AI-Powered Conversational Diabetes Diagnosis System

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I. Motivation and Objectives

Diabetes, known as Diabetes Mellitus (DM), is a chronic metabolic disease primarily characterized by abnormally elevated levels of sugar (glucose) in the blood. The onset of diabetes is mainly associated with abnormal secretion or function of insulin, a hormone secreted by the pancreas responsible for regulating blood sugar levels. Normally, blood sugar levels rise after food intake, triggering the secretion of insulin which then prompts muscle and fat cells to absorb glucose, thereby maintaining blood sugar levels within a normal range. However, in individuals with diabetes, there is an abnormality in insulin secretion or action, leading to ineffective control of blood sugar levels [1]. Diabetes is a complex chronic illness requiring continuous medical attention and multifactorial risk-reduction strategies to maintain glycemic control within a desirable range. Patient self-management education and support are crucial in preventing acute complications and minimizing the risk of long-term complications [2]. Diabetes poses a global issue with significant social, health, and economic impacts. It is estimated that in 2010, 285 million people worldwide (approximately 6.4% of the adult population) were afflicted with this disease, and this number continues to grow [3].

Diabetes detection and early prevention are pivotal in mitigating the prevalence and public health impact of the disease. Mainstream detection methodologies primarily leverage biomarkers such as blood glucose levels, A1C tests, and insulin levels for prompt and accurate identification of diabetic individuals. Additionally, advancements in machine learning and data mining models have shown promise in enhancing diabetes diagnosis by analyzing patient medical data, with higher accuracy rates observed when integrated with physician assessments [4]. For early prevention, lifestyle interventions encompassing dietary control, increased physical activity, and weight reduction have been established as fundamental and effective measures to delay or prevent the onset of Type 2 diabetes [5]. Screening initiatives targeting high-risk populations for early identification and intervention of diabetes, including early-stage Type 2 diabetes and prediabetes screening, constitute another crucial preventative strategy [6], [7]. However, several shortcomings persist, including delayed detection due to often asymptomatic early-stage Type 2 diabetes [4], accessibility restrictions to detection and prevention resources especially in resource-limited regions, and varied efficacy of screening endeavors influenced by factors like accuracy of screening methods, coverage, and public acceptance of screening initiatives. Continuous research and public health interventions are essential to refine detection methods, enhance prevention efficacy, and alleviate the public health burden of diabetes.

Diabetes is a matter of substantial concern for individuals and society. Concurrently, with the advancements in technology, the self-monitoring and early prevention of diabetes have become increasingly affordable and accessible, showing significant promise in mitigating the challenges posed by this ailment. Coupled with the rapid evolution of artificial intelligence (AI) in recent years, it is an aspirational venture to integrate AI into this domain. The strong predictive power of AI, along with the human-centric interaction capabilities and extensive knowledge of large language models, can be harnessed for early prevention and dissemination of knowledge regarding diabetes, which we believe will provide positive assistance. This project is anchored on this objective, representing a preliminary exploration and attempt to construct a conversational preliminary diagnostic system. This system aims to facilitate better self-examination and learning of preventive knowledge among users, thereby contributing to a proactive approach towards diabetes management and prevention.

II. Related Work

Digital self-monitoring for Diabetes. Digital tools are increasingly integral in diabetes self-monitoring. Notable applications include the American Diabetes Association's Standards of Care app, and others focused on blood glucose tracking, lifestyle management, and automated insulin delivery [8]. The emergence of mobile health (mHealth) significantly supports self-monitoring endeavors in diabetes, as defined by the World Health Organization [9]. Utilization of digital monitoring devices has led to a 0.38% reduction in hemoglobin A1c levels, indicating enhanced diabetes self-management, despite the challenges posed to patients and healthcare providers by the rapidly evolving digital health landscape [10]. Research also underscores the utility of mHealth tools in fostering collaborative decision-making between providers and patients, enhancing diabetes treatment delivery and self-management tool development across diverse populations [11].

Artificial Intelligence for Diabetes. Recent advancements in Artificial Intelligence (AI) have significantly impacted diabetes management. Notably, research has explored a Reinforcement Learning-based algorithm for insulin dosing in Type 2 Diabetes, offering safety-enhanced recommendations [12].

Additionally, the integration of AI with digital health technologies holds promise for improved efficiency in diabetes care, potentially reducing healthcare costs [13]. AI has also revolutionized the prevention and management of diabetes, with machine learning aiding in the development of predictive models for risk assessment [13]. The growing interest in AI-driven digital health tools further exemplifies the potential for enhanced patient and provider outcomes in diabetes management [12].

Large Language Models in Healthcare. The advent and evaluation of large language models (LLMs) like Med-PaLM and Flan-PaLM have demonstrated significant potential in the medical domain, particularly in medical question answering tasks [14]. Their capabilities extend to answering questions, summarizing, and translating text, often at a level indistinguishable from human abilities [15]. The development of LLMs, including prominent models like ChatGPT and GPT-4, is considered a major technological breakthrough, showing immense potential to positively impact healthcare [16]. While LLMs hold the promise of democratizing medical knowledge and improving healthcare access, concerns regarding misinformation dissemination and scientific misconduct due to lack of accountability and transparency are also notable [15].

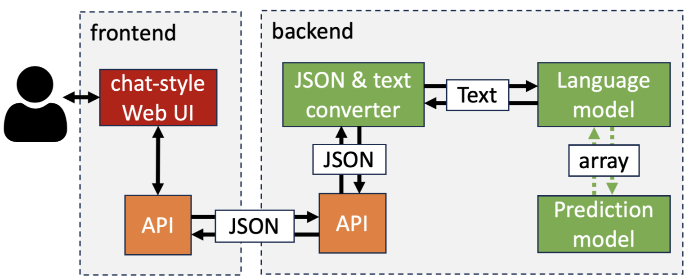

Fig. 1. The system architecture

III. Proposed Work

We propose a simple and user-friendly system, depicted in figure 1, which allows users to converse with the system as they would with a human online, in order to determine potential diabetes-related concerns. This system leverages the capabilities of current advanced large language models and deep learning techniques. It is comprised of four primary components: 1) a prediction model for diabetes diagnosis, 2) a Large Language Model (LLM) that simulates interactions with a medical professional, 3) a user-centric chat-style web interface, and 4) a backend infrastructure to ensure seamless integration and operation of the aforementioned components. In alignment with the proposed system architecture, the necessary work and processes to develop this system encompass code and data resource management, prediction model training, configuration of the large language model, backend and frontend framework development, UI design, and the implementation of an effective communication mechanism.

The Prediction Model. We utilize techniques from deep learning and ensemble learning, training them on high-quality

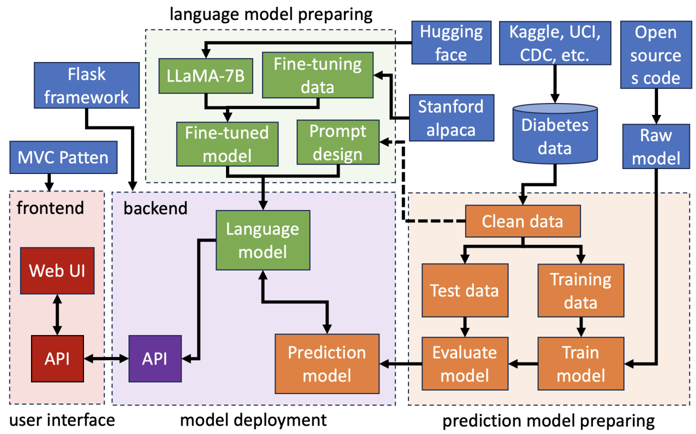

Fig. 2. The workflow

datasets selected and cleaned from plenty of online diabetes datasets to build a high-accuracy binary classification model. It will give accurate results based on the users' condition when users can provide all the information the system asks for. Additionally, our system offers not just highly accurate results but also the confidence or probability associated with these results. This feature enables the system to provide more detailed recommendations tailored to individual states or users, enhancing the user's trust in the system. Recognizing that some users might be unfamiliar with their conditions or may not provide complete information, we've optimized our model to address such scenarios. By leveraging data science techniques, such as extracting feature importance and utilizing models designed to handle missing data, we ensure that the system can still offer fair predictions even with incomplete data.

Human-Computer Interaction Design.

We utilize the LLaMA from Meta AI as our foundational language model. Employing the Stanford alpaca fine-tuning method allows us to enhance the conversational abilities of the model. Simultaneously, we integrate specific prompts to instruct the model on role-playing and data formatting for interactions with the prediction model. Once the fine-tuning is complete, the language model can gather necessary information during conversations with users. In addition, it is capable of sending and receiving information to and from the prediction model, seamlessly switching its output format between structured and unstructured data. We have also developed a chat-style web interface to enable users to send messages and receive feedback directly from our language model. From a user's viewpoint, they are first greeted warmly, followed by a detailed introduction. They then engage in patient and professional communication, eventually receiving precise results and suggestions, and benefit from thorough follow-up. The ideal outcome is for users to feel as if they are conversing with nursing staff and be motivated to either improve their lifestyle or seek timely medical intervention based on the guidance provided.

The Support Frameworks. To ensure the seamless deployment of both models and allow users to interact with the system in real-time, the integration of frontend and backend frameworks is crucial. We utilize the Flask framework for our backend development, apply the MVC Pattern for frontend construction, and employ REST API and JSON files for the transmission of messages between the two. To provide a clearer understanding, we introduce a specific operational scenario. Once a user submits a message via the web interface, it is transformed into a JSON file and relayed to the backend API. This JSON is then converted to text data suitable for the language model. The language model processes this input and produces a response, which is then packed in a JSON file and sent to the frontend. After processing this file, the response appears on the user's screen. However, depending on the conversational context, the language model will decide to either continue the dialogue with the user or, if all requisite information has been collected, forward an array to the prediction model. Upon receiving this array, the prediction model returns the prediction accompanied by its confidence or probability score. The language model then interprets these numerical values into comprehensible text as a response for the system to deliver to users.

Our current objective is to construct an AI-driven diabetes diagnosis system that assesses the risk of diabetes in users through interactive conversations. The project's primary goal is to develop this system from scratch and ensure its functionality. Nevertheless, beyond our initial design, we envision several valuable improvements for its future. Our current scope, constrained by time and resources, limits their inclusion. For example, a deeper analysis of a user's health metrics could offer further suggestions, like evaluating dietary patterns to provide tailored nutritional guidance. Introducing an account management subsystem would allow the system to remember user attributes, paving the way for personalized services. This could range from health coaching reminders via text messages to app notifications promoting wellness. Collectively, these additions would further empower users to manage their diabetes concerns affordably and expertly.

IV. Plan of Action

The resources required for this project encompass data, computational resources, and essential programming libraries. We can source the data from public websites such as Kaggle, the UCI Machine Learning Repository, and the CDC. The computational resources will be provided either by our personal laptops or school servers. Key libraries include Python libraries like pandas, Scikit-learn, Xgboost, Pytorch, Flask, and Hugging Face, all of which are freely available as open source. Additionally, we will implement the MVC Pattern using the .NET framework from Microsoft.

Our presentation is scheduled for Nov. 22nd, and we have outlined the following roadmap. We've already defined the tasks and allocated them among team members based on their interests and skills. Each member is focused on their assigned part, aiming to complete it by early November. In the remaining days, we will integrate all components and address any issues that arise to ensure the system operates correctly. We've scheduled weekly meetings every Friday to discuss challenges or obstacles, ensuring steady progress. As members complete their tasks, they will showcase their accomplishments during meetings, allowing for team review and evaluation.

For the division of our project, Jorge and Motto will handle the prediction model. Jorge will focus more on model prediction and data processing, while Motto will concentrate on model confidence, feature engineering, and the model API. Chris will handle the backend, while Lianet will take charge of the frontend. They will collaborate to ensure the communication between the two. Hongpeng will work on the large language model component, including prompt engineering, LLM fine-tuning, and LLM deployment.

For our project division, Jorge and Motto are in charge of the prediction model. Jorge will predominantly focus on data processing and model prediction, while Motto will delve into feature engineering, model confidence, and model deployment. Chris will be responsible for the backend, and Lianet will manage the frontend. They will collaborate to ensure seamless communication between the backend and frontend. Meanwhile, Hongpeng will handle the large language model component, handling tasks such as prompt engineering, LLM fine-tuning, and LLM deployment.

V. Evaluation and Testing Method

Our system comprises two primary components: 1) the prediction model and 2) the user interaction system. For the prediction model, we will use the cross-validation method to evaluate its accuracy and determine the optimal model. Regarding the user interaction system, we plan to design it from the frontend to the backend. Finally, during our presentation, we will showcase its user interaction capabilities through either a live demo or a demonstration video.

References

[1] M. J. Dean L, "The genetic landscape of diabetes," 2004, chapter 1, Introduction to Diabetes. Available from: National Center for Biotechnology Information (US), Bethesda (MD). Published 2004 Jul 7. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK1671/

[2] "Introduction," *Diabetes Care*, vol. 38, pp. S1–S2, 12 2014. [Online]. Available: https://doi.org/10.2337/dc15-S001

[3] K. Kaul, J. M. Tarr, S. I. Ahmad, E. M. Kohner, and R. Chibber, "Introduction to diabetes mellitus," *Advances in Experimental Medicine and Biology*, vol. 771, pp. 1–11, 2012.

[4] M. K. M. Mohammad Ehsan Farnoodian and H. Mokhber, "Detection and prediction of diabetes using effective biomarkers," *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 0, no. 0, pp. 1–13, 2023. [Online]. Available: https://doi.org/10.1080/21681163.2023.2264937

[5] A. D. Association, "Standards of Care in Diabetes—2023 Abridged for Primary Care Providers," *Clinical Diabetes*, vol. 41, no. 1, pp. 4–31, 12 2022. [Online]. Available: https://doi.org/10.2337/cd23-as01

[6] A. Vasavada and L. Taub, *Diabetes Mellitus Screening*. Treasure Island, FL: StatPearls Publishing, 2022. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK554615/

[7] N. Laiteerapong and A. S. Cifu, "Screening for prediabetes and type 2 diabetes mellitus," *JAMA*, vol. 315, no. 7, pp. 697–698, 2016.

[8] K. Doyle-Delgado and J. J. Chamberlain, "Use of Diabetes-Related Applications and Digital Health Tools by People With Diabetes and Their Health Care Providers," *Clinical Diabetes*, vol. 38, no. 5, pp. 449–461, 12 2020. [Online]. Available: https://doi.org/10.2337/cd20-0046

[9] G. A. Fleming, J. R. Petrie, R. M. Bergenstal, R. W. Holl, A. L. Peters, and L. Heinemann, "Diabetes Digital App Technology: Benefits, Challenges, and Recommendations. A Consensus Report by the European Association for the Study of Diabetes (EASD) and the American Diabetes Association (ADA) Diabetes Technology Working Group," *Diabetes Care*, vol. 43, no. 1, pp. 250–260, 12 2019. [Online]. Available: https://doi.org/10.2337/dci19-0062

[10] S. Li and J. Wang, "Chapter 16 - digital health technologies for patients in diabetes self-management education and support," in *Diabetes Digital Health and Telehealth*, D. C. Klonoff, D. Kerr, and E. R. Weitzman, Eds. Academic Press, 2022, pp. 201–213. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780323905572000066

[11] R. J. Shaw, A. Barnes, D. Steinberg, J. Vaughn, A. Diane, E. Levine, A. Vorderstrasse, M. J. Crowley, E. Wood, D. Hatch *et al.*, "Enhancing diabetes self-management through collection and visualization of data from multiple mobile health technologies: protocol for a development and feasibility trial," *JMIR Research Protocols*, vol. 8, no. 6, p. e13517, 2019.

[12] G. M. Davis, H. Shao, and F. J. Pasquel, "Ai-supported insulin dosing for type 2 diabetes," *Nature Medicine*, pp. 1–2, 2023.

[13] S. Ellahham, "Artificial intelligence: the future for diabetes care," *The American journal of medicine*, vol. 133, no. 8, pp. 895–900, 2020.

[14] K. Singhal, S. Azizi, T. Tu, S. S. Mahdavi, J. Wei, H. W. Chung, N. Scales, A. Tanwani, H. Cole-Lewis, S. Pfohl *et al.*, "Large language models encode clinical knowledge," *Nature*, vol. 620, no. 7972, pp. 172–180, 2023.

[15] J. Clusmann, F. R. Kolbinger, H. S. Muti, Z. I. Carrero, J.-N. Eckardt, N. G. Laleh, C. M. L. Löffler, S.-C. Schwarzkopf, M. Unger, G. P. Veldhuizen *et al.*, "The future landscape of large language models in medicine," *Communications Medicine*, vol. 3, no. 1, p. 141, 2023.

[16] P. Systems. (2023) Application of large language models (llms) in healthcare. Accessed: 2023-10-15. [Online]. Available: https://www.persistent.com/insights/whitepapers/application-of-large-language-models-llms-in-healthcare/