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Artificial Intelligence based Patient Health Assessment and Recommendation: A Phase 2 Field Study

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Abstract

Introduction: Health assessments are systematic evaluations used to determine a person's overall health status. These typically include medical history review, physical examination, lifestyle analysis, mental health and diagnostic tests. Health assessments serve multiple purposes like early detection, preventive care, personalized treatment, health monitoring and help individuals understand their health and make informed decisions.

Artificial Intelligence (AI) can enhance health assessments and recommendations, especially in resource-limited settings. Sevamob provides artificial intelligence assisted disease management platform to organizations and developed *MedicalEvaluationAI*, an AI tool for health assessments and recommendations. It uses large language model to analyze a patient's overall health by integrating medical records, history, symptoms, diagnostics, and demographics. The system generates a "Health Score" (0–100) along with actionable "Recommendations" to guide next steps in care management.

Methods: A total of 414 patients with diverse health conditions were included in this study. For each patient, the AI tool was provided demographics info and full medical record from Sevamob's patient data management system. It consists of history of present illness, past medical and surgical history, family history, social history, 10-point physician exam findings, allergies, medications and diagnostic data. The tool was asked to generate a health score (0 – 100, where 100 represents perfect health) from its own black box rubric along with actionable recommendations to guide next steps in care management. The AI output was compared with the consensus analysis from a panel of expert doctors who reviewed the same patient data. Further validation in larger and more diverse populations is recommended to evaluate scalability and long-term clinical utility.

Results: Of the 414 cases, the AI produced results for all patients. Concordance with physician evaluations was observed in 396 cases (**95.7%**), while 18 cases (**4.3%**) were marked as failed, indicating partial or complete disagreement with physician judgment.

Conclusion: MedicalEvaluationAI shows high accuracy and clinical reliability in holistic patient health assessment. It is particularly suitable for deployment in primary care and community health programs where expert doctors are scarce.

Index terms: Artificial intelligence, health assessment, predictive healthcare, recommendation

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Introduction

Health assessments are systematic evaluations used to determine a person's overall health status. These typically include medical history review, physical examination, lifestyle analysis, mental health and diagnostic tests. Health assessments serve multiple purposes like early detection, preventive care, personalized treatment, health monitoring and help individuals understand their health and make informed decisions. Healthcare systems in low-resource settings face significant challenges in timely and accurate health assessments due to limited availability of physicians.

[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 holistic health assessments and recommendations 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.

Adoption of artificial intelligence tools in clinical practice requires careful, meticulous confirmation of their clinical performance and utility before the adoption.[18] Based on this need, we launched a cross-departmental prospective quality improvement project to incorporate artificial intelligence technology for health assessments and outline the resource requirements for implementation. The solution presented here empowers medical experts to gain an appreciation of and enable the assessment of the appropriateness of the AI system for health assessments. We have also shown that this solution can be deployed in resource constrained settings of developing countries like India. The use of artificial intelligence-based health assessments 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, analysis and risk assessment and computer vision for object counting. The system can work in low resource settings.

Sevamob has developed MedicalEvaluationAI, an artificial intelligence tool designed to analyze a patient's overall health by integrating medical records, history, symptoms, diagnostics and demographics. The system generates a health score (0–100) along with actionable recommendations to guide next steps in care management. This approach empowers frontline healthcare workers with limited training to perform reliable assessment and referrals.[26]

The present study was conducted to evaluate the accuracy of MedicalEvaluationAI against a consensus analysis from expert physicians, who reviewed the same patient data.

Study Design

This was a prospective, observational field study conducted on 414 patients with diverse health conditions. For each patient, the AI tool was provided demographics info and full medical record from Sevamob's patient data management system. It consists of history of present illness, past medical and surgical history, family history, social history, 10-point physician exam findings, allergies, medications and diagnostic data. The tool was asked to generate a health score (0 – 100, where 100 represents perfect health) from its own black box rubric along with actionable recommendations to guide next steps in care management. The AI output was compared with the consensus analysis from a panel of expert doctors who reviewed the same patient data. Further validation in larger and more diverse populations is recommended to evaluate scalability and long-term clinical utility.

Data Collection and Reference Standard

Each patient's medical record, history, presenting symptoms, diagnostics and demographics info were recorded. MedicalEvaluationAI generated a health score and recommendations for next steps. The AI output was compared with the consensus analysis from a panel of expert doctors who reviewed the same patient data.

AI Model and Workflow

Sevamob MedicalEvaluationAI employs large language model. The model is designed to analyse medical record, history, presenting symptoms, diagnostics and demographics info of patients.

Performance Evaluation

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

Results

Performance Matrix: Sevamob MedicalEvaluationAI vs. Doctor's Panel

Metric	*Count*	*% of Total Cases (N=414)*
Total Cases	414	100%

Metric	*Count*	*% of Total Cases (N=414)*
Correct Predictions (AI vs Doctor's Panel)	396	95.7%
Incorrect Predictions	18	4.3%

Key Performance Indicators (KPIs)

- AI Output Coverage: 100% (414/414 cases produced results)
- Concordance with Doctor Panel: 95.7% (396/414 cases aligned with physicians)
- Overall Accuracy: 95.7%

Interpretation

Sevamob MedicalEvaluationAI demonstrates high accuracy and reliability, with potential for augmenting physician workflows in routine health assessments while reducing turnaround time. This validates its utility as an important tool in frontline healthcare.

Discussion

This study demonstrates that MedicalEvaluationAI provides high degree of accuracy and reliability in generating health assessments. Out of the 414 cases, the AI produced results for all patients. Concordance with physician evaluations was observed in 396 cases (95.7%), while 18 cases (4.3%) were marked as failed, indicating partial or complete disagreement with physician judgment.

Implications: MedicalEvaluationAI can serve as a reliable tool in primary healthcare centers, community health camps and CSR health programs. It can support frontline healthcare workers in doing accurate and timely health assessments and evaluating next steps.

Strengths:

- High accuracy

- Fast, scalable, low training requirement for frontline staff

Limitations:

- Relatively small study sample (414 patients). The small sample size limits the generalizability.
- Limited disease categories tested
- Further large-scale validation studies are warranted to assess scalability across diverse patient populations and patient data formats

Conclusion

Sevamob MedicalEvaluationAI demonstrates high accuracy and reliability, with potential for augmenting physician workflows in routine health assessments while reducing turnaround time. This study supports its role as a reliable AI-based tool, particularly in primary care and resource-limited settings. Its integration into community health programs could significantly enhance early detection, monitoring and treatment.

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