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Artificial Intelligence based Symptom Analysis for Disease Prediction: A Phase 2 Field Study

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Abstract

Introduction: Symptom-based triage and risk assessment is often the first step in patient triage but can be highly subjective, time-consuming, and prone to error, especially in resource-limited settings. Artificial Intelligence (AI) can enhance triage and reduce errors in triage and risk assessment , especially in resource-limited settings. Sevamob provides artificial intelligence enabled healthcare platform to organizations and developed *SymptomsAI*, an AI system for disease prediction using symptoms of patients. It uses large language model for initial disease prediction based on patient symptoms and clinical data. To determine the accuracy of Sevamob SymptomsAI, we used an Android smartphone/tablet with the Sevamob app. The app was operated by a nurse.

Methods: A total of 49 patients with diverse symptoms were included in this clinical study. SymptomsAI generated the top three most likely disease predictions based on patient demographic and clinical data (age, gender, height, weight, symptoms). The AI output was compared with consensus diagnoses from a panel of expert doctors. The small sample size limits the generalizability and further studies are recommended for robust validation.

Results: Compared to the expert panel consensus, SymptomsAI achieved an accuracy of **93.88%** (46 correct predictions out of 49) with an error rate of **6.12%** (3 incorrect predictions). In 44 cases, the AI, the doctors, and the disease(s) matched exactly. In 2 additional cases, AI matched with doctors' differential diagnoses. In only 3 cases, AI results were incorrect. Patient safety and adverse event tracking are paramount. Mis-predictions were reviewed by clinicians.

Conclusion: SymptomsAI demonstrates high accuracy and reliability as a symptom-based triage tool. It is particularly suitable for deployment in primary care and community health programs where expert doctors are scarce.

Index terms: Artificial intelligence, symptom-based diagnosis, predictive healthcare, screening

Introduction

Healthcare systems in low-resource settings face significant challenges in accurate and timely triage and risk assessment due to limited availability of specialists. Symptom-based triage remains the most common first-line approach, but variability in clinical judgment may lead to missed or delayed diagnoses. Also, in remote areas, due to lack of doctors and specialist doctors, timely triage and risk assessment at initial level is not possible, which may lead to increased morbidity. [3] Artificial intelligence (AI) has shown great promise in augmenting triage and risk assessment across various specialties, including medicine, Gynaecology, radiology, dermatology, and ophthalmology etc. However, its application in symptom-based disease prediction is relatively new. [2,4,5,6] The diagnostic and predictive analysis of medical photos, for instance, photographs of retina [8] and skin lesions, microscopic pathological images[10-12] and radiological images. are one of the clinical practice fields where artificial intelligence is expected to have a major influence.[10,11,15].This potential usefulness is largely due to advances in deep learning with artificial deep neural networks (NN),which consist of a stack of multiple layers of artificial neuronal links that loosely simulates the brain's neuronal connections, and methods specialized for analysis of images, such as the convolution neural network, a particular form of deep neural network that conceptually mimics the visual pathway [13,16,18]. Adoption of artificial intelligence tools in clinical practice requires careful, meticulous confirmation of their clinical performance and utility before the adoption.[18] Based on the urgent need for data standardization and interoperability in internal Medicine, we launched a cross-departmental prospective quality improvement project to incorporate Symptoms based artificial intelligence technology and outline the resource requirements for implementation. The solutions presented here empower medical experts to gain an appreciation of and enable the assessment of the appropriateness of the AI system for triaging. We have also shown that current AI systems can aid in the timely triage and risk assessment in resource constraint setting of developing countries like India. The use of artificial intelligence-based triage and risk assessment and data regarding the same is scarce to our best knowledge.

Sevamob provides artificial intelligence enabled healthcare platform to organizations. It uses deep learning for image recognition, large language models for triaging and computer vision for object counting. The software can then be used for triaging and screening of medical conditions . The system can work in low resource settings. .

Sevamob has developed SymptomsAI, a structured diagnostic decision support system that utilizes patient demographic data and symptoms to provide the top three possible disease predictions. This approach empowers frontline healthcare workers with limited training to perform reliable triage and referrals.[26]

The present study was conducted to evaluate the accuracy of SymptomsAI against a consensus triage and risk assessment from expert physicians.

Study Design

This was a prospective, observational field study conducted on 49 patients presenting with diverse symptoms. The small sample size limits the generalizability and further studies are recommended for robust validation.

Data Collection and Reference Standard

Each patient's basic demographic details (age, gender, height, weight) and presenting symptoms were recorded. SymptomsAI generated its top three possible disease predictions. These were compared against a consensus triage and risk assessment from an expert physician panel.

AI Model and Workflow

SymptomsAI employs large language model. The model is designed to handle structured symptom inputs and outputs ranked disease predictions.

Performance Evaluation

Performance was evaluated using confusion matrix elements and standard metrics: accuracy, error rate, Concordance with doctors' diagnosis. Patient safety and adverse event tracking are paramount. Mis-predictions were reviewed by clinicians.

Results

Confusion Matrix (N = 49)

- True Positive (TP + Matches with Doctors): 46
- False Predictions (FP/FN): 3

Performance Metrics

- Accuracy: 93.88%
- Error Rate: 6.12%

Concordance Breakdown

- Disease, Doctor, and SymptomsAI SAME: 44 cases (86.3%)
- Doctor and SymptomsAI SAME: 2 cases (3.9%)
- SymptomsAI Errors: 3 cases (5.9%)

Interpretation

SymptomsAI demonstrated excellent agreement with the panel of doctors, misclassifying only 3 cases. This validates its utility as a triage tool in frontline healthcare.

Discussion

This study demonstrates that SymptomsAI provides highly accurate disease prediction from symptom inputs. With an accuracy rate of nearly 94%, the system is comparable to other AI-driven triage and risk assessment tools reported in the literature.

The small number of errors (3 out of 49 cases) suggests robustness, though continuous model training with larger datasets is necessary. Interestingly, in two cases, SymptomsAI's predictions aligned with one doctor's triage and risk assessment even when other doctors differed, highlighting its role as an additional expert opinion.

Implications: SymptomsAI can serve as a reliable triage tool in community health camps, primary care centers, and CSR health programs. It can support healthcare workers by reducing delays in triage and risk assessment and ensuring timely referral.

Strengths:

- High diagnosis accuracy
- Fast, scalable, low training requirement for frontline staff

Limitations:

- Relatively small study sample (49 patients). The small sample size limits the generalizability and further studies are recommended for robust validation.
- Limited disease categories tested
- Larger, prospective studies across diverse populations are needed to further validate the system

Conclusion

SymptomsAI demonstrates high accuracy and low error rate for disease prediction from structured symptom data. This study supports its role as a reliable AI-based triage tool, particularly in primary care and resource-limited settings. Its integration into community health programs could significantly enhance early disease detection and treatment.

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