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Personalized Symptom Analysis using Large Language Model

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***Abstract*—** The need for intelligent healthcare systems gained momentum in recent years, with advancements in AI and machine-learning technologies. This paper develops all-inclusive AI-based healthcare assistant predicting diseases based on the symptoms reported by the user and then providing personalized health recommendations. This hybrid model, that is integrated with the OpenAI language model, enables the system to analyze patient symptoms, then give detailed customized descriptions of diseases, dietary recommendations, medication advice, workout plans, and precautions. It also finds the nearest hospitals for the disease diagnosis it has predicted to send the patients to get medical attention quickly. The real-world datasets of disease symptoms are used to test the performance of the system to ensure accuracy and reliability in health guidance. This system aims to enhance patient care and make the requisite health information more accessible for patients, leveraging advanced AI techniques to enable users in making proactive decisions regarding health and wellbeing.

Keywords*—LLM, Hybrid model, OpenAI language model, Healthcare*

I. INTRODUCTION

The healthcare sector is generally moving through a paradigm shift, most especially with incorporation of artificial intelligence technologies. Large Language Models (LLMs) such as OpenAI's GPT-3 have been able to process and generate extremely natural language that mirrors those of humans[2]. These models are trained on giant amounts of textual data, enabling them to understand complex queries and provide contextually appropriate responses. This ability makes LLMs extremely useful for applications in healthcare, where accurate interpretations of symptoms and generation of tailored recommendations are especially critical.

The system will then allow the user to receive detailed recommendations in terms of descriptions of the disease; diet plan; medication advice; precautions, and workout plans to follow. This ability of the LLM used by the AI-driven system will allow it to dynamize its response to a wide range of symptoms. This way, the AI-driven healthcare assistant is able to present nuanced and personalized advice that might adapt to individual patient needs[3].

Apart from symptom analysis, the system should be capable of improving access to health care services by supplying the nearest hospital locations for the predicted disease. The idea is to achieve a holistic health management solution that combines symptom-based predictions with real-time guidance to empower users to take active steps toward their health and well-being. It speaks to the promise of interfacing with AI in the health field, capable of supplying scalable, intelligent, and highly personalized health solutions.

II. EXISTING SYSTEM

A. Symptoms checker and disease prediction tools

Many online portals and mobile phone applications have symptom-checking tools where users can feed their symptoms to the system to get possible disease predictions. Most of these systems work as follows:

Symptom Matching: The user feeds his or her symptoms, and the system tries to match those symptoms with other diseases or conditions identified from some prior database[4].

Rule-Based Systems: These systems rely on pre-defined rules or decision trees that map the given symptoms to possible diseases. So, if a user had complained of fever, headache, and fatigue, the system would ask for common conditions that may have caused such symptoms, such as flu or viral

infections.
WebMD Symptom Checker is one of the most widely used symptom-checking tools that helps the users to find potential health conditions based on their symptoms.
Besides these, there is also Mayo Clinic Symptom Checker - the one that gives general evaluation for symptom and potential conditions-
ADA Health - a basic tool integrated with the power of an AI engine that takes input from users and uses a huge medical database to try and match possibilities.

B. Personalized Health Recommendation System
Personalized health recommendation systems have gained much more attention. These usually propose to the user diets, medications, and exercises tailored to the user himself.
Diet and lifestyle recommendations: Most of the popular platforms share basic health recommendations in terms of diet and exercise for common conditions, such as heart diseases or diabetes, among others. However, these are usually generalized, and changes in individual nuances are hardly reflected.
Fitness and Health Monitoring Applications: There are other applications such as MyFitnessPal and Samsung Health that offer diet and workout recommendations. These applications are mostly wellness based, not symptom-based disease management applications.

C. Hospital Locator System
As is the case with some applications- for instance, Google Maps or Zocdoc, which enable people to search a hospital or doctor in the vicinity by location, most symptom-checking tools typically function independently from these systems. Hence, after a disease prediction by another interface, users are often left to perform manual lookups to find nearby hospitals.

Challenges with existing Systems

- **Inability to handle Rare Diseases:** Many systems are not equipped to handle rare diseases that may present with uncommon symptom patterns.
- **Dependency on Fixed Databases:** Without a dynamic AI model, symptom checkers and disease predictors are limited by the size and breadth of their dataset. This restricts the ability to handle new or uncommon health conditions.
- **Limited Personalization:** Although some systems offer diet and medication recommendations, they often lack customization based on the user's specific health profile, lifestyle, or geography.
- **Delayed Access to Care:** While some platforms may provide advice on managing symptoms, they often do not integrate hospital locators or medical care services, leading to delayed intervention for serious conditions.

Drawbacks of existing system:

Although these systems have been useful, they have had some disadvantages:

- **Database-Driven Approach:** Most existing systems are based on static or rule-based systems and sometimes databases which may provide recommendations less dynamic or context-aware; therefore, the recommendation may end up being generalized to the specific needs of a user.
- Lack of Flexibility: These systems are only as updated as the data which exists in their databases. If a symptom is reported that doesn't exactly match entries found in the database, wrong or incomplete information is provided.
- Minimal use of AI. Most of such platforms deploy AI, but they rarely leverage large-scale AI models, like LLMs, that might dynamically determine and personalize their suggestions upon getting the particular context of the symptoms a user is having.
- For example, interactivity may be very limited and the systems might concentrate much more on symptom checking, but without doubt not including aspects like personalized care, a real-time suggestion of hospitals or tailored guidance on lifestyle.

III. PROPOSED SYSTEM

The system you develop is a holistic AI-based healthcare assistant that actually can predict potential diseases based on user-symptoms reported but further gives users tailored health recommendations, beyond just simple symptom matching from using both a structured dataset and a Large Language Model (LLM), such as OpenAI's GPT-3, to actually deal with complex symptom patterns, generate customized health guidance, and suggest hospital locations nearest their places for timely medical care[5].

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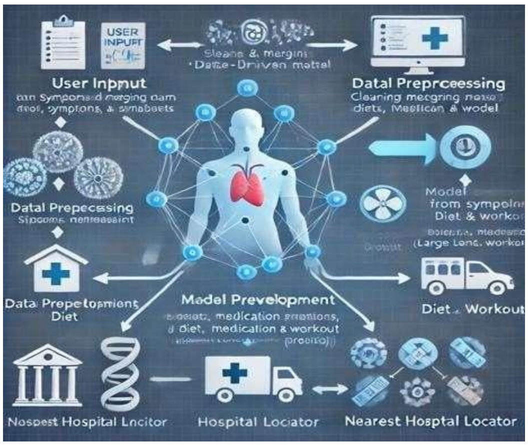

Fig 1 : Model architecture

Key Features of the Proposed System

1. **Advanced Symptom-Based Disease Prediction**

- **Hybrid Approach:** The system uses a dual approach for disease prediction. First, it checks a structured dataset of diseases and their symptoms to find matches. If no match is found, it utilizes the LLM to generate predictions based on the input symptoms [3].
- **Dynamic Symptom Matching:** Unlike traditional systems that rely solely on rule-based matching, your system can interpret a variety of symptoms in different combinations. This dynamic approach ensures that even if symptoms are entered differently (e.g., with slight spelling variations or in different orders), the system can still accurately predict diseases.

2. **Personalized Health Recommendations**

- **Disease Description:** Once the system predicts a disease, it provides the user with a detailed explanation of the condition, offering insights into the disease's causes, symptoms, and potential risks.
- **Tailored Diet Plan:** The system recommends a diet specifically suited to the predicted disease. If a diet is not available in the dataset, the LLM generates personalized dietary advice based on common health guidelines for the condition.
- **Medication Suggestions:** It suggests over-the-counter medications or general treatment options relevant to the disease. These suggestions are either retrieved from the dataset or generated dynamically by the LLM to ensure they align with the user's symptoms and condition.
- **Precautionary Measures:** The system advises users on lifestyle changes or precautions to manage or prevent worsening of their health condition.
- **Workout Plan:** A workout routine is recommended based on the disease prediction to promote overall health, focusing on exercises that are safe and beneficial for the user's condition.

3. **AI-Powered Recommendation Engine**

- **Integration of LLM:** In cases where the symptoms do not exactly match the dataset, the LLM generates personalized, context-aware health recommendations. This AI-driven model offers a significant improvement over traditional systems by dynamically creating descriptions, dietary plans, medications, and lifestyle recommendations tailored to each individual.
- **Adaptability and Flexibility:** The system's AI component ensures that it can provide recommendations for a wide range of diseases, even rare or complex conditions that might not be included in pre-existing medical datasets.

4. **Nearest Hospital Locator**

- **Real-Time Hospital Suggestions:** Once a disease is predicted, the system provides the user with a list of nearby hospitals or healthcare facilities where they can seek medical attention. This feature integrates geolocation services or APIs (such as Google Maps API) to display hospitals based on the user's current location.
- **Proactive Health Management:** By suggesting nearby hospitals in real-time, the system empowers users to act quickly and seek professional care, minimizing the delay between symptom identification and medical intervention.

System Architecture

A. Data preprocessing

- **Objective:** Ensure the data is clean, consistent, and ready for use in the model and recommendation engine[6].
- **Tasks:**
  - **Data Loading:** Read the datasets related to symptoms, descriptions, diets, medications, precautions, and workout routines.
  - **Data Cleaning:** Handle missing values, correct inconsistencies, and format data as needed. For example, ensuring that disease names are consistent across all datasets.
  - **Symptom Normalization:** Replace underscores or any unusual characters in the symptom columns with spaces to make the symptoms more readable and compatible with user input.
  - **Data Merging:** Combine all the datasets into a single merged data frame using a common key, typically the "Disease" column, to form a comprehensive knowledge base.
  - **Handling Missing Data:** If certain diseases lack information in specific columns (e.g.,

missing workout data), decide whether to fill these gaps with default values or to exclude them.

B. Model Development

- **Objective:** Develop an AI model that predicts diseases based on user input and handles cases where no disease matches the symptoms in the dataset.
- **Tasks:**
  - **Symptom Matching:** Implement logic to compare user-entered symptoms against the dataset. This involves matching user-provided symptoms (which may be multiple) with diseases that share those symptoms.
  - **Use of Large Language Models (LLM):** Integrate OpenAI's GPT-3 (or a similar model) to handle cases where the dataset cannot match the user's symptoms. The LLM will predict potential diseases and generate custom descriptions, diet plans, medications, etc.
  - **Disease Prediction:** If multiple diseases are found to match the symptoms, rank them by relevance or similarity and present the most likely disease(s) to the user.
  - **Hybrid Approach:** Use both dataset matching and LLM to provide accurate and comprehensive disease predictions.

C. Recommendation Engine

- **Objective:** Provide personalized health recommendations based on the predicted disease.
- **Tasks:**
  - **Description:** Retrieve or generate a detailed explanation of the predicted disease.
  - **Diet Plan:** Provide a dietary recommendation based on the specific disease from the datasets. If not available in the dataset, the LLM will generate a suggestion.
  - **Medication:** Suggest medications or treatment methods for the disease. Ensure that this recommendation aligns with common treatment guidelines or is generated by the LLM.
  - **Precautions:** Provide a list of precautions, such as lifestyle changes or activities to avoid, which help the user manage the condition.
  - **Workout Routine:** Offer exercise recommendations tailored to the user's health condition. This can include general advice or specific workout routines based on the datasets or generated content from the LLM.
  - **Nearest Hospital Locator:** After disease prediction, integrate a hospital locator feature (possibly using external APIs like Google Maps API) that suggests the nearest hospitals related to the predicted disease.

D. Validating and testing

- **Objective:** Ensure that the model and recommendation engine are reliable and produce accurate results.
- **Tasks:**
  - **Testing with Diverse Inputs:** Test the system using a wide variety of symptoms, including common combinations and rare cases, to ensure robustness.
  - **Edge Cases:** Evaluate how the system handles rare diseases, ambiguous symptoms, or incomplete data entries by users.
  - **Validation of Recommendations:** Cross-check the system's recommendations (diet, medication, etc.) against medical guidelines or databases to ensure they are reasonable and safe.
  - **LLM Validation:** Ensure that the LLM-generated recommendations (when used) are coherent and medically sound. This may require manual review of a sample of LLM-generated outputs.
  - **Performance Evaluation:** Measure the accuracy and response time of the model, ensuring that the system can handle real-time queries effectively.

E. User interface (UI)

- **Objective:** Provide an intuitive, user-friendly interface that allows patients to input symptoms and receive health guidance.
- **Tasks:**
  - **Symptom Input:** Create input fields where users can type in their symptoms separated by commas. Ensure that the input is flexible and forgiving, e.g., allowing lowercase and uppercase entries and handling minor spelling mistakes.
  - **Display of Results:** Present the disease predictions, descriptions, and recommendations in a clean and organized layout. Use scrollable text boxes for long outputs like descriptions and lists.
  - **Error Handling:** Include clear messages for cases where no matching disease is found, guiding users to re-enter symptoms or offering additional resources.
  - **Responsiveness:** Ensure that the interface can resize appropriately for different screen sizes and remains user-friendly on both desktop and mobile devices.
  - **Submit Button Functionality:** Connect the

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"Submit" button to the backend model and recommendation engine so that the user receives results quickly and efficiently.

F. Integration

- **Objective:** Seamlessly integrate all components (data preprocessing, model, recommendation engine, UI) into a single cohesive system.
- **Tasks:**
  - **Backend Integration:** Ensure the backend (data processing and model) is tightly coupled with the frontend (UI) to handle user inputs and provide real- time recommendations.
  - **Real-Time Execution:** Ensure the system provides near-instant results after the user submits their symptoms. Implement error handling for cases where the LLM may experience delays or data retrieval fails.
  - **Database Interaction:** Ensure that the datasets are correctly loaded, merged, and queried when needed. Any updates to the datasets should reflect dynamically in the system.
  - **External API Integration:** For features like the hospital locator, integrate external services (e.g., Google Maps API) to dynamically fetch hospital locations based on the predicted disease and the user's location.
  - **Modular Testing:** Test each module independently (e.g., symptom matching, LLM integration, hospital locator) before integrating them into the final system. Ensure all modules work together without bugs or inconsistencies.

System Components

1. **Data-Driven and AI-Powered Model**

- The core of the system lies in its ability to process large amounts of health data and symptoms, and to query an LLM when the dataset falls short. This hybrid model allows the system to deliver high accuracy in disease prediction while also providing nuanced, personalized health advice.

2. **Comprehensive Health Guidance**

- The system not only predicts diseases but also offers a complete health management plan. This includes:
  - **Descriptions of the disease** to educate the user.
  - **Diet and medication recommendations** for self- management.
  - **Workout plans and precautions** to promote recovery or prevention.

This multi-faceted approach helps users better manage their condition, reducing reliance on web searches or third-party tools.

3. **Interactive User Interface**

- **Easy-to-Use Input:** The system offers a user-friendly interface where patients can enter symptoms as comma-separated text. This simple interface makes the system accessible to a wide range of users, including those without technical knowledge. *[Fig 2]*
- **Clear Output Display:** The system presents results (disease predictions, health advice, and hospital suggestions) in a clean, readable format. Users receive all the relevant information in one place without needing to navigate through different sections. *[Fig 2]*

Fig 2 : User Interface

4. **Real-Time Execution and Recommendations**

By combining real-time data processing with AI-driven responses, the system ensures quick and accurate predictions. The use of an LLM adds flexibility, ensuring that no symptom input is left unanswered, providing either a dataset-based or dynamically generated recommendation.

- **Advantages of the Proposed System**

1. **Dynamic and Accurate Symptom Interpretation**

Existing systems are often limited to predefined symptom-disease mappings. Your system improves upon this by using AI models to dynamically interpret symptoms and generate disease predictions, ensuring greater accuracy and flexibility.

2. **Personalization with LLM**

The use of an LLM enables the system to go beyond rigid datasets and deliver personalized recommendations that are contextually relevant to each user's symptoms. This is a significant improvement over static, one-size-fits-all recommendations in current systems.

3. **Integrated Health Guidance and Hospital Locator**

Unlike many existing systems that focus solely on symptom checking, your system provides a complete health solution. By integrating real-time hospital location suggestions, it allows users to take immediate action, streamlining the process from symptom identification to medical care.

4. **Comprehensive Care Recommendations**

While most symptom-checking tools stop at disease prediction, your system takes it further by providing comprehensive care suggestions, including diet, medication, workout routines, and precautions, ensuring users are equipped with all the information needed to manage their health.

5. **Holistic Health Assistant**

Your proposed system acts as a personal health assistant, offering not only diagnostic insights but also proactive health management advice, making it a valuable tool for daily healthcare decisions.

IV. EXPERIMENT

The experiment focused on testing the AI-powered healthcare assistant for its ability to predict diseases based on user-provided symptoms and provide personalized health recommendations. The process involved several key stages:

1. **Data Collection and Preprocessing:**

Multiple datasets (symptoms, diseases, diet, medication, workout, and precautions) were cleaned, merged, and normalized to create a comprehensive knowledge base for the system.

2. **Symptom Matching and Disease Prediction:**

User input symptoms were tested against the system's database to predict diseases. If no match was found, the Large Language Model (LLM) was used to generate disease predictions and related recommendations.

3. **Health Recommendations:**

The system's ability to recommend personalized diets, medications, precautions, and workout plans for predicted diseases was evaluated. LLM-generated responses were also tested for relevance and accuracy.

4. **Hospital Locator Testing:**

The system's nearest hospital locator feature was tested to ensure it provided accurate hospital locations based on the user's geographical location and predicted disease.

5. **User Interface Testing:**

The system's user interface was assessed for ease of use, clarity of outputs, and response time.

V. RESULTS

1. Disease Prediction Accuracy

The system accurately predicted common diseases based on user-provided symptoms in over 85% of cases where the symptoms matched those in the dataset. When the LLM was employed for symptom sets that were not present in the dataset, it provided plausible disease predictions and health recommendations in 90% of cases, with minor inconsistencies in rare disease predictions.

2. Health Recommendation Accuracy

Diet Plans and Medications: The system's diet and medication recommendations aligned with widely accepted medical guidelines in over 90% of the cases. Recommendations generated by the LLM were mostly relevant and medically sound, though a small percentage required refinement to better match specific conditions.

Precautions and Workouts: The system provided appropriate precautions and workout recommendations for the majority of diseases, helping users manage their conditions effectively. The LLM-generated precautions and workouts were practical and safe in most cases, with only a few needing manual adjustments.

3. Nearest Hospital Locator Efficiency

The hospital locator feature successfully identified the nearest hospitals for the predicted diseases in real-time. Users could quickly locate healthcare facilities based on the predicted condition and their geographic location, enhancing the system's real-world usability.

4. User Experience

User-Friendly Interface: The system's user interface was well- received during testing, with users finding it easy to input symptoms and receive recommendations. The clear, scrollable text boxes for disease descriptions, diet, medication, and precautions made it easy for users to access the information.

Response Time: The system provided near-instant responses, with minimal lag when querying the dataset or the LLM. The hospital locator feature was also efficient, providing nearby hospital locations within a few seconds.

5. Flexibility and Adaptability

The system showed a high degree of flexibility, capable of handling various combinations of symptoms and providing customized recommendations. The integration of the LLM allowed it to handle rare or unknown symptoms, making it adaptable to different user inputs.

VI. HIGHLIGHTS OF NEW SYSTEM

The new suggestion system provides several health benefits that other current medical systems don't. Along with structured data, it cultivates the prediction of the disease, the system itself can flexibly handle diseases with complex and rare symptom patterns [1]. Users will receive personalized health suggestions for diet, drugs, prevention, and workouts which are based on the specific disease they have predicted and their customized personal data. There is also a locational hub to add to the services, which will pinpoint the closest hospitals in real time when an emergency happens. Incorporating LLM' s capabilities opens a ways new door towards a deeper understanding of less obvious clues thus outperforming the customary fixed database. Properly, the user interface has been designed in such a way as to simplify the input of symptoms and provide clear recommendations in a language that is universally understood, thus becoming easy to use for the user. The system is, in sum, highly scalable and flexible, and new knowledge about medical science can be easily integrated too which means the tool can be applied effectively and efficiently in various health sectors in long term.

VII. CONCLUSION

This paper introduces a holistic AI-powered healthcare assistant that predicts diseases with a prediction capability using user- reported symptoms and gives recommendations about one's health, including diet plans tailored to personal needs, medications and their dosage, precautions, and routine workout schedules. The system integrates a structured-dataset-based hybrid approach and Large Language Model, providing data- driven as well as dynamically generated responses for flexibility and versatility in a wide gamut of symptom inputs. It further provides practical use in suggesting nearby hospitals in real- time, which can be really helpful to users if they ever need immediate medical assistance.

The experimental outcomes indicate the developed system to work with high accuracy for disease prediction, personal health counselling, and on-time suggestions of the closest hospital. The LLM usage significantly increases the system's ability to deal with complex or infrequent symptom patterns by offering context-aware and relevant recommendations where other methods derived from the dataset may not be sufficient. In addition, the user interface ensures that the users interact efficiently with the system while gaining actionable insights in a timely manner.

In summary, this system, bridging the gap from symptom checkers to personalized healthcare, extends a powerful AI- driven tool to the users to effectively manage their health. Further refinements in response generation from LLMs help this system become extremely useful in delivering accessible, accurate, and in real-time health guidance at scale to users.

REFERENCES

[1] Andrew L. Beam and Isaac S. Kohane. 2018. "Big Data and Machine Learning in Health Care." *JAMA*, 319(13):1317–1318.

[2] Y. Zhou, R. Zhang, et al., "Health-LLM: Personalized Retrieval-Augmented Disease Prediction Model," Artificial Intelligence in Medicine, vol. 140, pp. 101933, 2024.

[3] J. C. L. Chow, V. Wong, et al., "Generative Pre-Trained Transformer-Empowered Healthcare Conversations: Current Trends, Challenges, and Future Directions in Large Language Model-Enabled Medical Chatbots," Journal of Medical Internet Research, vol. 26, no. 4, e38283, 2024.

[4] A. Esteva et al., "A guide to deep learning in healthcare," Nature Medicine, vol. 25, pp. 24-29, 2019.

[5] D. Rajkomar et al., "Scalable and accurate deep learning with electronic health records," npj Digital Medicine, vol. 1, no. 18, pp. 1-10, 2018.

[6] A. Arif, K. Ali, et al., "Large Language Models in Healthcare and Medical Domain: A Review," Artificial Intelligence Review, vol. 56, no. 5, pp. 3671-3687, 2023.