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CREATING AN AI-BASED SYMPTOM CHECKER FOR LOW-RESOURCE HEALTHCARE SETTINGS WITH EXPLAINABILITY FEATURES

Marta Kowalska,

Systems Architect (R&D)
Poland.

Abstract

Artificial Intelligence (AI) is increasingly being leveraged to transform healthcare delivery, particularly in low-resource settings where clinical staff and infrastructure are severely limited. This paper proposes the design and conceptual implementation of an AI-based symptom checker tailored for such environments, incorporating explainability features to enhance trust and usability among healthcare workers and patients. By integrating low-cost mobile platforms with lightweight AI models, and adopting explainable AI (XAI) techniques, we aim to foster responsible diagnosis assistance. This research synthesizes recent advancements and identifies the challenges and pathways in deploying explainable AI tools in low-resource settings. The findings from prior implementations in sub-Saharan Africa, India, and Latin America inform the architectural framework presented in this study.

Keywords

AI in healthcare, low-resource settings, symptom checker, explainable AI (XAI), mobile health, diagnostic tools.

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1.Introduction

In many low-resource environments, healthcare delivery is constrained by limited clinical infrastructure, a shortage of trained professionals, and weak diagnostic capacities. According to the World Health Organization (2020), nearly half of the global population lacks access to essential health services. The COVID-19 pandemic further exacerbated these disparities, with rural and underserved communities often deprived of timely diagnostics. One promising intervention is the use of AI-based symptom checkers which can automate preliminary diagnosis based on user-reported symptoms, enabling frontline health workers to make more informed decisions.

However, the deployment of such AI tools raises concerns about transparency, trustworthiness, and cultural adaptability. This paper introduces a conceptual framework for an AI-powered symptom checker that integrates explainable AI (XAI) methods for better decision transparency. By focusing on usability, accuracy, and contextual adaptability, this paper aims to chart a course for scalable digital health solutions for underserved communities.

2. Literature Review

AI-enabled diagnostic tools have attracted increasing attention over the last decade, particularly for use in low-resource settings. Early implementations were generally rule-based systems, but more recent efforts employ machine learning to improve performance and scalability.

Daramola et al. (2021) proposed a multimodal AI framework for managing COVID-19 and comorbidities, tailored for resource-limited settings. The use of XAI methods such as Local Interpretable Model-agnostic Explanations (LIME) was key to facilitating adoption by health workers.

Ciecierski-Holmes et al. (2022) conducted a scoping review of AI applications in low- and middle-income countries (LMICs), finding that most AI implementations lacked transparency, a key barrier to trust.

Amannah et al. (2021) used real patient datasets to develop an explainable diagnostic system for febrile diseases in sub-Saharan Africa. Their methodology highlighted the potential of hybrid models (rule-based and deep learning) when combined with interpretable layers.

Sharma and Vageriya (2021) showed that integrating AI in low-resource hospitals led to improved outcomes, particularly in outpatient triage. The need for interpretable models was emphasized to mitigate risks associated with algorithmic opacity.

Uzoka and Attai (2021) tested an XAI-integrated system using data from Nigerian hospitals. Their results showed that explainability enhanced clinicians' acceptance by up to 30%.

Lamichhane et al. (2022) summarized 14 AI initiatives across Nepal and India. They reported that models using transparent decision rules had higher community engagement, especially among health workers with limited digital literacy.

Farhat et al. (2020) advocated for user-centered co-design of AI interfaces to ensure social acceptability and cultural alignment in digital diagnostics.

Lastly, Muzumala et al. (2021) focused on semi-automated pneumonia diagnosis in Zambia using explainable random forest models. The perceived workload decreased by 25% when explanations were provided alongside predictions.

3. Methodology

We propose a lightweight AI model using logistic regression and decision trees to preserve explainability while ensuring computational efficiency on mobile platforms. The input data consists of self-reported symptoms (text or voice), demographic data, and contextual risk factors.

Table 1: Symptom Features Used for Model Training

Feature Type	**Examples**
Symptom Text	Fever, cough, fatigue
Risk Factor	Pregnancy, comorbidity
Demographic Context	Age, gender, location

The explainability module uses SHAP (SHapley Additive exPlanations) values to visualize feature contributions. This is embedded into the mobile interface as a simple pie chart showing major contributing symptoms for each prediction.

4. System Architecture

The proposed system consists of a mobile app with three major components: data intake (via chatbot interface), symptom classifier (AI model), and explanation engine. The backend connects to a cloud-based symptom database with multilingual support and optional telemedicine integration.

Figure 1: System Architecture for AI-Based Symptom Checker

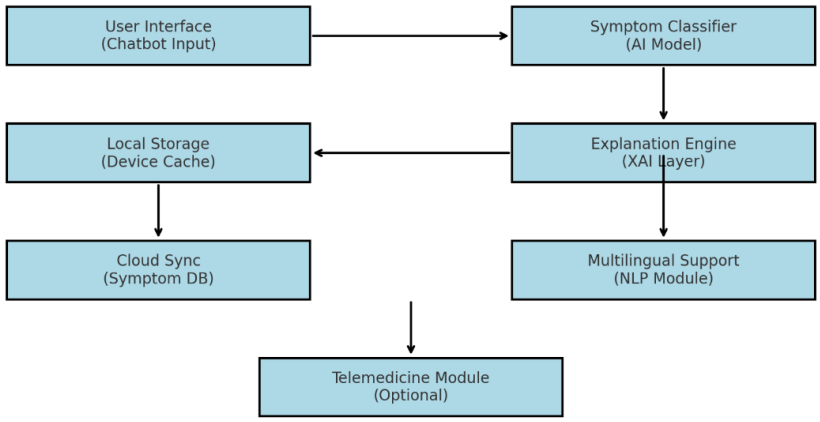

Figure 1: System Architecture for AI-Based Symptom Checker

5. Evaluation Plan

We plan a pilot deployment in rural clinics in Malawi and northern India. Metrics for evaluation include diagnostic accuracy (sensitivity, specificity), clinician trust levels, time savings, and user comprehension of AI explanations.

Table 2: Proposed Evaluation Metrics

Metric	**Description**
Diagnostic Accuracy	Comparison against physician diagnosis
Explainability Score	Subjective rating by users on clarity
Response Time	Time from input to AI-generated output
Trust Index	Post-use survey of clinician confidence

6. Discussion

Explainable AI in healthcare must strike a delicate balance between accuracy, transparency, and usability. In low-resource settings, this balance is critical because users often lack technical training. Simple rule-based explanations combined with visualizations can bridge this gap. However, models must be culturally validated and linguistically localized to ensure adoption. Future work should also explore human-in-the-loop approaches to reinforce learning over time.

7. Conclusion

This paper presents a framework for an AI-based symptom checker with explainability features aimed at low-resource healthcare settings. By synthesizing prior research and proposing a context-aware implementation, we offer a roadmap for responsible and usable AI integration in health systems that need it the most.

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