

## Enhancing Rural Healthcare Accessibility Through Ai-Driven Multilingual Symptom Triage On Low-End Smartphones

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### Abstract

Access to timely and accurate healthcare remains a persistent challenge in rural and semi-urban areas, predominantly where medical infrastructure is weak, professionals are scarce, and digital tools are inaccessible due to language or literacy barriers. This paper presents a lightweight, rule-based AI symptom triage system designed for deployment on low-end smartphones with support for regional languages such as Hindi and Kannada. The system allows users to report symptoms through a simple text-based interface and receive condition-based suggestions and guidance on whether home care or medical attention is needed. Developed using open-source platforms like Gradio, the tool focuses on usability and accessibility, with minimal computational requirements. A pilot deployment was conducted in a rural Indian setting, where the system received positive user feedback—especially regarding its language support, ease of use, and decision-making guidance. Preliminary results propose that such a system can help bridge the healthcare access gap by enabling informed self-triage. This study contributes to research on AI-assisted primary care systems in low-resource settings and lays the groundwork for future integration of voice support, machine learning-based diagnosis, and linkage with local healthcare providers.

**Keywords:** AI in healthcare, rural health, symptom checker, multilingual interface, rule-based diagnosis, mobile health tools

### 1. Introduction

Access to basic and timely healthcare remains a critical challenge in rural and semi-urban regions, particularly in emerging economies such as India, where nearly 65% of the population resides in rural areas with a significantly low doctor-to-patient ratio [1], [13]. Health service accessibility is further impaired by poor transportation, low income, and the lack of language-friendly digital interfaces [13], [20]. While government initiatives and telemedicine platforms strive to bridge this gap, digital health tools are frequently constrained by their dependence on English-language interfaces and the requirement for high-end smartphones, limiting their accessibility in resource-limited settings [17], [20]. In recent years, symptom checker applications have gained popularity for self-triage and health guidance. Studies

by Semigran et al. [1], Wallace et al. [2], and Schmieding et al. [3] illustrate that even though these tools can offer valuable advice, their diagnostic accuracy and triage performance vary widely. Benchmarking studies such as those in [3], [7], [21] have highlighted inconsistencies in both medical correctness and usability when compared to trained physicians. Many popular tools (e.g., Ada, Babylon, Your.MD) have shown less than 60% accuracy for first-attempt diagnosis [3] [15]. To address these challenges, AI-powered health assistants have emerged as promising tools in healthcare delivery. Chatbot-based systems for symptom checking [5], remote patient monitoring [14], and cough-based COVID-19 screening [6] offer scalable solutions with potential for personalization and localization.

However, the deployment of such systems in low-resource and multilingual settings is still underexplored [17][18]. Multilingual and speech-enabled systems like Medlingua [15] and Jarvis Health [17] have attempted to address linguistic barriers, yet many lack tailored support for rural dialects or low-literate populations [19]. Moreover, systematic studies [20] and review [22] emphasize that most digital tools ignore key human-centered design elements like explainability, trust, and cultural adaptability which are critical factors for adoption in rural contexts. In this paper, we propose a lightweight, ML-powered AI health triage system trained on a physician-verified dataset, optimized for low-end smartphones and offering regional language support (Hindi and Kannada). Developed using Gradio and tested in a rural Indian community, the tool aims to offer accessible, explainable, and localized symptom triage support in underserved settings.

## 2. Literature Survey

### 2.1. Symptom Checkers and Diagnostic Accuracy

Symptom checkers are digital tools that allow users to input health complaints and receive possible diagnoses and triage advice. Semigran et al. [1], Wallace et al. [2], and Schmieding et al. [3] evaluated several such platforms and found significant variability in diagnostic performance, with first-attempt accuracy ranging from 19% to 55%. Despite the proliferation of tools like Ada, Babylon, and Your.MD, their medical validity and usability remain limited in low-resource, multilingual settings [6], [10]. Recent benchmarking studies [7] [21], [22] show that many symptom checkers underperform compared to trained clinicians and sometimes even laypersons. These tools often lack explainability, cultural adaptability, and language support necessary for widespread rural adoption.

### 2.2. AI Chatbots and ML-Based Health Assistants

Artificial intelligence and chatbot-based systems have gained traction in healthcare, offering scalable, automated preliminary care. You and Gui [5] and Berry AC et al. [11] emphasized that trust and

usability are crucial factors in self-diagnosis via chatbots. Imran et al. [6] and Pranjal Kumar et al. [9] showed that lightweight models can detect and classify conditions like COVID-19 and cardiac risks, although such models typically assume internet connectivity and advanced hardware. Recent focus has shifted from rule-based systems to machine learning (ML)-driven models, which offer improved prediction accuracy and adaptability. In particular, XGBoost, a gradient-boosted decision tree algorithm, has shown exceptional performance in structured medical datasets due to its speed, interpretability, and scalability. Several studies have successfully applied XGBoost for triage and diagnosis:

- Fang et al. [24] used XGBoost for COVID-19 diagnosis from symptom and demographic data.
- Hyunjung Yun et al. [25] developed a triage tool combining XGBoost and vitals for severity prediction.
- Ibomoiye et al., [26] integrated SHAP analysis to interpret symptom relevance and suggested that SHAP values have several desirable properties that make them a powerful tool for interpreting ML models.
- Garrido et al. [27] applied XGBoost for emergency department triage, highlighting its clinical utility.

These results demonstrate the suitability of XGBoost for building interpretable, accurate triage systems that can be extended to rural healthcare settings.

### 2.3. Multilingual Interfaces and Human-Centered Design

Studies [13] [18] consistently highlight that symptom checkers and chatbots must support regional languages and voice interfaces to serve low-literate populations effectively. Tools such as Healthily and MedSLT attempted to address multilingual support but often lack coverage for rural dialects or offline functionality. Usability and trust are also critical. Hildt E [23] found that explainability increased user confidence, while the Dankwa-Mullan I [4] called for greater oversight and transparency in AI-driven tools used in underserved areas.

### 3. Methodology

The proposed system is a lightweight, rule-based AI assistant designed to provide basic health triage via multilingual input on low-cost smartphones. The goal is to support users in remote regions with no access to clinical expertise, particularly those who are not comfortable with English interfaces.

#### 3.1. Dataset Generation Using Rule-Based Engine

To build the machine learning model, a synthetic dataset was generated using a rule-based inference engine designed with verified physician inputs and global triage protocols (e.g., WHO). A curated set of health conditions (e.g., fever, cough, diarrhea, fatigue, vomiting) was mapped to associated symptom combinations. Each rule followed an IF–THEN format and was tagged with severity levels (home care, non-urgent, urgent) and multilingual guidance. This engine was not deployed to users but served as a controlled data generator, validated by a medical expert. The dataset was then split for model training (80%) and testing (20%).

#### 3.2. ML Model - XGBoost

The triage classification model was developed using XGBoost, trained on the physician-verified synthetic dataset. Each record represented symptoms as binary vectors and was labeled with one of three triage levels. The model achieved 88% accuracy on the test set. SHAP (SHapley Additive exPlanations) was used to interpret model behavior, identifying fever, vomiting, and fatigue as top predictive features.

#### 3.3. Language and Interface Design:

The user interface was created with Gradio, an open-source Python GUI toolkit. It supports bilingual interaction (Hindi and Kannada) and allows users to enter symptoms via dropdowns or short prompts. Triage results are shown with color-coded flags (green: home care, red: urgent) and recommendation messages in local languages. To better support users with limited literacy, the system is being extended to include offline voice input and output in future updates. This enhancement will use tools like Vosk, an open-source speech-to-text engine that supports Indian languages, for capturing spoken symptoms. For generating audio responses, lightweight text-to-

speech engines such as Coqui TTS or eSpeak NG will be integrated. These components are designed to work efficiently on low-end devices without internet access, making them ideal for deployment in rural areas.

#### 3.4. Platform and Tools

Python and Flask were used in the backend to build the triage app. The app was deployed as a Progressive Web App (PWA) ensuring its compatibility with lower edge Android smartphones (< 2 GB RAM). This setup enables to access the app offline without relying on constant internet. JSON and binary formats are used to store locally, all the essential files including the trained XGBoost model and the symptom logic. Optimized with Joblib, the model supports quick loading using very low memory. Since the app performs only inference and not model training, it runs competently even on basic smart phones. Without the need of internet, the app was tested successfully on entry-level smart phones. This confirms its strong potential for use in rural as well in regions with low-network connectivity.

#### 3.5. Deployment and Pilot Testing

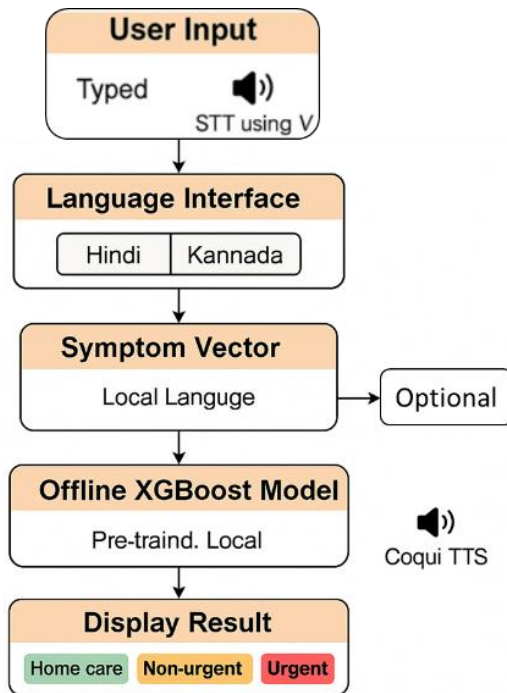
The triage app was deployed and offline tested in a rural community center in Karnataka. The real-world pilot involved 52 participants who provided valuable feedback on usability, trust, and accessibility. The feedback of the participants was evaluated on:

- Interface user-friendliness
- Confidence in triage recommendations
- Preference of language for interaction
- Willingness to reuse the app

The identity of the responses was de-identified, and stored with the intention of usage for future analysis. Table 1 shows Pilot User Feedback (n = 52)

**Table 1 Pilot User Feedback (n = 52)**

Metric	Score / Percentage
Interface ease of use (avg)	4.2 / 5
Trust in triage output	78%
Preferred local language	94%
Willingness to reuse the app	65%



**Figure 1 Architecture of The Deployed Offline AI-Based Symptom Triage System. The App Supports Multilingual Text-Based Input and Triage Output and Has Been Deployed in A Rural Setting. Voice Input/output Support Is Planned for Future Versions to Enhance Accessibility for Low-Literate Users**

## 4. Research Gaps and Objectives

Despite the proliferation of AI-based health tools, major gaps remain in usability, linguistic accessibility, offline functionality, and contextual suitability for rural and semi-urban users.

### 4.1. Research Gaps

- Most existing symptom checkers operate only in English or other international languages, excluding large non-English-speaking populations [13] [18].
- Many AI-driven triage tools assume consistent internet access and high-end smartphones, which are often unavailable in rural areas [6] [18].
- Current systems frequently lack human-centric design, especially for users with low digital and health literacy [19] [20][22].

- Very limited research focuses on offline-capable, multilingual ML-based triage systems optimized for low-resource environments and accessible via simple interfaces [8].

### 4.2. Objectives

- This study was undertaken to address the key gaps identified in existing healthcare triage solutions, particularly in rural and underserved communities. The main objectives were as follows:
- To generate a reliable dataset for machine learning by using a physician-verified rule-based engine that maps symptoms to triage outcomes.
- To build a multilingual, lightweight health triage application that can run offline and is optimized for low-end smartphones. The user interface was developed to support both Hindi and Kannada, ensuring accessibility across different user groups.
- To train and test an XGBoost-based classifier capable of accurately predicting triage categories—such as home care, non-urgent care, or urgent care—based on the symptoms entered by users.
- To pilot the application in a rural setting, evaluating its effectiveness in terms of ease of use, user trust, language preference, and its influence on healthcare decision-making.
- To explore the integration of voice features in future updates, aiming to make the system more inclusive for users with limited literacy or difficulty typing.

## 5. Results and Discussion

The pilot was deployed in a rural community in Karnataka which was introduced to 52 participants.

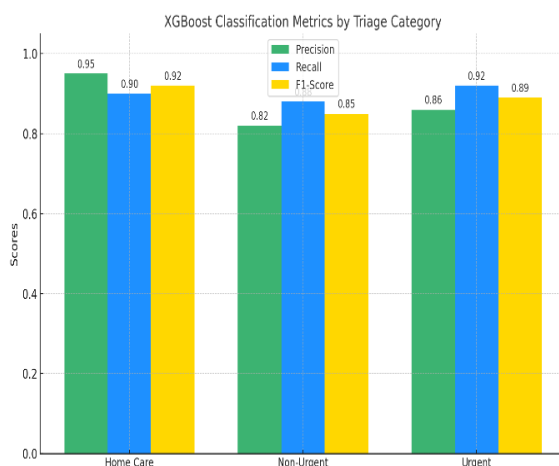
- **Usability:** 85% of users reported the interface was easy to navigate, with bilingual prompts significantly improving comprehension. Users unfamiliar with English preferred Hindi or Kannada versions, highlighting the importance of localized interfaces.
- **Trust and Acceptance:** About 78% trusted the recommendations, especially when the



advice was clear and provided in their native language. This aligns with prior findings that explainability and language support enhance user confidence.

- **Decision Impact:** Nearly 65% indicated that the app helped them decide whether to seek clinical care or manage symptoms at home, demonstrating potential to reduce unnecessary clinic visits and alleviate healthcare burdens.
- **Limitations:** A few participants shared that typing their symptoms was difficult, especially for those with limited literacy, and suggested that voice-based interaction would make the app more accessible. Additionally, the system occasionally gave overly cautious advice recommending clinical visits even for mild symptoms. This conservative strategy is consistent with what has been observed in similar symptom-checking applications.

Despite these limitations, the results indicate that a lightweight, multilingual, ML-driven triage application can effectively support health-related decision-making in rural settings, even on low-end smartphones. The feedback also highlights the need to broaden language support and integrate voice-based features, which could significantly improve accessibility for users with limited literacy or typing ability.



**Figure 2 XGBoost Model Performance Across Triage Categories**

Bar chart illustrating the precision, recall, and F1-score for each triage class (Home Care, Non-Urgent, and Urgent) in the offline symptom triage system. The model demonstrates consistently high performance, particularly for urgent and home care classifications, supporting its suitability for rural, multilingual healthcare deployment.

### Conclusion and Future Work

This study presents a practical, AI-based symptom triage solution tailored to address the unique healthcare challenges faced in rural regions of India. Built around a lightweight, XGBoost-based machine learning model and offering bilingual support in Hindi and Kannada, the app delivers reliable health guidance directly on low-cost smartphones—without requiring internet connectivity. The system was trained using a synthetic dataset generated from a physician-verified rule engine and deployed in a rural setting where 52 participants engaged with the app. Field testing showed that users found the interface easy to use, appreciated the multilingual support, and often used the tool to make informed healthcare decisions. These results suggest that lightweight, multilingual ML tools can meaningfully support decision-making and improve early triage in underserved communities.

### Future Work Includes

- Integrating offline voice recognition and synthesis to accommodate low-literacy users;
- Expanding the symptom-condition dataset using local epidemiological inputs and real patient data;
- Adding support for additional regional languages;
- Establishing collaborations with local medical practitioners to facilitate smooth patient referrals and follow-up mechanisms.;
- Conducting long-term impact assessments across broader user groups.
- By continuing to refine and scale this approach, AI-powered offline triage systems can contribute significantly to equitable healthcare access in resource-constrained environments.

## References

- [1]. [1] Semigran HL, Linder JA, Gidengil C, Mehrotra A, "Evaluation of symptom checkers for self diagnosis and triage: audit study", *BMJ*. 2015 Jul 8;351:h3480. doi: 10.1136/bmj.h3480. PMID: 26157077; PMCID: PMC4496786.
- [2]. Wallace W et al., "The diagnostic and triage accuracy of digital and online symptom checker tools: a systematic review", *NPJ Digit Med*. 2022 Aug 17;5(1):118. doi: 10.1038/s41746-022-00667-w. PMID: 35977992; PMCID: PMC9385087.
- [3]. Schmieding ML, Mörgeli R, Schmieding MAL, Feufel MA, Balzer F, "Benchmarking Triage Capability of Symptom Checkers Against That of Medical Laypersons: Survey Study", *J Med Internet Res*. 2021 Mar 10;23(3):e24475. doi: 10.2196/24475. Erratum in: *J Med Internet Res*. 2021 May 6;23(5):e30215. doi: 10.2196/30215. PMID: 33688845; PMCID: PMC7991983.
- [4]. Dankwa-Mullan I, "Health Equity and Ethical Considerations in Using Artificial Intelligence in Public Health and Medicine", *Prev Chronic Dis*. 2024 Aug 22;21:E64. doi: 10.5888/pcd21.240245. PMID: 39173183; PMCID: PMC11364282.
- [5]. You Y, Gui X, "Self-Diagnosis through AI-enabled Chatbot-based Symptom Checkers: User Experiences and Design Considerations", *AMIA Annu Symp Proc*. 2021 Jan 25;2020:1354-1363. PMID: 33936512; PMCID: PMC8075525.
- [6]. Ali Imran et al., "AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app", *Informatics in Medicine Unlocked*, Volume 20, 2020, 100378, ISSN 2352-9148, <https://doi.org/10.1016/j.imu.2020.100378>, J. Chen, W. Zhang, and X. Wang, "A Benchmark for Automatic Medical Consultation System: Frameworks, Tasks and Datasets," *arXiv:2204.08997*, 2022. [Online]. Available: <https://arxiv.org/abs/2204.08997>
- [7]. Md. Obaidur Rahman et al., "Internet of Things(IoT) based ECG monitoring system for rural healthcare," *arXiv preprint arXiv:2208.02226*, 2022. [Online]. Available: <https://arxiv.org/abs/2208.02226>
- [8]. Pranjal Kumar, Siddhartha Chauhan, Lalit Kumar Awasthi, "Artificial Intelligence in Healthcare: Review, Ethics, Trust Challenges & Future Research Directions", Vol 120, Issue C, <https://doi.org/10.1016/j.engappai.2023.105894>
- [9]. Riboli-Sasco E et al., "Triage and Diagnostic Accuracy of Online Symptom Checkers: Systematic Review", *J Med Internet Res*. 2023 Jun 2;25:e43803. doi: 10.2196/43803. PMID: 37266983; PMCID: PMC10276326.
- [10]. Berry AC et al., "Online symptom checker diagnostic and triage accuracy for HIV and hepatitis C", *Epidemiol Infect*. 2019 Jan;147:e104. doi: 10.1017/S0950268819000268. PMID: 30869052; PMCID: PMC6419737.
- [11]. Abensur Vuillaume L, Turpinier J, Cipolat L, Arnaud-Dépil-Duval, Dumontier T, Peschanski N, et al. (2023) "Exploratory study: Evaluation of a symptom checker effectiveness for providing a diagnosis and evaluating the situation emergency compared to emergency physicians using simulated and standardized patients", *PLoS ONE* 18(2): e0277568. <https://doi.org/10.1371/journal.pone.0277568>
- [12]. Tuan, Dang Anh. "Bridging the Gap Between Black Box AI and Clinical Practice: Advancing Explainable AI for Trust, Ethics, and Personalized Healthcare Diagnostics.", (2024).
- [13]. Thanveer Shaik et al., "Remote patient monitoring using artificial intelligence: Current state, applications, and challenges,"[Online]. Available: <https://doi.org/10.48550/arXiv.2301.10009>
- [14]. Himel GMS, Hasan MS, Salsabil US, Islam MM, "MedLingua: A conceptual framework

- for a multilingual medical conversational agent”, *Methods X*. 2024 Feb 22;12:102614. doi: 10.1016/j.mex.2024.102614. PMID: 38439929; PMCID: PMC10909737.
- [15]. Aboueid S et al., “Young Adults' Perspectives on the Use of Symptom Checkers for Self-Triage and Self-Diagnosis: Qualitative Study”, *JMIR Public Health Surveill*. 2021 Jan 6;7(1):e22637. doi: 10.2196/22637. PMID: 33404515; PMCID: PMC7817365.
- [16]. Varisha Khanam, 2025, “Jarvis Health: An AI-Based Voice-Enabled Symptom Checker Chatbot for Preliminary Health Assessment”, *International Journal of Engineering Research & Technology (IJERT)* Volume 14, Issue 05 (May 2025)
- [17]. Nwankwo et al., (2024), “Telemedicine and AI to Improve Healthcare Access in Rural Settings”, *International Journal of Life Science Research Archive*. 07. 59-077. 10.53771/ijlsra.2024.7.1.0061.
- [18]. Secinaro, S., Calandra, D., Secinaro, A. et al. “The role of artificial intelligence in healthcare: a structured literature review”, *BMC Med Inform Decis Mak* 21, 125 (2021). <https://doi.org/10.1186/s12911-021-01488-9>
- [19]. Ruby Khan, Sumbal Khan, Hailah M. Almohaimeed, Amany I. Almars, Bakht Pari, “Utilization, challenges, and training needs of digital health technologies: Perspectives from healthcare professionals”, *International Journal of Medical Informatics*, Volume 197, 2025, 105833, ISSN 1386-5056, <https://doi.org/10.1016/j.ijmedinf.2025.105833>. (<https://www.sciencedirect.com/science/article/pii/S1386505625000504>)
- [20]. Hammoud M, Douglas S, Darmach M, Alawneh S, Sanyal S, Kanbour Y, “Evaluating the Diagnostic Performance of Symptom Checkers: Clinical Vignette Study”, *JMIR AI*. 2024 Apr 29;3:e46875. doi: 10.2196/46875. PMID: 38875676; PMCID: PMC11091811.
- [21]. Chustecki M. “Benefits and Risks of AI in Health Care: Narrative Review”, *Interact J Med Res*. 2024 Nov 18;13:e53616. doi: 10.2196/53616. PMID: 39556817; PMCID: PMC11612599.
- [22]. Hildt E. “What Is the Role of Explainability in Medical Artificial Intelligence? A Case-Based Approach”, *Bioengineering (Basel)*. 2025 Apr 2;12(4):375. doi: 10.3390/bioengineering12040375. PMID: 40281735; PMCID: PMC12025101.
- [23]. Fang, Zheng-gang & Yang, Shu-qin & Lv, Cai-xia & An, Shu-yi & Wu, Wei. (2022), “Application of a data-driven XGBoost model for the prediction of COVID-19 in the USA: a time-series study”, *BMJ Open*. 12. e056685. 10.1136/bmjopen-2021-056685.
- [24]. Yun H, Choi J, Park JH, “Prediction of Critical Care Outcome for Adult Patients Presenting to Emergency Department Using Initial Triage Information: An XGBoost Algorithm Analysis”, *JMIR Med Inform*. 2021 Sep 20;9(9):e30770. doi: 10.2196/30770. PMID: 34346889; PMCID: PMC8491120.
- [25]. Ibomoie Domor Mienye et al., “A survey of explainable artificial intelligence in healthcare: Concepts, applications, and challenges, *Informatics in Medicine Unlocked*”, Volume 51, 2024, 101587, ISSN 2352-9148, <https://doi.org/10.1016/j.imu.2024.101587>. (<https://www.sciencedirect.com/science/article/pii/S2352914824001448>)
- [26]. Garrido NJ, et al., “Innovation through Artificial Intelligence in Triage Systems for Resource Optimization in Future Pandemics”, *Biomimetics (Basel)*. 2024 Jul 18;9(7):440. doi: 10.3390/biomimetics9070440. PMID: 39056881; PMCID: PMC11274710.