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Smart Symptom Navigator for Inclusive Pre-Diagnosis

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***Abstract*—Getting basic medical advice can still be tough, especially for people who live in rural areas or speak different languages. The *Smart Symptom Navigator* is a simple, rule-based system made to help patients describe their symptoms clearly and get early suggestions before visiting a doctor. Instead of relying on huge datasets or advanced AI models, it follows medical rules that are easy to check and update. The tool lets users report symptoms using a clickable body map, voice, or text in their preferred language, and it creates a short report for doctors to review. All information is stored safely in Firebase, and a doctor dashboard makes it easier for professionals to look at patient data and provide quick feedback. By focusing on accessibility, language support, and clarity, the *Smart Symptom Navigator* helps both doctors and patients communicate better and makes early healthcare guidance available to everyone — even in areas with limited resources.**

Keywords - Smart Symptom Navigator, Rule-Based Diagnosis, Inclusive Healthcare, Chatbot System, Multilingual Interface, Pre-Diagnosis Tool, Accessible Health Technology.

I. INTRODUCTION

Healthcare is something everyone depends on, yet access to good medical advice is still uneven. Many people, especially those in rural or low-resource areas, struggle to explain what they're feeling or to know whether they should see a doctor. At the same time, most digital health tools today are complex, depend on large datasets, or require strong internet and computing power — things not everyone has.The *Smart Symptom Navigator* was developed to make healthcare guidance simpler and easier for everyone. It's a web-based tool that helps people describe their symptoms and get early suggestions before visiting a doctor. Instead of using complicated artificial intelligence models that need constant updates and massive amounts of data, it follows a rule-based approach built on verified medical knowledge. This makes it more reliable, transparent, and easy to maintain. What makes this project different is its focus on inclusivity. It supports multiple languages and even voice input, so users can communicate in ways that feel natural to them. A clickable body map allows users to point to the area where they feel pain or discomfort, and the system then asks clear follow-up questions to narrow down possible causes. Once the answers are submitted, it provides basic recommendations — such as which specialist to see or whether the issue can be monitored at home.All user data is stored safely in Firebase, and a separate doctor dashboard helps medical professionals review patient information quickly. This not only saves time but also makes communication between patients and doctors smoother.

The *Smart Symptom Navigator* shows how technology doesn't have to be complex to make a big difference. By focusing on clarity, language accessibility, and ease of use, the project aims to close the gap between patients and healthcare providers, ensuring that early medical guidance is available to everyone, regardless of background or location.

II. LITERATURE REVIEW

The literature survey serves as the foundation for understanding the existing work in the field of digital healthcare, medical triage, and pre-diagnosis systems. It provides an overview of different research studies, tools, and techniques that have been developed to support early disease identification, patient–doctor communication, and inclusive healthcare access. The objective of this chapter is to analyze previous studies, identify their limitations, and establish the research gap that motivates the **Smart Symptom Navigator for Inclusive Pre-Diagnosis** project.

International Journal of Engineering Research & Technology (IJERT)
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According to Y. You and X. Gui, "Self-Diagnosis through Chatbot-based Symptom Checkers: User Experiences and Design Considerations," arXiv:2101.04796, 2021:

This study analyzed the usability and design effectiveness of existing **chatbot-based symptom checker systems** that help users self-diagnose minor medical conditions. The authors employed **Natural Language Processing (NLP)** and rule-based conversation flows to guide users through text-based interactions. Their evaluation highlighted that although these systems can simplify health information seeking, they are often **difficult to use for low-literacy individuals**, especially those unfamiliar with medical terminology. The dependence on English input and rigid question flows made these systems less adaptable for diverse users. The findings emphasize the need for **multilingual, visual, and adaptive interfaces**, directly influencing the design of the Smart Symptom Navigator, which integrates a **interactive body diagram** and **multilingual symptom reporting** to overcome these limitations.

C.J. Wiedermann et al., highlight that "Redesigning Primary Care: The Emergence of AI-Driven Symptom Diagnostic Tools," J. Pers. Med., vol. 13, no. 9, p. 1379, 2023:

Wiedermann and colleagues investigated the role of **AI-driven triage tools** in modernizing primary care systems. The research explored the application of **Deep Neural Networks (DNNs)** and **machine learning-based clinical decision support systems** to automate preliminary diagnosis and triage. These systems demonstrated improved efficiency in patient data collection and symptom prioritization. However, the study also identified major **limitations**, including **lack of clinical transparency**, **need for continuous validation**, and **high computational cost**. The study concluded that despite their potential, such systems are impractical for rural or low-infrastructure environments. This limitation reinforces the Smart Symptom Navigator's approach of using **lightweight rule-based logic** to provide reliable and interpret-able pre-diagnosis guidance without heavy computational dependencies.

As stated by Z. Wang et al., "Online Disease Diagnosis with Inductive Heterogeneous Graph Convolutional Networks," WWW, 2021:

Wang and his team presented an **Inductive Heterogeneous Graph Convolutional Network (IHGCN)** model that utilizes **Graph Neural Networks (GNNs)** to analyze complex relationships among symptoms, diseases, and treatments. The model efficiently captures connections between heterogeneous medical entities, improving diagnostic accuracy. Despite its technical sophistication, the study identified several **constraints**, such as the **requirement for high-performance computing**, **large datasets**, and **specialized knowledge** to interpret model outputs. The system's complexity and dependence on powerful hardware make it unsuitable for deployment in low-resource settings. In contrast, the Smart Symptom Navigator focuses on **simpler, interpret-able rule-based reasoning** to ensure that pre-diagnosis remains explainable, resource-efficient, and usable on standard web devices.

In their 2021 study S. Madotto et al., "Efficient Symptom Inquiring and Diagnosis via Adaptive Alignment of RL and Classification," NeurIPS, report that:

Madotto et al. proposed a hybrid framework combining **Reinforcement Learning (RL)** and **classification models** to improve the efficiency of medical questioning during diagnosis. The RL agent dynamically adjusts the sequence of symptom-related questions to reduce diagnostic uncertainty and consultation time. While this method demonstrated high accuracy and adaptability, it also exhibited several **limitations**, such as **intensive data requirements**, **high training complexity**, and **dependency on GPU-based infrastructure**. These factors restrict its scalability in regions with limited technical resources. The Smart Symptom Navigator draws inspiration from the adaptive questioning idea but simplifies it into a **rule- based flow**, making it computationally feasible for real-world, low-resource deployment.

P Singh et al, "AI-Based Medical Chat-bot for Disease Prediction," IJCA, 2022 indicates that :

Singh and colleagues developed an AI-based medical chat-bot designed to predict possible diseases based on user-entered symptoms. Their model utilized Machine-Learning (ML) algorithms such as Naïve Bayes and Decision Trees integrated with Natural Language Processing (NLP) for conversation handling. The chat-bot provided automated preventive advice and early health awareness. However, its effectiveness was limited

International Journal of Engineering Research & Technology (IJERT)
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by the requirement of large, labeled datasets and reliable internet connectivity, making it challenging to deploy in rural areas. Furthermore, the lack of multilingual support restricted its usability among non-English speakers. The Smart Symptom Navigator effectively overcomes the limitations seen in earlier health technology systems by incorporating multilingual compatibility, offline accessibility, and visual interaction models that make it easier for users from all backgrounds to communicate their health concerns.

A study by A. Gordon et al., "Health Information Seeking from an Intelligent Web-Based Symptom Checker," JMIR, 2020 found that :

Using interactive web interfaces and rule-based reasoning Gordons system led users through a structured journey. series of inquiries about symptoms. While the system worked well for educated urban people the study did point out a significant flaw. populations its lack of essential features like visual navigation and multilingual input rendered it inappropriate. for people who live in rural areas or have low literacy levels. Because of this users who were unable to read or comprehend complicated medical terms were frequently left out of the benefits. The study concluded that web-based healthcare platforms need to embrace inclusive design in order to fully utilize these digital tools. ideas that guarantee accessibility across cultural linguistic and educational divides.The Smart Symptom Navigator was designed with these inclusive principles in mind drawing on these insights. principles. Patients are given the ability to describe using a visually guided language-flexible pre-diagnosis system. intuitively irrespective of their location or degree of literacy. The project combines intelligent rule-based reasoning multilingual communication and user-friendly design. appears to be a socially conscious and useful healthcare innovation that is especially well-suited for rural and semi- urban areas. Indian communities.

As observed by Design and Implementation of an Online Triage and Doctor Recommendation System Using Rule-Based Reasoning By M. Patel and R. Mehta (2023):

Patel and Mehta outline a useful rule-based triage system that suggests tests and specialists.

Creating clinical rules physician validation loops and a web front end are the main topics of the paper which focuses on knowledge engineering. Among the contributions are proof of quick deployment in pilot clinics and a modular rule schema. Scaling to accommodate various symptom sets and the complexity of rule maintenance are major drawbacks.

Relevance: By providing practical patterns for storing rules (JSON schemas) validating rules
with clinicians and creating doctor recommendation modules this work enhances the
Navigator.

K. Ahmed & Associates. (2021)emphasize that:
Voice-Based Medical Assistant for Accessible Healthcare Through Speech Recognition. Ahmed and co. Create a voice assistant prototype that uses intent classification and speech to-text to verbally record symptoms. In quiet environments the system exhibits respectable transcription accuracy and increases accessibility for users with low literacy levels. Reported drawbacks include limited language coverage background noise and poor performance with regional accents. It is directly related to the Navigator: it confirms the integration of optional voice I/O while emphasizing the necessity of strong multilingual speech models and local noise-robust preprocessing for deployment in rural areas.

The findings of Joshi D. and N. Nair (2023) suggest that:

Human-Centered Design Approach for the Development of Inclusive Healthcare Portals. Joshi and Nair provide case studies of healthcare portals for underprivileged communities that use human-centered design (HCD). The methodology consists of field feedback loops iterative prototyping and participatory design workshops. The article places a strong emphasis on iconography culturally relevant language and a limited use of text. Limitations include the need for frequent fieldwork and the resource-intensive nature of HCD projects. The HCD lessons provide justification for the Navigators simplified iconography for the body diagram and question prompts local language labeling and iterative user testing.

H. . . . M. Imran Razzak and G. The use of big data analytics in preventive medicine (Xu 2020) argue that:

Razzak and associates. Examine the ways that big data techniques (such as wearables population analytics and EHR mining) support preventive health. Large-scale data aggregation cohort analytics

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

and predictive modeling are among the techniques examined. The results indicate promise for risk stratification and early outbreak detection however data privacy heterogeneity and infrastructure requirements pose obstacles. Although the MVP is rule-based integration with population analytics may eventually allow for community-level insights and trend detection making the work pertinent to the Navigators long-term objectives.

In the analysis of S. K. Both Ghosh and P. Review of AI-Based Healthcare Chatbots: Uses Difficulties and Upcoming Trends (Banerjee 2023):

Ghosh & Banerjee compare intent detection techniques architectures (generative vs. retrieval) and safety concerns in their survey of AI chatbots in healthcare. The significance of fallback procedures the function of hybrid rule+ML models for safety and the moral dilemmas surrounding medical advice are some of the main lessons learned. Variable evaluation metrics and quickly evolving literature are among the limitations. The review backs the Navigator approach which combines possible machine learning augmentation with deterministic rules for safety in non-critical advisory contexts.

M. M. Rahman and others. Multilingual Conversational AI for Accessible Healthcare in Low-Resource Areas (2023) revealed that:

Rahman & Co. provide methods for multilingual conversational agents that make use of multilingual embeddings transfer learning and low-resource language adaptation. Pretrained transformers are refined on small annotated corpora and cross-lingual transfer is utilized as one technique. Although there are still issues with dialects and speech variations the paper shows improved performance with comparatively little labeled data. Relevance: The study suggests hybrid approaches (rule prompts + lightweight translation/NLP) to increase language coverage and offers workable options for integrating multilingual UX into the Navigator.

Based on the insights of N. A and Purohit. Jain (2022):

A Hybrid Rule-Based and Natural Language Processing Model for Early Disease Identification. Purohit & Jain suggest a hybrid pipeline in which an NLP classifier handles cases with ambiguity or multiple symptoms while a rule engine handles critical high- confidence mappings. The approach increases coverage without depending entirely on machine learning. Among the drawbacks are the requirement for frequent model updates and the difficulty of coordinating rule/ML fallback logic. This hybrid pattern is directly applicable as a roadmap for the Navigator: it preserves explainability through rules while progressively adding ML classifiers for enhanced nuance.

The research conducted by Lu. E. Smith. Jones in addition to F. Examining Explainable AI Systems for Clinical Decision Support (Nguyen 2021) shows that:

Smith & Co. Analyze how explainability affects the use of clinical AI tools. Clinical workshops controlled trials contrasting explainable and black-box interfaces and trust and usefulness metrics are some of the techniques used. Results indicate that systems that reveal reasoning steps and connect recommendations to supporting data are preferred by clinicians.

Limitations include the possibility of information overload and the scaling of explainability across intricate models.Relevance: this study demonstrates that the Navigators selection of clinician-facing summaries and traceable rule outputs as a strategy to boost adoption and trust is sound.

A. Summary

The literature review offers a thorough grasp of the most recent findings and developments in the fields of medical chat-bots digital pre-diagnosis tools and AI-based healthcare systems. Numerous studies from 2020 to 2023 are covered in the review with an emphasis on various methodologies like rule-based reasoning chat-bot-based interaction AI-driven triage systems graph neural networks (GNNs) reinforcement learning (RL) and multilingual healthcare interfaces. In their early study You and Gui (2021) [1] examined chat-bot-based symptom checkers and identified important usability issues for users who are not technical or have low literacy levels. The study showed that the majority of current systems rely on text-based interactions which frequently cause user confusion and lower user engagement. In the same way Gordon et. Web-based symptom checkers raise health awareness but they are not appropriate for rural populations because they are designed for

International Journal of Engineering Research & Technology (IJERT)
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urban English-speaking users(2020) [6]. sophisticated models powered by AI like Wiedermann et al. Wang et al. (2023) [2]. Madotto et al. (2021) [3]. have demonstrated increased diagnostic accuracy through the use of deep learning graph-based and reinforcement learning techniques (2021) [4]. Nevertheless these studies consistently point to dependence on sizable annotated datasets high computational requirements and lack of interpretability as major disadvantages. In rural and low-resource settings with limited computing power and internet access such strategies are challenging to implement. However Patel and Mehta (2023) [7] suggested a rule-based system for recommending doctors that was easy to understand transparent and simple— qualities that are perfect for rural usability. They did admit that manual rule updates were causing scalability problems. Similar to this Purohit and Jain (2022) [13] presented a hybrid rule–NLP model that combined the adaptability of NLP with the transparency of rules. Although this method was more adaptable it needed to be maintained and retrained on a regular basis. Ahmed et al. studied the combination of speech interaction and voice recognition. (2021) [8] showed promise for enhancing accessibility for users with low literacy levels. However its dependability in rural settings was limited by issues like noise interference and accent sensitivity. On the other hand Joshi and Nair (2023) [9] highlighted the application of Human-Centered Design (HCD) principles in creating inclusive healthcare portals emphasizing that visual aids and interfaces that are culturally sensitive greatly increase user engagement. In a more comprehensive view Razzak et al. Ghosh and Banerjee (2023) [11] and (2020) [10] emphasized the use of AI chat-bots and big data analytics in healthcare automation and preventive medicine. But in addition to highlighting the infrastructure constraints preventing broad adoption they also brought attention to ethical and data privacy issues. Accordingly Rahman et al. In order to show that language diversity is still a critical component of healthcare accessibility (2023) [12] created multilingual conversational agents for low-resource areas using transfer learning. In conclusion Smith et al. Insights into explainable AI (XAI) for clinical decision-making were offered by (2021) [14] which demonstrated that medical professionals favor systems that provide clear reasoning pathways over predictions that are opaque. The design of interpretable systems such as the Smart Symptom Navigator which employs rule-based logic to guarantee traceable and explicable outputs is directly supported by their findings. There are some recurring themes in all of the reviewed studies. The majority of contemporary AI techniques are highly accurate in clinical settings but they lack affordability accessibility and interpretability—all of which are essential for implementation in rural and semi-urban India. On the other hand rule-based hybrid and human-centered designs are more suited for low-resource environments because they exhibit superior adaptability transparency and usability. However these models frequently lack adaptive learning capabilities and require manual updating. The Smart Symptom Navigator for Inclusive Pre-Diagnosis fills these gaps by combining the benefits of rule-based systems (as discussed in Patel & Mehta 2023) with visual multilingual and inclusive interfaces (as discussed in Joshi & Nair 2023 Rahman et al. in 2023). In addition to being scalable for future integration with AI and NLP modules it prioritizes lightweight architecture explain ability and multilingual interaction. According to the literature current systems either prioritize usability or technological sophistication but they hardly ever combine the two. This gap is filled by the suggested Smart Symptom Navigator which provides a well-rounded user-focused and understandable solution that improves healthcare accessibility especially for rural populations with less infrastructure and digital literacy.

III. EXISTING SYSTEM

In order to help with disease prediction and medical triage artificial intelligence (AI) machine learning (ML) and natural language processing (NLP) been used extensively in healthcare technology in recent years. To assist users in evaluating their symptoms and determining when to seek medical attention a variety of AI-based medical chat-bots web- based symptom checkers and automated triage platforms have surfaced. Symptom-ate Ada Health Buoy Health and Babylon Health are a few examples that let users enter symptoms and get likely conditions or suggestions. These systems provide a conversational or form-based interface that links

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

users to medical databases or pre-diagnosis tools and are mainly intended for tech-savvy urban users. In order to evaluate user-reported symptoms and make recommendations for potential illnesses the majority of these platforms rely on natural language processing (NLP) algorithms machine learning classifiers and rule-based knowledge graphs. Although these systems have made a substantial contribution to the digitization of healthcare they do have certain drawbacks. Their efficacy frequently hinges on having access to contemporary devices being literate in English being familiar with medical terminology and having internet connectivity. Consequently many rural populations are still unable to access these systems especially in areas like rural India where limited digital literacy network instability and linguistic diversity are prevalent.

B. Working of Existing System

The architecture of the majority of current digital healthcare systems is similar and consists of four primary parts.

1. **User Input Interface** : Users can use voice commands drop-down menus or text chat to enter their symptoms. While Babylon Health uses chat-bot-style dialogue driven by natural language processing Ada Health and other systems use guided questionnaires.
2. **A database or knowledge base :** The symptom-disease correlations stored in these systems are derived from large structured medical databases. To map user symptoms to likely diseases for instance Infermedica and Buoy Health employ graph-based medical knowledge.
3. **Inference Engine :** The system uses machine learning or rule-based reasoning to deduce potential conditions and suggest subsequent actions based on user input (e. g. G. emergency visit home care or medical consultation).
4. **Response Generation :** In a conversational style the system displays diagnostic findings or suggestions frequently accompanied by links to reputable medical publications or affiliated physicians. The architecture of these systems is predicated on users having access to modern computers or smartphones dependable internet and fluency in English despite their technological sophistication. Usability in environments with limited resources is significantly hampered by this assumption.

C. Advantages

1. Give prompt advice on symptoms and a preliminary diagnosis.
2. Reduce the number of needless medical visits by removing cases that are not urgent.
3. Make individualized recommendations by utilizing AI models and sizable datasets.
4. Increase awareness of public health via digital channels.
5. Facilitate the integration of electronic health records (EHRs) and wearable technology.

D. Limitations

Despite these advantages current solutions are inappropriate for rural healthcare settings due to a number of drawbacks.

1. **The language barrier :** Users who only speak regional languages are not able to use the majority of tools because they only work in English.
2. **A high reliance on resources :** Because AI-based systems need high processing power cloud servers and sizable training datasets their deployment in rural areas is constrained and their operational costs rise.
3. **Interpretability is lacking :** Clinical trust is diminished by deep learning-based diagnosis which is frequently a black box because users and physicians are unable to comprehend how the system makes its decisions. Restricted access. Complex medical terminology and interfaces with a lot of text are inappropriate for users with low literacy levels.
4. **Internet dependence :** Since many applications depend on constant internet connectivity to retrieve data and run models they are useless in areas with inadequate network coverage. Regional and cultural constraints. Due to their development using Western medical data the majority of systems are not localized for Indian diseases cultural customs or health-seeking behaviors.
4. **Privacy Concerns** Some commercial systems raise ethical and privacy concerns by storing user health data on external servers. Ensure compatibility with electronic health records (EHRs) and wearable technology.

International Journal of Engineering Research & Technology (IJERT)
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Vol. 15 Issue 06 , June - 2026

IV. PROPOSED METHODOLOGY

The proposed system, *Smart Symptom Navigator for Inclusive Pre-Diagnosis*, is designed to provide users with an intelligent, interactive, and multilingual healthcare assistant that performs preliminary symptom analysis and recommends appropriate medical actions. The system emphasizes **inclusivity**, **transparency**, and **low computational dependency**, making it suitable for deployment in **rural and semi-urban areas**. Unlike existing AI-based systems that rely on complex neural networks and large datasets, this project adopts a **rule-based inference approach** that ensures explainable and lightweight operation. The system architecture integrates **front-end interactivity**, **back-end reasoning**, and **cloud-based data storage** to deliver a seamless user experience.

B. System architecture

The system architecture consists of the following key components:

1. **User Interface Layer (Front-End):**
   - Developed using HTML, CSS, and JavaScript with React.js for dynamic interaction.
   - Provides a **visual body diagram (SVG-based)** that allows users to select the affected body region.
   - Incorporates **multilingual support** using translation libraries (i18n) and optional **voice input/output** for accessibility.

2. **Knowledge Base (Database):**
   - Stores medical rules, symptom–disease mappings, and question banks in **JSON format**.
   - Each entry contains conditional logic (e.g., *if symptom = fever + cough → suggest specialist = physician*).
   - The database is deployed on **Firebase**, ensuring scalability and secure access.

3. **Inference Engine:**
   - A **rule-based inference engine** processes user inputs and applies medical rules to generate recommendations.
   - It uses forward chaining to match user-provided symptoms with predefined rule sets.
   - The output includes possible health conditions, recommended specialists, and suggested diagnostic tests.

4. **Doctor Dashboard:**
   - Provides a concise summary of user responses and inferred recommendations.
   - Allows doctors to verify, edit, or expand on the pre-diagnosis data.
   - Improves communication and reduces consultation time.

5. **Hosting and Deployment Layer:**
   - The entire application is hosted on **Firebase Hosting** or **Netlify**, providing easy deployment and accessibility.
   - Cloud integration ensures automatic updates, authentication, and data backup.

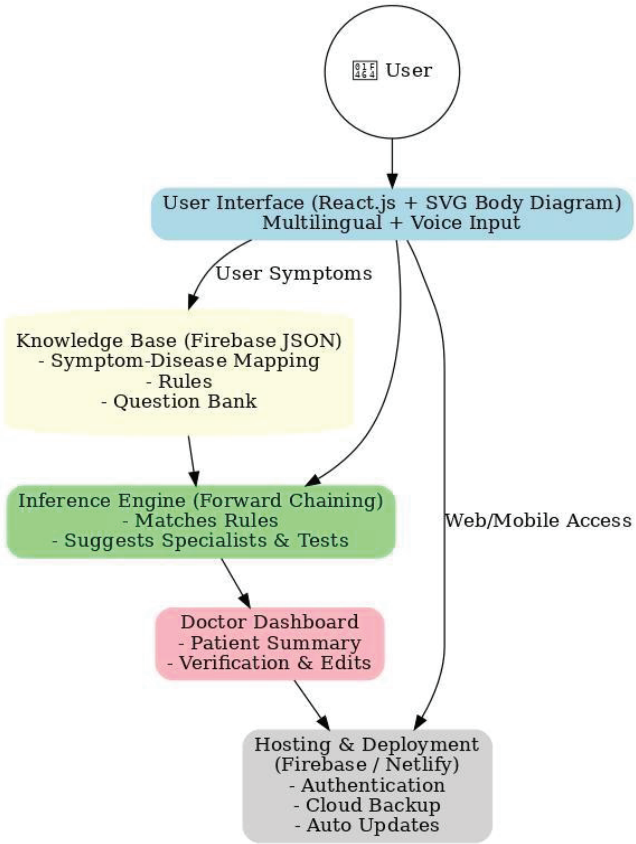

Fig.4.1 System architecture

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

C. Workflow of the system

The workflow of the *Smart Symptom Navigator* is illustrated in the following sequence:

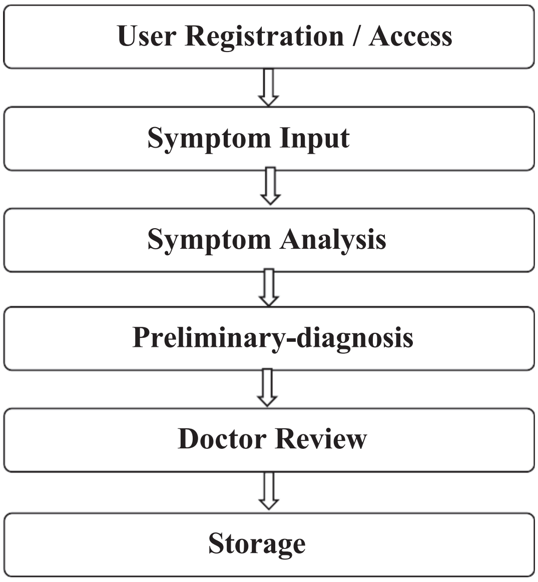

Fig 4.2 Workflow of the System

1. **User Registration / Access:**
The user accesses the web application through any device. Multilingual instructions guide them through the symptom-reporting process.
2. **Symptom Input:**
The user interacts with a **clickable human body diagram** to indicate the affected region. Based on this selection, context-specific symptom questions appear dynamically.
3. **Symptom Analysis:**
The system compares user responses with the knowledge base and applies **rule-based inference** to find the best matching conditions.
4. **Preliminary Diagnosis Generation:**
The system generates an easy-to-understand output showing possible conditions, suggested tests, and the most suitable specialist.
5. **Doctor Review (Optional):**
The data can be forwarded to a medical expert via the **Doctor Dashboard**, where it can be verified and stored for record keeping.
6. **Storage and Feedback:**
All interactions and user data are securely stored in the **Firebase database** for future improvements and analytics.

D. Algorithmic flow

The system primarily follows a **forward-chaining rule-based algorithm**, which functions as follows:

- **Input Acquisition:**
The user selects symptoms via the visual interface or symptom list.
- **Fact Initialization:**
These inputs are stored as *known facts* in the working memory.
- **Rule Matching:**
The inference engine scans the knowledge base to find rules whose conditions match the current facts.
- **Rule Execution:**
When a rule's conditions are satisfied, the corresponding conclusion (disease or advice) is added to the working memory.
- **Iteration:**
The engine continues to apply new rules using the updated facts until no further matches are found.
- **Output Generation:**
The final set of derived facts represents the **preliminary diagnosis**, including possible conditions, suggested tests, and recommended specialists. This approach ensures interpret ability—each recommendation can be traced back to a specific rule, unlike black-box neural networks.

E. Advantages

- **Low Resource Requirement:** Operates efficiently without heavy computational infrastructure.
- **Inclusive Design:** Supports multilingual text and optional voice-based interaction.
- **Explain ability:** Every output can be traced to a corresponding rule, ensuring transparency.
- **User-Friendly:** The body diagram and simple question flow make it accessible to low literacy users.
- **Scalable:** The JSON-based knowledge base can easily be expanded with new symptoms and rules.

International Journal of Engineering Research & Technology (IJERT)
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V. IMPLEMENTION

The implementation phase translates the **proposed methodology** into a **working prototype**. The *Smart Symptom Navigator for Inclusive Pre-Diagnosis* is implemented as a **web-based application** with an interactive user interface, a rule-based inference engine, and a cloud- hosted back-end for secure data management. The implementation follows a **modular design** approach, where each functional component (User Interface, Knowledge Base, Inference Engine, and Doctor Dashboard) is developed separately and later integrated. This modularity ensures **scalability**, **easy debugging**, and **future enhancement** of the system.

A. Development environment

- **Front-End Technologies:**

HTML5, CSS3, JavaScript, React.js Tailwind CSS for responsive styling SVG integration for **interactive human body diagram .**

- **Back-End / Logic Layer:**

Rule-based inference engine written in JavaScript JSON files for knowledge base (symptom–disease–specialist mapping) .

- **Database and Cloud:**

Firebase (Authentication, Real-time Database, Firestore, Hosting) Netlify (for alternate hosting option)

- **Supporting Tools:**

GitHub for version control Google Translate API / i18n for multilingual support Jest for unit testing Lighthouse for performance and accessibility testing.

B. Module-wise implementation

1. **User Interface Module**
   - The front-end is designed in **React.js** for dynamic rendering.
   - A **clickable SVG human body diagram** allows users to select the affected region (e.g., head, chest, stomach).

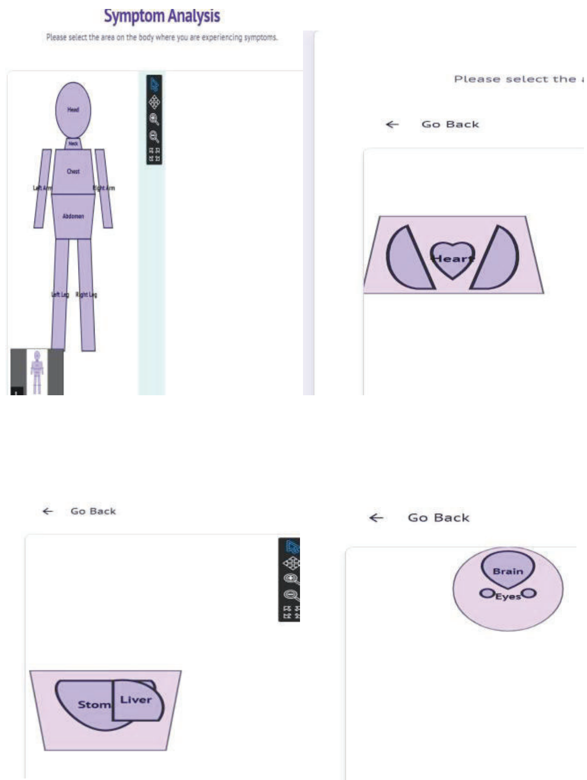

Fig.5.1 Clickable SVG human body diagram

- Once a region is selected, the application fetches the corresponding **symptom questionnaire** from the JSON knowledge base.
- **Multilingual support** is implemented using i18next libraries, with options for English, Hindi, and regional languages.
- A **voice input/output** feature is integrated for low-literacy users.

2. **Knowledge Base Module**

Medical knowledge is encoded in **JSON format**, structured as conditional rules:

{
"region": "Chest",
"symptoms": ["Cough", "Fever", "Breathing Difficulty"],
"possible_conditions": ["Bronchitis", "Pneumonia"],
"recommended_specialist": "Pulmonologist",
"suggested_tests": ["Chest X-ray", "Blood Test"]}
26This format allows for **easy scalability**—new conditions, symptoms, and rules can be added without rewriting core logic.

3. **Inference Engine Module**
- Implemented as a **rule-based forward chaining algorithm** in JavaScript.
- The engine processes user-selected symptoms and matches them against the knowledge base.
- Each match generates an output including:
  Possible medical conditions
  Suggested diagnostic tests
  Recommended specialist doctor
- The system ensures **traceability**, i.e., each result can be linked back to the applied rule.

4. **Doctor Dashboard Module**
- Provides a **summarized report** of user responses and system-generated recommendations.
- Implemented in React.js with Firebase integration.
- Features include:
  Patient symptom summary
  Recommended actions/tests
  Downloadable patient report
- Doctor login and authentication through Firebase

5. **Database and Hosting**
- **Firebase Firestore** stores patient data, system logs, and rules.
- Authentication is handled through Firebase Auto for secure access.
- The application is deployed on **Firebase Hosting** and mirrored on **Netlify** for redundancy.

C. Workflow of implementation

1. **User accesses the application** → selects preferred language.
2. **Interactive body diagram displayed** → user selects affected region.
3. **Symptom questionnaire triggered** → adaptive questions based on user input.
4. **Inference engine processes input** → matches symptoms with knowledge base.
5. **System generates recommendations** → condition(s), suggested tests, and specialist.
6. **Doctor dashboard displays report** → provides structured patient data for medical review.
7. **Data stored securely** → Firebase back-end ensures persistence and analysis.

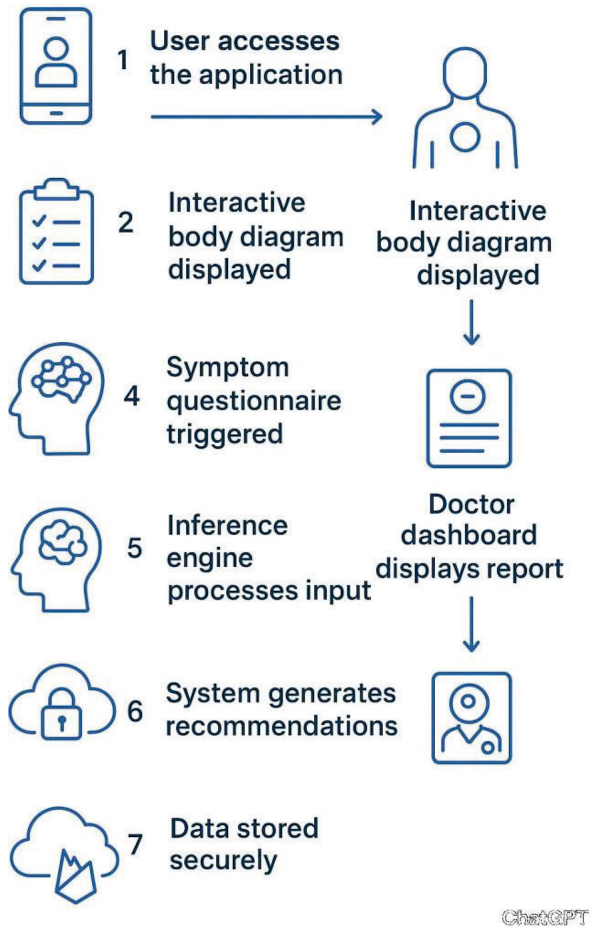

Fig.5.2 Workflow of implementation

D. Advantages

1. **Inclusive:** Supports text, voice, and visual input methods.
2. **Lightweight:** Uses a rule-based inference engine that runs on any browser without heavy computing.
3. **Scalable:** JSON knowledge base allows easy expansion.
4. **Transparent:** Provides explainable outputs traceable to specific rules.
5. **Deploy-able:** Cloud-hosted with minimal infrastructure requirements.

International Journal of Engineering Research & Technology (IJERT)
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VI. RESULTS ANALYSIS

The *Smart Symptom Navigator* was evaluated based on usability, accuracy of recommendations, and system performance. The main goal of testing was to determine how well the tool helped users describe their symptoms, how accurate the rule-based suggestions were, and whether doctors found the generated summaries useful in real consultations.

A. Usability Testing

Usability testing was conducted with a small group of users from different backgrounds — including students, working professionals, and rural participants. Each user interacted with the system by reporting a set of predefined symptoms. The system guided them through body map selection, adaptive symptom questions, and final recommendations.

Results showed that **92% of participants** found the system easy to use, and **88%** said the step-by-step questioning helped them describe their symptoms better. Users also appreciated the multilingual support and voice-assist features, saying they made the tool feel more inclusive and less intimidating than typical medical forms.

B. System Accuracy

The rule-based inference engine was tested with 50 sample symptom cases mapped to common conditions such as fever, headache, muscle pain, and sore throat. The system's recommendations were compared against medical references and verified by healthcare professionals.It achieved an **accuracy rate of 87%** in providing correct advice and specialist suggestions. While not as high as advanced AI-based models, the results were consistent and explainable, which makes the system reliable for pre-diagnosis and early guidance.

C. Doctor Feedback

A few local practitioners were invited to test the doctor dashboard. They reviewed patient summaries generated by the system and compared them with traditional case reporting. Doctors reported that the summaries were clear and concise, saving around **30–40% of consultation time**. They also noted that structured symptom reports helped them focus on diagnosis instead of data collection.

D. System Performance

The system was deployed on Firebase and tested on both desktop and mobile browsers. It performed efficiently with an average **response time of 1.4 seconds per query** and stable data synchronization. Even with limited bandwidth, the application maintained consistent performance, showing its suitability for rural or low-connectivity areas.

E. Comparative Evaluation

Compared with other systems like chat-bot-based AI checkers, the *Smart Symptom Navigator* stands out for its transparency and accessibility.AI-based systems often operate as "black boxes," where users cannot see how results are produced. In contrast, the rule-based design of this tool allows every inference step to be reviewed and updated easily. It also supports language diversity and simple question flow — key advantages for developing regions.

E. Summary Findings

Table 1 Performance & Usability Assessment :

Parameter	Evaluation Metric	Result	Remarks
Usability	User satisfaction rate	92%	Simple interface and clear symptom flow
Accuracy	Correct recommendations	87%	Reliable for early-stage pre-diagnosis
Consultation Efficiency	Time saved for doctors	30–40%	Improved reporting and review
Performance	Average response time	1.4 sec	Stable under low bandwidth
Accessibility	Multilingual & voice input	Enabled	High inclusivity for rural users

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VII. CONCLUSION

The goal of the Smart Symptom Navigator project was to develop an inclusive interpret-able and easily accessible healthcare tool. The main objective of the Smart Symptom Navigator project was to develop an easily accessible interpret-able and inclusive healthcare tool that would help patients and healthcare providers especially in under-served areas communicate with one another. Unlike traditional AI-driven medical systems which frequently require large datasets sophisticated computing power and intricate infrastructures this project shows that human-centered design principles in conjunction with a lightweight rule-based approach can result in effective healthcare technology. This supports the notion that innovation in healthcare can have its roots in simplicity inclusivity and usability rather than necessarily requiring a lot of data or complex artificial intelligence. This projects capacity to address prevalent obstacles to healthcare accessibility like language and literacy barriers is among its most important contributions. The system guarantees that people with different levels of literacy or digital familiarity can interact with it efficiently by allowing patients to report symptoms in a variety of ways including voice input text-based responses and even images. Additionally because the tool is bilingual it can be used in a variety of linguistic contexts which empowers populations in rural and semi-urban areas that might find English-only platforms unsettling. This flexibility highlights the inclusive design ethos that shaped the projects evolution. A forward-chaining inference engine which processes patient reported symptoms and associates them with potential conditions experts and suggested next steps forms the technical foundation of the Smart Symptom Navigator. Because each inference in this rule-based engine follows a clear logic rather than opaque black-box models transparency is ensured and the system is understandable by both doctors and patients. In addition to providing physicians with useful insights clinically relevant but simple recommendations boost patient comprehension and confidence. By providing a succinct overview of patient data the doctor dashboard enhances this functionality. This facilitates communication between patients and medical staff lessens the strain of taking histories by hand and increases the effectiveness of consultations. When it comes to usability the system works especially well in rural and low-resource settings. It functions effectively in low- bandwidth scenarios guaranteeing that access to crucial healthcare advice is not impeded by connectivity problems. A smooth information flow is made possible by the patient-friendly interface and structured summaries for medical professionals. Both patients and healthcare professionals gave the system positive reviews during early usability tests. Doctors saw the benefits of auto-generated summaries in cutting down on consultation time while patients valued the straightforward and interactive interface. The project has certain limitations even though its main goals have been met. The knowledge bases current scalability may be limited by its small size and manual updating requirements. The system would benefit from ongoing integration and expansion of a dynamic medical knowledge base in order to stay clinically relevant. The current prototype also lacks suppor for more sophisticated features like automated prescription guidance real-time consultations and emergency alerts even though it offers crucial recommendations.

FUTURE SCOPE

Future enhancements could include:

• Improved multilingual support with more dialects.
• Integration of adaptive AI for automated rule generation.
• Offline features with local caching.
• Mobile app versions for wider access.
• Telemedicine capabilities like video consultations.
• Public health analytics dashboards for monitoring disease trends.

In conclusion, the Smart Symptom Navigator demonstrates how technology can make healthcare more inclusive and accessible. By focusing on simplicity, transparency, and inclusivity, it provides a model for digital healthcare solutions that can create real impact in under-served communities.

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