is for speaking, become activated when chatbot is in speaking mode. The second screen is for listening; when chatbot completes speaking and waiting for user's response, listening screen appears so that user can understand that it is user's turn to talk. The two testing screens are shown in Fig. 6.

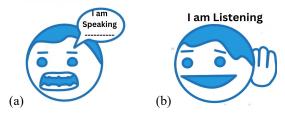


Fig. 6. Chatbot Screens, (a) speaking mode, & (b) listening mode

Third screen is designed to use by doctors and medical assistants. It shows patient's report which contains necessary medical information required for providing treatments. The report is generated according to the conversation between chatbot and patient. The report also contains body temperature, pulse rate, and oxygen saturation level of patient which are acquired by the sensors modules.

C. Machine Learning Model

Machine Learning (ML) model used in the interactive chatbot for diabetes patient pre-screening is shown in Fig. 7. Inputs of the system are voice signals which is converted into text. The text data are preprocessed, and stop words are removed. Bag of words representation of input text is generated to use in the model. The Sequential neural network model predicts intent of next question based on the preprocessed data. The output is returned as a list of probabilities, one for each intent in data dictionary. Classes with probability values lower then the threshold value 0.25 are filtered out. Remaining list of probabilities is then sorted to get intent with maximum probability. A return list is generated which contains the name of the intent and its probability which can be used in the system to identify next question. The dataset used in this model contains 13 intents in total. The number of intents can be increased if new questions need to be added to the system.

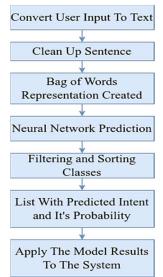


Fig. 7. Flowchart of overall process of the system

D. External Device

System enables patients to interact with a chatbot to provide their information, while an external sensory module collects physical health data. The Raspberry Pi, serving as the processing unit, features 4GB of RAM and a 64-bit architecture, making it a versatile and robust single-board computer. Its enhanced performance capabilities, smoother multitasking, and compatibility with a wide range of software optimized for 64-bit computing make it an ideal platform for various projects, from IoT applications to multimedia centers.

To interface Max30100 pulse oximeter with Raspberry Pi, I2C (Inter-Integrated Circuit) protocol is used. I2C facilitates serial communication between Raspberry Pi and Max30100 sensor, enabling transmission of data such as heart rate and blood oxygen saturation levels. The DS18B20 temperature sensor, on the other hand, is connected to Raspberry Pi using 1-Wire protocol. This protocol allows communication with DS18B20 sensor through a single data wire, simplifying wiring and connection process. With 1-Wire, Raspberry Pi can accurately measure temperature readings from DS18B20 sensor.

E. Experimental Setup

The system includes a display and a box containing necessary devices and circuits. Display is placed at the upper part of the box. When a patient comes to doctor's chamber, he talks with chatbot first and gives information and body measurements. The proposed overall setup is presented in Fig. 8. Final system with hardware device is presented in Fig.9.

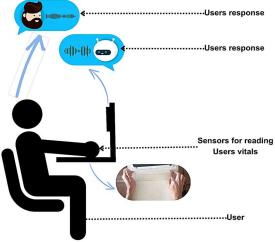


Fig. 8. Conceptual setup of the system

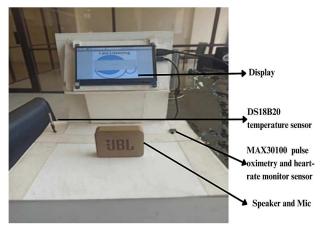


Fig. 9. Experimental setup of the system with necessary modules

IV. RESULT AND EVALUATION

The system's primary purpose is to develop a prescreening tool for individuals with diabetes in a doctor's office. Assessing how well the system performs tasks like gathering information, storing it, and interpreting documents based on this data is crucial. In this regard, two evaluation processes are conducted; one is to evaluate machine learning model and another is to test sensor modules. ML model evaluation determines the chatbot's performance, while the sensor evaluation assessed the system's information compilation capability.

A. Machine Learning Model Evaluation

The system includes ML models to identify intent of next question that a chatbot is going to ask after answering the current question. The Feedforward Sequential Neural Network (FSNN) model and LSTM are used to perform the task. Several test cases are used to evaluate these ML models. An example test case is given below. Feedforward sequential model is able to predict intent of the next question correctly with an accuracy of $\approx 99.99\%$. On the other hand, 50% accuracy is achieved by LSTM.

User: Hello

Chatbot: Hi there! I am happy to chat with you. Could you

please tell me your name?

User: My name is Kaushik.

Chatbot: Nice to meet you. Please provide your age.

User: my age is 23

Chatbot: Please tell me if you're facing any health

concerns?

User: I have high blood sugar.

Chatbot: Do you have any family history of diabetes?

User: My mother has diabetes.

Chatbot: Have you been diagnosed with any other medical

conditions except diabetes?

User: No other medical condition.

Chatbot: Are you monitoring your blood sugar levels at

home?

User: Yes, I am monitoring my blood sugar levels at

home.

Chatbot: What is the recent blood sugar reading?
User: My recent blood sugar reading is 12.

Chatbot: Do you take any medication? **User**: No, I don't take any medication.

Chatbot: Please put your hand on the marked position for

30 seconds.

For this test case the output of FSNN and LSTM models are given in Table 1. Here sentences are taken from conversation and chatbot predicts its intention. Probability vs Intents graphs for second test case are presented in Figure 10 where the better performance of FSNN model is reflected over LSTM.

B. Sensor Evaluation

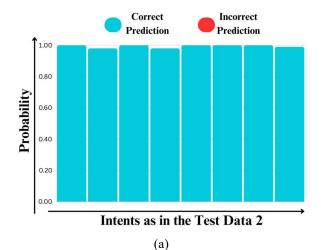
Comparison between data values from used sensor and medical grade equipment is conducted. In this case, two measurements are taken sequentially. This comparison results are presented in Table 2. By analyzing the results, it is observed that most of the sensors' data show little bit of fluctuations form its original value at the starting of the measurements but settles down to the actual values within a few moments. These data differences are shown in Fig. 11 as line diagrams for better visualization.

Table 1. Intent prediction for Feedforward Sequential Neural Network (FSNN) model and LSTM for test data (Correct=Y and Incorrect=N)

	Predicted Intent		Prob	ability	Result	
Sentence	FSNN	LSTM	FSN N	LSTM	FSN N	LSTM
Hello	name	name	1	1	Y	Y
My name is John	age	age	1	1	Y	Y
My age is 23	Inquire problem	Inquire problem	1	1	Y	Y
I have diabetes	Family history	Other diseases	0.98	0.97	Y	N
My mother has diabetes	Other diseases	Sugar readings	1	0.93	Y	N
No other condition	Sugar readings	Sugar readings	0.96	1	Y	Y
My recent blood sugar is 12	medicati on	Inquire problem	1	0.96	Y	N
No, I don't take any medication	End	Medicati on	0.86	0.82	Y	N

Table 2. Comparison between three sensor measurements and medical grade equipment

Т	Sensor Name	No of attempts					
Types	Sensor Name	1	2	3	4	5	
Temperature (Celsius)	DS18B20 Temperature Sensor	88	94	92.7	80.8	92	
	Digital thermometers by Microlife	98	99	98.8	99.3	98	
SPO2 (%)	Jumpe Fingertip Pulse Oximeter	96	99	98	98	96	
	MAX30100 Heart- Rate Sensor IC	72	64	88	83	87	
Heart rate (BPM)	Jumpe Fingertip Pulse Oximeter	112	100	105	108	110	
	MAX30100 Heart- Rate Sensor IC	72	64	122	90	87	



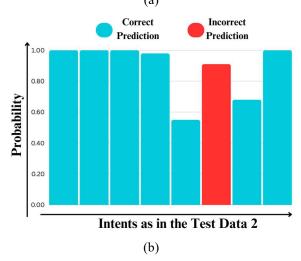


Fig. 10. Probability vs Intents graph for (a) FSNN model, and (b) LSTM model for Test Case 2

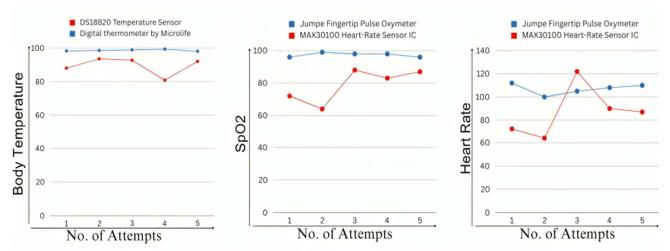


Fig. 11. Visualization of the comparison between three sensor measurements and medical grade equipment

V. CONCLUSION

This study describes a distinctive patient-support system prototype intended to aid in diabetes pre-screening. The system interacts through a user-friendly chatbot interface and collects data using simple health sensors. A deep learning model analyzes user responses to guide the conversation and extract relevant information. This conversational data is then paired with sensor measurements (pulse oximetry and

temperature) to produce a preliminary report on diabetes risk. This study observed problems in existing pre-screening chatbots, primarily concerned with question-answering rather than real-time data collecting. The suggested system provides a user-friendly method to overcome communication gap between patients and physicians. By speeding up information collection and minimizing unnecessary visits, the system can increase efficiency for both patients and healthcare practitioners. However, developing method has some

limitations. The lack of a large conversation dataset for training deep learning model, along with ethical constraints on patient testing, hampered system's full optimization. Furthermore, contemporary sensor technology requires more accuracy.

Future development of this project may include emotion recognitions [12], integrating blood pressure measures, using higher-quality sensors, and allowing users to choose between chat-only or sensor data collection-only. The research could be improved, particularly in terms of methodology, system design, and justifications for the tools and techniques used. Furthermore, system's capabilities might be improved to include pre-screening for additional chronic conditions. The ultimate goal is to commercialize this system and make it widely available in hospitals and clinics. This widespread usage has potential to facilitate more efficient patient-doctor interactions, resulting in earlier diagnoses and better patient outcomes.

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