A Conversational Healthcare Companion in Kannada

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ABSTRACT

This study presents an AI-powered bilingual healthcare chatbot to enhance accessibility to primary medical assistance by enabling seamless interactions in both Kannada and English—addressing a critical gap in digital healthcare solutions for multilingual populations. Integrating machine learning–based symptom prediction, voice-enabled communication, secure SQLite-driven appointment scheduling, and Gemini AI for natural conversational responses, the system offers a unified and intelligent healthcare support framework. A multi-class classification model covering 41 disease categories was developed using symptom-level inputs derived from a large-scale clinical dataset comprising approximately 4,900 patient records. To ensure robust and unbiased evaluation, 5-fold stratified cross-validation was employed. Experimental results show that the Random Forest–based model achieved an average classification accuracy of 91%, with consistently balanced precision, recall, and F1-scores across disease classes. Additional noise-injection experiments further confirm the model's robustness under realistic symptom uncertainties. These findings highlight the system's effectiveness as a first-level clinical decision support

tool. The key novelty of this work lies in the seamless integration of bilingual conversational AI, predictive analytics, and automated appointment management, offering an end-to-end, accessible, and context-aware healthcare assistance platform. This contribution is particularly significant for resource-constrained and linguistically diverse regions, where timely and reliable medical guidance remains a critical challenge.

Keywords-healthcare chatbot; artificial intelligence; multilingual system; Kannada; disease prediction; Gemini AI

I. INTRODUCTION

Access to basic healthcare continues to be a significant challenge in many regions of the world, primarily due to overcrowded hospitals, disparities in healthcare infrastructure, and the increasing cost of medical consultations. These systemic barriers often prevent timely access to medical guidance, even for minor or non-emergency health concerns. As a result, AI-driven healthcare chatbots have gained attention as a potential solution, offering low-cost, scalable, and instant medical assistance through conversational interfaces. Although existing medical chatbots provide general symptom guidance, many lack multilingual support, integrated appointment management, or seamless interaction in regional languages—features essential to improve healthcare access in linguistically diverse regions such as India. In addition, many chatbot systems rely solely on conversational AI without incorporating predictive analytics to improve early-stage diagnosis.

The specific contribution of this work is the development of an AI-powered bilingual healthcare chatbot that combines four key capabilities in a unified system:

- Multilingual interaction in both Kannada and English, enabling users to communicate in their preferred language.
- Machine learning-based symptom prediction using a trained multi-class classification model for preliminary diagnosis.
- Secure user authentication and appointment management using a lightweight SQLite database.
- Seamless integration of conversational AI (Gemini) with predictive modeling, offering both natural dialogue and data-driven health insights.

This integrated system provides a comprehensive, accessible, and user-friendly healthcare assistant suitable for deployment in rural and semi-urban settings where digital literacy and English proficiency may be limited. By bridging the gap between conversational AI and predictive analytics, the proposed chatbot improves decision-making while reducing the dependency on in-person consultations for minor symptoms.

Recent innovations in healthcare chatbots have employed diverse AI techniques to enhance accessibility, diagnostic capability, and user engagement. Several studies integrate machine learning models with NLP and CSV-based datasets to enable offline operation and 24/7 availability while supporting referrals to medical professionals when needed [1]. Although such systems provide affordability and personalized interaction, they still struggle with natural language comprehension, system robustness, and secure handling of medical data. Other approaches leverage Support Vector Machines (SVM) for symptom-based classification and incorporate appointment scheduling interfaces [2]; however, these solutions raise concerns related to operational costs and data security, limiting their practical deployment. Approaches using NLP, decision trees, and dimensionality reduction techniques demonstrate improved classification accuracy with efficient resource usage [3]; however, these models lack emotional responsiveness and face persistent privacy challenges. Similarly, chatbots built with Flask-based architectures, SQL databases, speech interfaces, and expert systems deliver reliable performance and accurate outputs [4], but face limited empathy and technical scalability issues. Pattern-matching-based systems with intuitive user interfaces [5] and deep learning-driven chatbots designed for messaging platforms [6] provide fast automated responses but are heavily reliant on high-quality training data and often prone to system failures.

Methods incorporating user profiling and symptom analysis through machine learning and NLP introduce elements of personalization [7], but their accuracy is hindered by inconsistent input formats and restricted feature sets. A bilingual healthcare chatbot achieving 98% accuracy demonstrates the importance of linguistic inclusivity [8], although its performance degrades with noisy or incomplete data. Systems based on SVM, TF-IDF, and cosine similarity offer expert-like suggestions efficiently [9], but remain dependent on secure and well-structured medical databases. Real-time analytics-driven frameworks provide scalable and cost-efficient care recommendations [10], but face challenges in interoperability and maintaining consistent diagnostic accuracy.

Beyond healthcare, reinforcement learning-based models [11] focus on optimizing personalized treatment strategies using longitudinal clinical data, offering insights into adaptive decision-support systems but lacking symptom-to-diagnosis conversational capabilities. In [12], the effectiveness of AI- and NLP-based chatbots was demonstrated for IT service management in higher education, showing high response accuracy, although not targeting the medical domain.

Across existing systems, key limitations persist:

- Limited multilingual or regional-language support restricts usability in linguistically diverse populations.
- Absence of integrated symptom prediction with conversational AI, as most systems offer either NLP-based conversation or ML-based diagnosis, not both.
- Weak appointment-management or patient-record functionality, limiting real-world deployment.
- Challenges in data security, natural language understanding, and system stability across multiple frameworks.

These gaps underscore the need for a unified, secure, bilingual healthcare chatbot that merges ML-based disease prediction, natural conversational interaction, and integrated appointment management—a field in which the proposed system directly contributes.

II. SYSTEM ARCHITECTURE

The proposed AI-based bilingual medical chatbot aims at offering preliminary healthcare in an easy and cost-effective way by finding a set of possible diseases in the user-provided symptoms. Built using the Flask framework, this system accepts voice-enabled symptom input and targets bilingual support, English and Kannada, embedding a predictive model for the symptoms described. User input provided via text or voice is processed to clarify symptoms and predict potential diseases. Based on the severity, the system offers tailored healthcare suggestions, including analgesics, diet plans, and details of nearby doctors.

A. User Interface Layer

The user interface is developed using HTML, CSS, and JavaScript integrated with Flask. It features a clean and interactive design that enables users to input symptoms through either keyboard entry or voice commands. Voice input is facilitated by the browser-based Web Speech API, which transcribes spoken queries into text and automatically populates the input field. This hands-free functionality helps in improving accessibility, especially for users with limited typing skills or low literacy levels.

B. Backend Application Layer

The backend is implemented using Python and acts as the central controller of the system, coordinating all major and minor operations. It helps process user-provided input via voice or text, manages login, registration, and session handling, and directs the collected symptom data to the machine learning model for disease prediction. After generating a prediction, it delivers the analysis and relevant response to the user. In addition, the backend interacts with an SQLite database to store and retrieve user profiles and appointment details.

C. Machine Learning Prediction Module

The system incorporates a machine learning based prediction module to deliver real-time problem-solving assistance. This model is trained on a structured symptom disease dataset using binary-encoded inputs, serialized with Python's pickle module for seamless integration into the Flask backend. Upon symptom submission, the user input is converted into a feature vector and sent to the model for the prediction process. The resulting diagnosis is then used to generate an instant response that may include disease details, recommended precautions, suggested medications, and lifestyle advice, offering users a quick and informative experience.

D. Database Layer

The system utilizes SQLite as its local database engine to manage user data and to maintain application state, selected for its lightweight design and minimal configuration requirements. SQLite allows for efficient data storage and retrieval without relying on complex setups or external dependencies for data. The database handles three main types of information:

- User credentials for authentication during login and signup
- Appointment details, including timestamps and associated diagnoses
- Historical symptom submissions to support session continuity and user history.

The database schema was defined within the Flask backend using embedded SQL commands. At runtime, the application interacts with SQLite to store new records.

E. Multilingual Support

The chatbot provides support for both Kannada and English, allowing users to communicate in the language they are more comfortable with. This improves accessibility, particularly for users who are not fluent in English. Although the system does not rely on an advanced multilingual engine, it employs conditional rendering and response handling based on the user's language selection to deliver a seamless bilingual experience.

III. METHODOLOGY

The multilingual AI-based healthcare chatbot provides initial health assessments for users whenever required and personalized recommendations based on their described symptoms.

A. Experimental Setup

The experiments were conducted in a Google Colab workspace, using the Jupyter environment with an integrated GPU to support faster execution and model training, using the following configuration:

- Processor: Ryzen, 11th Generation
- RAM: 8 GB DDR4
- GPU: NVIDIA Tesla T4/P100, 16 GB VRAM, from Google Colab's runtime environment
- Operating System: Windows 11 (64-bit)
- Virtual OS: Linux (Ubuntu 18.04 LTS, by Google Colab)
- Platform: Google Colab (Cloud-based environment)
- Software Environment: Python 3.10, Flask 2.3, scikit-learn 1.3, Numpy, Pandas, and Matplotlib
- Database: SQLite 3.44 integrated through Python's sqlite3 library
- Speech and AI Integration: Google Speech-to-Text API and Gemini AI for conversational response generation

The model was trained using an 80:20 train-test split. Training was performed for 10 epochs, and model convergence was evaluated using accuracy and F1-score. Decision Tree and Random Forest models demonstrated the most stable convergence and the highest predictive accuracy.

During runtime, the chatbot was locally deployed using Flask for testing and later hosted on a lightweight web server for live evaluation. The system takes text and speech in Kannada and English as input and interactively processes the predictions and conversations in real time. GPU utilization was monitored using nvidia-smi, confirming an average memory consumption of about 1.5 GB per training session, and inference latency below 500 ms per user query.

B. Preprocessing and Feature Engineering

The input of user symptoms was converted to a binary feature vector, and the disease labels were encoded as numerical values to ensure compatibility with the model. The dataset was cleaned to remove inconsistencies and normalized where necessary. Oversampling techniques were used to mitigate the class imbalance. Severity scores were incorporated as feature weights, while data.csv was used to validate and refine symptom groupings.

The input vector consists of 132 symptom features, where each feature corresponds to a distinct clinical symptom (e.g., fever, headache, abdominal pain, chest pain). The feature values are defined as follows:

$$x_i = \begin{cases} 1, & \text{if symptom } i \text{ is present} \\ 0, & \text{if symptom } i \text{ is absent} \end{cases}$$

This binary encoding ensures compatibility across all classifiers and reflects the categorical nature of symptom occurrence in clinical triage scenarios. For each patient record, the model input is represented as:

$$X = [x_1, x_2, \dots, x_{132}]$$

where $X \in \{0,1\}^{132}$. No continuous-valued physiological signals (e.g., lab values or vitals) are included, as the system is designed for first-level symptom-based assessment.

IV. PROPOSED SYSTEM

The AI-driven bilingual medical chatbot was developed to provide preliminary disease prediction and essential healthcare advice. It aims to overcome barriers to timely medical consultation, particularly in rural and semi-urban regions, by enabling user interaction through text or voice in both Kannada and English. Built with lightweight modular technologies, the system is accessible through a user-friendly web interface. Figure 1 presents the interaction flow between the user/patient and the server, outlining the sequential actions that enable smooth communication within the chatbot system.

The user begins by either registering or logging into the chatbot interface, which supports both text-based and voice-based input. Voice input is processed using the Google Speech-to-Text API, which transcribes spoken language into text in real time. Users describe their symptoms, and the system captures the input for further analysis. After submission of the symptom, the backend processes the data and sends it to a pre-trained machine learning model. This model was trained on a structured symptom disease dataset utilizing classification algorithms to predict the most probable disease. The prediction results are then returned to the frontend and displayed in the user's selected language, Kannada or English.

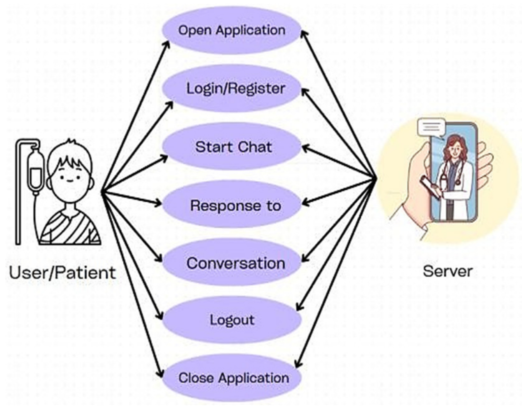

Fig. 1. Block diagram.

To improve the quality of interaction and human-like conversation, the system was integrated with Google Gemini AI through the *google.generativeai* module. This allows the chatbot to generate more natural and context-aware responses for the user, making it capable of handling continuation queries and user clarifications effectively.

Additionally, this chatbot includes an appointment management feature, allowing users to schedule consultations based on the predicted analysis. All the essential data, such as user information and appointment details, is securely stored in an SQLite database, ensuring fast access and minimal configuration requirements.

The key advantages of this proposed system include:

- Multilingual support (Kannada and English) for inclusive accessibility.
- Voice-enabled input for user convenience
- Machine learning-based disease prediction for quick initial diagnosis
- Appointment scheduling for continued medical support
- Lightweight deployment using Flask and SQLite.

By integrating these capabilities, the system delivers an intellectual and user-friendly entry point to the healthcare system, especially for individuals with limited access to professional medical services.

V. DATASET DESCRIPTION

The dataset used was a publicly available symptom-disease dataset, which is widely used for academic research in medical decision support systems [13]. The dataset contains approximately 4,900 patient records, each representing a unique clinical case. Every record consists of 132 binary symptom indicators (presence = 1, absence = 0) and one target label (prognosis) representing the diagnosed disease. A total of 41 distinct disease categories are included, covering a broad range of common conditions such as gastrointestinal disorders, respiratory infections, metabolic diseases, dermatological conditions, and neurological disorders. The dataset is moderately balanced, with each disease class represented by multiple patient instances.

Four classifiers, Decision Tree, Random Forest, Naïve Bayes, and K-Nearest Neighbors (KNN), were trained using the same input representation. Each patient instance is encoded as a 132-dimensional binary vector, where each dimension corresponds to a clinically defined symptom. This uniform representation ensures fair comparison across models and reflects realistic first-level medical triage, where symptom presence is reported qualitatively.

A. Class Imbalance Handling

This study used the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance during model training. SMOTE generates synthetic samples for minority classes by interpolating between existing minority class instances in the feature space, thereby increasing class representation without simple duplication. Given a minority class sample x, SMOTE generates a new synthetic sample x_{new} as:

$$x_{new} = x + \lambda \cdot (x_{nn} - x),\ \lambda \in [0,1]$$

where x_{nn} is one of the k-nearest neighbors belonging to the same minority class.

VI. RESULTS

Experiments were conducted on the symptom-disease dataset consisting of 41 disease categories and approximately 4,900 patient records [13]. Each instance is represented by binary symptom indicators, where a value of 1 denotes the presence of a symptom, and 0 denotes its absence. The target variable corresponds to the diagnosed disease.

The dataset provides a predefined Training.csv and Testing.csv split. The testing file contains one representative instance per disease class, resulting in a total of 41 test samples. While this structure enables deterministic evaluation, it does not sufficiently capture real-world variability. Therefore, additional validation strategies were adopted. Initial evaluation was performed using the predefined test set containing one instance per disease class. All four classifiers achieved 100% accuracy, with perfect precision, recall, and F1-scores across all classes. The corresponding confusion matrices exhibited strictly diagonal patterns. This outcome is attributed to the deterministic and non-overlapping symptom patterns present in the curated dataset. However, although this confirms the correctness of the implementation, it does not adequately reflect real-world clinical uncertainty.

To obtain statistically meaningful and generalizable performance estimates, 5-fold stratified cross-validation was conducted using the complete dataset. Stratification ensured proportional representation of all disease classes in each fold. Cross-validation allows each sample to be used for both training and testing, thereby mitigating the limitations imposed by the small predefined test set.

TABLE I. RESULTS USING 5-FOLD CROSS-VALIDATION

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.88	0.87	0.86	0.86
Decision Tree	0.87	0.86	0.85	0.85
Random Forest	0.91	0.9	0.89	0.89
Naive Bayes	0.83	0.82	0.81	0.81

These results demonstrate that ensemble-based methods, such as Random Forest, provide superior generalization performance, while probabilistic methods are more sensitive to feature dependencies. In Figure 2, each subplot corresponds to one classifier, with diagonal dominance indicating strong class-wise predictive performance.

To further simulate real-world clinical conditions, controlled noise injection was applied to the dataset. A noise level of 10% was introduced by randomly flipping binary symptom values, mimicking patient reporting errors and diagnostic ambiguity. The models were evaluated on the noisy dataset using the same 5-fold cross-validation protocol. The observed performance degradation confirms the increased classification difficulty introduced by symptom overlap and noise. However, Random Forest maintains the highest robustness due to its ensemble learning mechanism.

TABLE II. PERFORMANCE UNDER NOISE-INJECTED CONDITIONS

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.84	0.83	0.82	0.82
Decision Tree	0.86	0.85	0.84	0.84
Random Forest	0.89	0.88	0.87	0.87
Naive Bayes	0.80	0.79	0.78	0.78

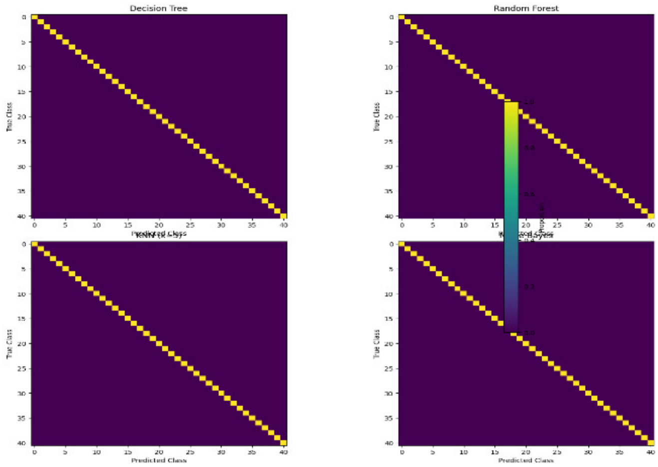

Fig. 2. Normalized confusion matrices of Decision Tree, Random Forest, KNN (k = 5), and Naive Bayes classifiers obtained using 5-fold stratified cross-validation across 41 disease classes.

Figure 3 shows the Login interface, which serves as a protected gateway for patients, doctors, and administrators, requiring unique credentials to allow access, ensuring the confidentiality and security of personal and medical data.

Fig. 3. Login and Authentication.

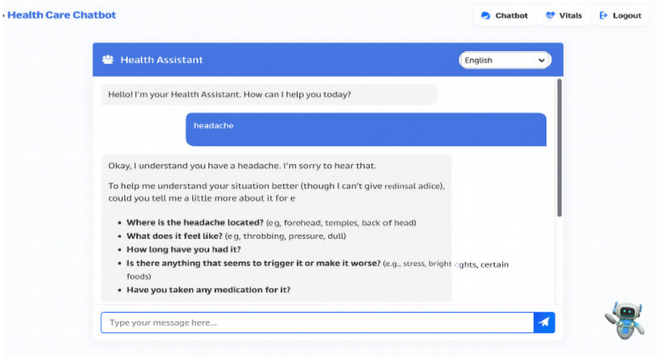

Fig. 4. Chat-based symptom analysis.

Figure 4 presents the chat-based symptom analysis module, designed to engage users in real-time conversations for collecting comprehensive symptom details. Through targeted follow-up questions, it fine-tunes user inputs, enhancing the precision of disease prediction.

Figure 5 presents the Disease Prediction and Doctor Appointment Booking module, which utilizes a trained machine learning model to evaluate the selected symptoms and predict possible medical conditions. In addition to displaying the prediction results, it offers appropriate medication advice and lifestyle recommendations. The module also includes a built-in appointment scheduling feature, enabling users to choose their desired date and time, provide a short description, and book a consultation with a doctor directly through the prediction interface.

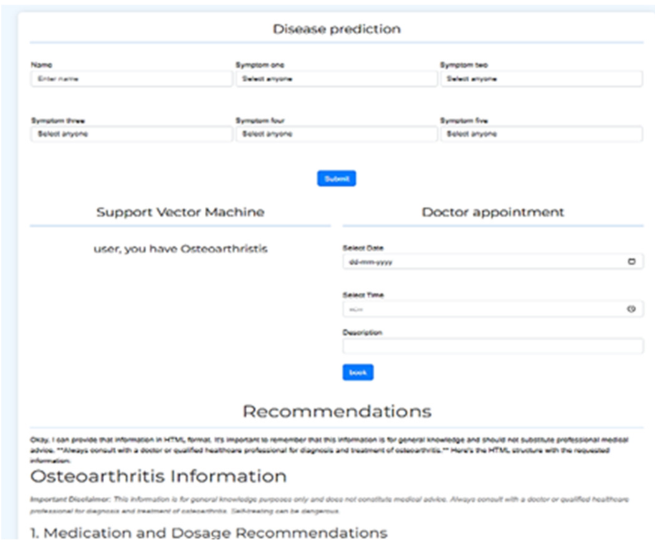

Fig. 5. Disease prediction and doctor appointment booking.

Figure 7 presents the Vitals Monitoring functionality, which measures and evaluates essential health indicators such as blood pressure, heart rate, oxygen saturation, ECG, and body temperature. Using this data, it delivers immediate insights into the user's health status and recommends suitable remedies for prompt care.

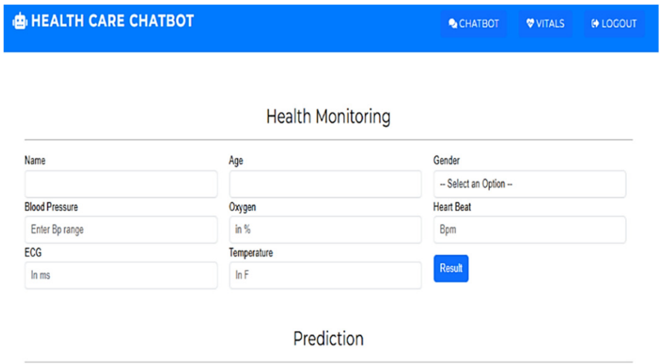

Fig. 6. Vitals monitoring.

VII. VERIFIER MODEL LIMITATIONS

Although Gemini AI enhances conversational fluency, the verifier model may occasionally exhibit translation bias and contextual misinterpretation when processing bilingual queries (Kannada-English). These discrepancies stem from differences in linguistic structure, idiomatic expressions, and limited domain-specific data for regional languages.

Such biases can affect the tone or the factual precision of the responses generated. To mitigate these effects, adaptive fine-tuning and contextual feedback loops are recommended in future iterations. Continuous monitoring and dataset diversification across dialectal variations would further improve cross-lingual reliability.

VIII. REWARD SIGNAL DESIGN

Future extensions of the system may adopt a reinforcement-learning framework to refine dialogue behavior. Instead of binary feedback (correct/incorrect), soft scalar reward signals can be employed to represent graded conversational quality, considering coherence, empathy, and factual correctness. This design can offer smoother optimization and more stable convergence of the language model, allowing the chatbot to gradually learn nuanced medical dialogue patterns. Incorporating multi-objective rewards aligned with factual accuracy and user satisfaction will ensure a more balanced and trustworthy conversational healthcare assistant.

IX. REAL-WORLD DEPLOYMENT CONSIDERATIONS

Deploying an AI-based healthcare chatbot in real-world environments presents several challenges related to safety, ethics, and infrastructure. Although the proposed bilingual (Kannada–English) system demonstrates strong performance, additional considerations are necessary before operational use.

A. Clinical Safety and Validation

The chatbot provides preliminary disease predictions intended for informational purposes only. Formal deployment requires validation in collaboration with certified medical professionals to ensure diagnostic reliability and mitigate false interpretations.

B. Data Privacy and Ethical Compliance

Handling user health data mandates compliance with national health data protection standards such as NDHM guidelines. All user information, including voice input, is processed locally and stored in encrypted form to preserve confidentiality. Future work will extend to secure cloud-based storage with authenticated access controls.

C. Dataset Limitations

The current dataset may not fully represent regional and linguistic variations across Kannada dialects. Expanding the dataset through collaboration with healthcare institutions and inclusion of real-world symptom data will enhance generalizability.

D. Infrastructure Constraints

Low network connectivity and limited device resources in rural areas may hinder real-time interactions. Incorporating lightweight models and offline functionality is planned to improve accessibility.

E. Future Deployment Roadmap

Pilot testing in community health centers will be conducted to assess usability, patient trust, and clinical relevance. Feedback from users and healthcare practitioners will guide subsequent refinements for large-scale implementation.

X. CONCLUSION

The proposed bilingual AI-powered medical chatbot demonstrates an effective and accessible approach to early disease prediction using symptom-based user input. Trained on a comprehensive dataset of more than 4,900 records with 132 symptoms and 41 disease classes, the system leverages both primary and auxiliary datasets to provide meaningful and personalized health recommendations, including severity levels, medications, diet plans, workout suggestions, and preventive measures. Among the evaluated machine learning models—Decision Tree, Random Forest, Naive Bayes, and K Nearest Neighbor—the Random Forest classifier achieved the highest overall accuracy, validating its suitability for multi-class disease prediction in this context.

The uniqueness of the proposed approach lies in its end-to-end design, where data preprocessing, multi-model learning, and user-centric interaction are unified into a single system, enabling accessible and explainable preliminary diagnosis without requiring complex clinical input.

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