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Artificial Intelligence based Lab Report Analysis for Summary and Recommendations: A Phase 2 Field Study

Ankit Agarwal[1], Shelley Saxena[2], Dr Ambarish Srivastava[3], Vivek Mishra[4], Balendra Singh[5]

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Abstract

Introduction: The lab reports reveal what's happening inside the body, often before symptoms appear. They help doctors pinpoint the exact cause of illness, reducing guesswork and misdiagnosis. They help in tracking the progression of chronic diseases. They show whether a treatment is working or needs tweaking. Artificial Intelligence (AI) can make it easier for both patients and frontline health workers to understand lab reports and evaluate next steps.

Sevamob provides artificial intelligence assisted disease management platform to organizations. It has developed *LabReportAI*, an artificial intelligence tool designed to analyze patient laboratory reports. The system generates both analysis and next steps to support clinical decision-making by frontline health workers. To determine the accuracy of Sevamob LabReportAI, we conducted a clinical study in which we used an Android smartphone/tablet with the Sevamob app. The app was operated by a nurse.

Methods: A total of 140 lab reports of patients with diverse case histories were included in this study. The reports included CBC, blood chemistry, urinalysis and microbiology in PDF or image format. For each patient, the AI tool was provided the lab report along with age, gender and present symptoms of the patient and asked to summarize the report and suggest next steps. The AI output was compared with the consensus analysis from a panel of expert doctors who reviewed the same lab reports. The small sample size limits the generalizability and further studies are recommended for robust validation.

Results: Out of 140 cases, the AI system successfully provided responses in 134 cases (95.7%). Six cases yielded no AI response due to report quality or data parsing limitations or not sufficient details available to produce analysis and next steps. Of the evaluable cases, concordance with the physician panel was observed in 133 out of 135 cases (98.5%). Only one discordant (incorrect) response was noted.

Conclusion: Sevamob LabReportAI demonstrates high accuracy and reliability, with potential for augmenting physician workflows in routine lab data interpretation while reducing turnaround time. It is particularly suitable for deployment in primary care and community health programs where expert doctors are scarce. Further large-scale validation studies are warranted to assess scalability across diverse patient populations and lab reporting formats.

Index terms: Artificial intelligence, lab report analysis, predictive healthcare, medical diagnosis

Artificial Intelligence based Lab Report Analysis for Summary and Recommendations: A Phase 2 Field Study

Introduction

Healthcare systems in low-resource settings face significant challenges in timely diagnosis and treatment due to limited availability of specialists. The lab reports are the body's report card, quietly but critically guiding a patient's care behind the scenes. They reveal what's happening inside the body, often before symptoms appear. They help doctors pinpoint the exact cause of illness, reducing guesswork and misdiagnosis. They help in tracking progression of chronic diseases. They show whether a treatment is working or needs tweaking. By understanding a lab report, frontline health workers and patients can take an informed decision about next steps.

[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 lab report analysis 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 lab report analysis 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 lab report analysis. 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 lab report analysis 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 LabReportAI, an artificial intelligence tool designed to analyse patient laboratory reports in diverse formats including images, PDFs, and structured form inputs. The system generates both analysis and next steps to support clinical decision-making. 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 LabReportAI against a consensus analysis from expert physicians, who reviewed the same lab reports

Study Design

This was a prospective, observational field study conducted on 140 lab reports of patients with diverse case histories. The reports included CBC, blood chemistry, urinalysis and microbiology in PDF or image format. For each patient, the AI tool was provided the lab report along with age, gender and present symptoms of the patient and asked to summarize the report and suggest next steps. The

AI output was compared with the consensus analysis from a panel of expert doctors who reviewed the same lab reports. The small sample size limits the generalizability and further studies are recommended for robust validation.

Data Collection and Reference Standard

The AI output was compared with the consensus analysis from a panel of expert doctors who reviewed the same lab reports.

AI Model and Workflow

Sevamob LabReportAI employs large language model. The model is designed to analyse patient laboratory reports in diverse formats including images, PDFs, and structured form inputs when presented in conjunction with patient age, gender and present symptoms.

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 Lab AI vs. Doctor's Panel

Metric	Count	% of Total Cases (N=140)
Total Cases	140	100%
No Result provided by AI	6	4.3%
No Result by Doctor's Panel (same as AI)	2	1.4%
Incorrect Result by AI	1	0.7%
Correct & Concordant Results (AI vs Doctor)	131	93.6%

Key Performance Indicators:

- **AI Output Coverage:** 95.7% (134/140 cases produced results)
- **Concordance with Doctor Panel**: 98.5% (133/135 evaluable cases)
- **Overall Accuracy (all cases)**: 93.6%

Interpretation

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

Discussion

This study demonstrates that LabReportAI provides high degree of accuracy and reliability in analysing lab reports. Out of 140 cases, the AI system successfully provided responses in 134 cases (95.7%). Six cases yielded no AI response due to report quality or data parsing limitations or not sufficient details available to produce analysis and suggest next steps. Of the evaluable cases, concordance with the physician panel was observed in 133 out of 135 cases (98.5%). Only one discordant (incorrect) response was noted.

Implications: LabReportAI can serve as a reliable tool in primary healthcare centers, community health camps and CSR health programs. It can support frontline healthcare workers by reducing delays in interpreting lab reports and evaluating next steps.

Strengths:

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

Limitations:

- Relatively small study sample (140 lab reports). 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 lab reporting formats.

Conclusion

Sevamob LabReportAI demonstrates high accuracy and reliability, with potential for augmenting physician workflows in routine lab data interpretation 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 disease detection and treatment.

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1st Author (Corresponding Author):

Dr. Ankit Agarwal, BDS

Sevamob Ventures USA Inc, Lucknow, U.P, India

Phone: +91-7408417918

Email ID: dragrawal@sevamob.com

ISSN 2250-3153
2nd Author: Shelley Saxena, BE, MBA

Sevamob Ventures USA Inc

3rd Author: Dr. Ambarish Srivastava, BDS

Sevamob Ventures USA Inc

4th Author: Vivek Mishra, MCA, MBA

Sevamob Ventures USA Inc

5th Author: Balendra Singh, MCA

Sevamob Ventures USA Inc