

Integrating OCR, NLP, and Deep Learning for Intelligent Healthcare Decision Support

Supriya Gupta Bani¹, Prof. (Dr.) Shashi Kant Gupta²

¹Computer Science and Engineering Lincoln University College, Petaling Jaya, Selangor-47301, Malaysia,

¹Ramdeobaba University Nagpur, India,

²Computer Science and Engineering Lincoln University College, Petaling Jaya, Selangor-47301, Malaysia

¹pdf.supriya@lincoln.edu.my, ¹supriya17gupta@gmail.com, ²shashigupta@lincoln.edu.my

Abstract

The volume of electronic health records, biomedical literature, medical reports and diagnostic images are rapidly growing, and present significant opportunities for intelligent healthcare analytics. Traditionally, however, data mining systems used in clinical settings are based on structured data and static analytical models, which are incapable of reacting to the heterogeneous and dynamic nature of clinical situations. In this paper, we introduce an integrated and adaptive clinical decision support framework named as CareAI, which integrates Optical Character Recognition (OCR), Natural Language Processing (NLP), deep learning-based image analysis, secure data management, personalized recommendations and an interactive AI chatbot. The proposed workflow will receive medical reports and diagnostic images, OCR them, generate concise clinical summaries using NLP models, analyze medical images using CNN model for disease detection, store the analyzed information in a machine-readable manner in a MongoDB database, and present the information in an interactive dashboard and chatbot. This framework is meant to enable clinical decision making, rural health care, telemedicine, monitoring of elderly, hospital information systems, and personal healthcare management. The results of the experiments presented here indicate that OCR rates of about 94% and reductions of over 65% in the length of the report, without loss of important clinical information, were obtained. The work showcases the viability of interoperability between different healthcare processing tasks in a single AI-driven system.

Keywords: Clinical Decision Support, Healthcare Analytics, OCR, NLP, Medical Image Analysis, CNN, AI Chatbot, MongoDB, Generative AI

1. Introduction

Healthcare organizations have massive and diverse amounts of data, including electronic health records (EHRs), biomedical literature, laboratory reports, prescriptions, discharge summaries, and diagnostic images. While these data sources have clinically valuable information, the magnitude and diversity of these data are difficult to manually process. Clinical decision making is a complex process as clinicians need to consider numerous factors in a short time frame. However, traditional clinical data mining techniques tend to be based on models and structured data sets that are not always available or adaptable. The information stored in these systems is not enough to support the information captured in scanned documents or medical images, and they may offer an incomplete level of support for clinical reasoning in real time and for personalized recommendations. Review of reports by hand introduces delays in diagnosis, adds burden on clinicians, and can be hard to come by in a timely manner. There are new developments in Artificial Intelligence, Machine Learning, Generative Models, Explainable AI, and Large language models that can be leveraged to create more adaptive clinical decision support systems. An intelligent system integrates document digitization, medical text processing, medical image analysis, secure storage and conversational interaction into a single workflow instead of treating information about healthcare as isolated records. The work put forward here is a sustainable and adaptive hybrid AI-based framework for clinical decision support and healthcare analytics – namely CareAI. The framework is designed to streamline critical information processing tasks, assist clinicians, and enable patients to access timely, accurate and organized information.

2. Problem Statement

Despite this, clinical decision making is still difficult due to the fact that healthcare data are heterogeneous, patient's situation changes and clinically relevant information is spread out among different data formats. Accurate, timely, contextual intelligence is crucial for important tasks like medical summarization, information retrieval, disease detection, diagnosis support and treatment planning. The proposed work highlights some drawbacks of the current healthcare systems: (i) manual reading of the reports, (ii) paper or PDF documentation are not easily processed by computer, (iii) limited automated disease detection, (iv) there is no intelligent summarization of the report, (v) patient interaction is limited. These restrictions can lead to a decrease in access to medical information, as well as an increase in workload and delay in the decision-making process. The goal is to create a framework for clinical decision making that is adaptive and intelligent, combining machine learning, generative AI with explainable AI, LLM, federated learning, and cloud computing concepts, which can aid in achieving accurate, transparent, privacy-focused, scalable, and real-time clinical intelligence.

3. Motivation

Current healthcare information systems often are mostly data repositories not intelligent analytical environments. Healthcare professionals may have to manually read the reports and find clinically important findings. Patients may also not be able to follow medical jargon and the implications of reports. Optimize manual processing of medical reports.

- Turn medical documents scanned to machine-readable information.
- Create short abstracts from long clinical reports.
- Assist automatic analysis of diagnostic medical images.
- Offer customized health care suggestions. Enhance patient engagement with an AI-powered chat feature.
- Have a single platform that integrates multiple healthcare functions.

4. Proposed CareAI Framework

The CareAI is designed to be an integrated platform that includes secure management of medical records, automatic report extraction, NLP-based summary generation, CNN-based disease detection, personalized healthcare recommendations, and an interactive AI chatbot. These elements are integrated in the framework to form a seamless pipeline from the beginning of the healthcare processes to the availability of clinical information.

4.1 Existing System versus Proposed System

Aspect	Existing System	Proposed CareAI
Report processing	Manual report reading	Automated OCR
Record format	Paper/PDF records	Digital structured database
Disease analysis	Manual diagnosis	AI-assisted disease detection
Report understanding	No automated summarization	NLP summarization
Patient interaction	Limited	AI chatbot
Application architecture	Separate applications	Integrated platform

5. System Workflow and Methodology

The CareAI workflow starts by uploading medical reports and diagnostic images. The scanned reports are directed to the OCR module that translates the printed data into machine-readable text. The NLP module then analyzes the extracted text to determine the key clinical content and create a summary of the content. CNN-based models are used for disease detection on the basis of diagnostic images. Processed information is stored in the database - MongoDB and can be accessed via an AI Chatbot and user dashboard.

CareAI is envisioned to be five integrated modules. The Medical Record Management module securely stores and integrates patient and clinical data with the help of MongoDB. Second, the OCR-Based Report Extraction module utilizes the Tesseract OCR software to convert medical reports, prescriptions, laboratory reports, and discharge summaries that are scanned into machine-readable text. Third, the NLP Based Clinical Summarization module extracts the important clinical findings and generates short summaries using Transformers/BERT. Fourth, the CNN-Based Disease Detection module detects diseases from medical images

using TensorFlow or PyTorch in an automated way. Lastly, the Personalized Recommendation and AI Chatbot module offers personalized healthcare support and interactive access to processed clinical information.

6. Dataset and Experimental Setup

The presented work identifies HAM10000 as the medical image dataset used for the image-analysis component. The dataset contains 10,015 dermatoscopic images and supports seven-class skin-lesion classification.

Parameter	Description
Dataset	HAM10000
Total images	10,015
Image type	Dermatoscopic images
Image format	JPG/RGB
Commonly distributed size	600 × 450 pixels
Number of classes	7
Task	Multi-class skin-lesion classification
Data type	Image + clinical/lesion metadata
Primary application	Automated skin-lesion analysis
Ground truth	Histopathology, follow-up, expert consensus, or confocal microscopy
Availability	ISIC Archive / Harvard Dataverse

6.1 Technology Stack

Component	Technology
Backend	FastAPI
Database	MongoDB
OCR	Tesseract OCR
NLP	Transformers / BERT
Image analysis	CNN models using TensorFlow or PyTorch
Implementation	Python-based AI technologies

7. Evaluation and Results

The experimental setup presented here tests the performance of OCR, effectiveness of NLP summarization, and CNN based disease classification. The quantitative results reported in the source material can be OCR and summarized.

7.1 OCR Performance

The OCR module was able to extract text information at medical reports with an accuracy of around 94%. The reported error rate was 6% for the same. The findings show that the OCR stage can significantly support manual transcription process and yield usable text for downstream NLP process.

Metric	Reported result
OCR accuracy	94%
OCR error rate	6%

7.2 NLP Summarization

The experimental result showed that the NLP module shortened the medical report content by over 65% with the clinical meaning of the medical report kept unchanged. The source material length is an average of 100% before summarization and 35% after summarization.

Measure	Reported result
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Before summarization	100%
After summarization	35%
Reduction	More than 65%

7.3 Image Classification Evaluation

This is clear from the source document, which states that CNN-based disease classification will be evaluated using diagnostic images and mentions the HAM10000 dataset as the image dataset. But no numeric value for CNN accuracy, precision, recall, F1-Score, confusion matrix, or any other metrics for image classification performance has been provided in the presentation.

8. Discussion

The most important advantage of the CareAI model is that several healthcare tasks powered by AI are combined into one process. OCR solves the problem of digitizing printed medical documents, NLP increases access to long clinical reports, and CNN analysis allows for the use of diagnostic images within the system. Information is stored using MongoDB and is used as an information storage layer, while the chatbot and dashboard provide the interaction layer.

According to the results achieved during the implementation of OCR and summary tasks, the presented pipeline can decrease the amount of manual work in terms of information processing and make it more compact. Nevertheless, when implementing the system in real-world conditions, the clinical decision support should be used along with clinical judgement. Further evaluation is needed to prove its reliability.

9. Conclusion

CareAI was introduced in this paper as a sustainable and adaptive hybrid framework for healthcare information processing and healthcare decision making. The proposed system makes use of optical character recognition (OCR), natural language processing (NLP), CNN-based analysis of medical images, secure data storage, personalized recommendations, and AI chatbot in an integrated manner. The performed experiments produced 94% OCR accuracy and over 65% report length reduction by summarizing medical reports using NLP. This proves that automation of such information processing in healthcare is feasible. The developed framework can be used in hospitals, rural healthcare, telemedicine, elderly care, and personal healthcare.

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