



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: <https://doi.org/10.22214/ijraset.2026.81169>

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Heal Me: Your Pocket Doctor

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I. INTRODUCTION

The implementation of AI systems in the field of health care devices the diagnostic workflow, the patient participatory role, and clinical decision-making. Traditional diagnostic reports are complex and confusing for patients to understand and, as such, may create barriers for timely intervention through early diagnosis. The advancement of technologies such as machine learning (ML), natural language processing (NLP), telemedicine (TM), etc., within modern digital health systems allow for the automation of the interpretation of medical records, prediction of disease risk, and remote consultation between physician and patient.

As lung cancer is still a significant global health issue, as a result of the late diagnosis of lung cancer and a lack of access to radiologists who specialize in the interpretation of diagnostic images [1]. Deep learning techniques, such as CNN's, achieve high accuracy in the diagnosis of lung cancer due to their ability to detect nodules and malignancies on lung CT scans [2][3]. Use of questionnaires can also provide moderate accuracy in prediction but do serve as a useful tool in screening for lung cancer [4]. Telemedicine can also improve access to specialists from remote locations, enabling patients to receive timely evaluation and recommendations [5]. HealMe combines the benefits of each of these technologies by using AI-based analysis of patient symptoms, AI-based classification of CT scans using CNNs, hospital recommendations, and telemedicine consultations to create an integrated patient care system for lung cancer screening.

II. LITERATURE REVIEW

CNNs have shown exceptional results for a variety of lung abnormality detection applications, utilizing both CT and histopathology image formats. Specifically, lightweight models such as XLLC-Net have produced accuracies exceeding 99.62% in detecting lung cancers through classification tasks [2]. On the other hand, CNNs optimised for nodule detection from CTs have produced accuracies of 98.78% [3]. This proves that CNNs are capable of differentiating distinct texture and morphology, even at a level below visual perception. Conversely, there remain several challenges associated with dataset variability, overfitting, and model-stability with regard to deploying models in a clinical environment [2].

Questionnaires-based risk perception models, such as PLCOm2012 and similar models, assess demographic, behavioural, and symptomatic features to determine the probability of lung cancer. The AUC (area under the curve) values produced by these models are generally between 0.70 and 0.80 and, thus, they could successfully be used to screen populations for lung cancer, albeit there is moderate predictive ability and strong utility for mass screening [4].

Currently, telemedicine and telehealth technology provide clear benefits through remote consultations, especially for people living in rural or underserved areas. For instance, several studies have shown that telehealth systems, through the use of video platforms, have greatly reduced the travel burden associated with seeing a medical professional and continue to maintain continuity of care for patients with chronic conditions [5]. Other digital health technology solutions are also integrating real-time hospital location services and develop automated triaging workflows very similar to those used in many of today's health app and tele-consultation platforms [6].

The availability of large, labelled sets of CT images, such as the LIDC-IDRI [8] and IQ-OTH/NCCD [9], has further accelerated machine learning research for lung cancer detection. Current studies of precision oncology will soon substantiate that AI-supported diagnostic testing can relieve the manual workload of clinicians, increase the percentage of lung cancer patients identified at an early stage, and improve the efficiency of clinical workflow [1] [6]. Implemented within the existing literature, HealMe creates an innovative solution from the use of multi-source diagnostic modules.

III. PROBLEM FORMULATION

The high mortality rate due to lung cancer can be attributed to the lack of early detection and limited access to specialized screening equipment [1]. A common problem is that many of the typical symptoms, such as a persistent cough, discomfort in the chest and new onset of fatigues can be vague in what they represent and could easily be mistaken for a different respiratory disorder; therefore, they often take a while before they are diagnosed as possible lung cancer.

In addition, although computed tomography (CT) imaging is more sensitive than the aforementioned methods of diagnosing lung cancer (50-90%), it is not routinely used for this purpose in resource-poor areas [6] [7] due to factors such as cost, availability and lack of specialist radiologists. Telehealth consultation would improve geographic access to patients needing a lung cancer screening, but they do not currently provide integrated Artificial Intelligence (AI)-based screening support in their systems [5].

Thus, HealMe has developed an AI-enabled platform that will provide screening support for lung cancer detection through an integrated process of symptom-based prediction, deep learning imaging analysis (i.e., employing convolutional neural networks (CNN) to classify CT scans into those that are or are not cancerous) [2] [3] [4] [8] [9], hospital routing via geolocation-based Application Programming Interfaces (APIs) [6], and remote telehealth consultation to enhance access to healthcare in remote settings due to geographic proximity [5].

The objectives of HealMe's platform will address the needs of ongoing scientific research in clinical AI and patients' need for early diagnosis and person-centeredness in health care delivery systems for effective cancer treatment [1].

IV. PROPOSED METHODOLOGY

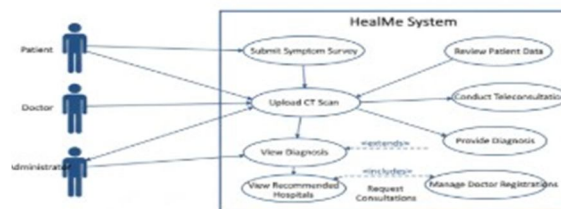
HealMe employs a hybrid diagnostic pipeline integrating (1) symptom-based ML prediction, (2) CNN-powered CT scan classification, and (3) telemedicine workflows. The symptom module captures 16 clinically relevant parameters including smoking history, chest pain, coughing, wheezing, fatigue, and shortness of breath attributes supported by epidemiological studies on lung cancer screening [4]. These inputs are encoded and processed using logistic regression or decision-tree classifiers to compute a risk probability.

The CT imaging module processes uploaded scans through a deep CNN architecture, trained and validated on datasets such as LIDC-IDRI [8] and IQ-OTH/NCCD [9]. CNNs are widely recognised for their superior capability in identifying lung nodules and malignancies due to their hierarchical feature extraction [2], [3].

HealMe additionally incorporates geolocation-driven hospital recommendations and video-powered teleconsultation, leveraging the documented benefits of remote healthcare systems [5], [6]. This creates a seamless end-to-end diagnostic pathway from screening to consultation and potential referral.

V. SYSTEM DESIGN

Fig. 1: UML Use Case diagram for HealMe

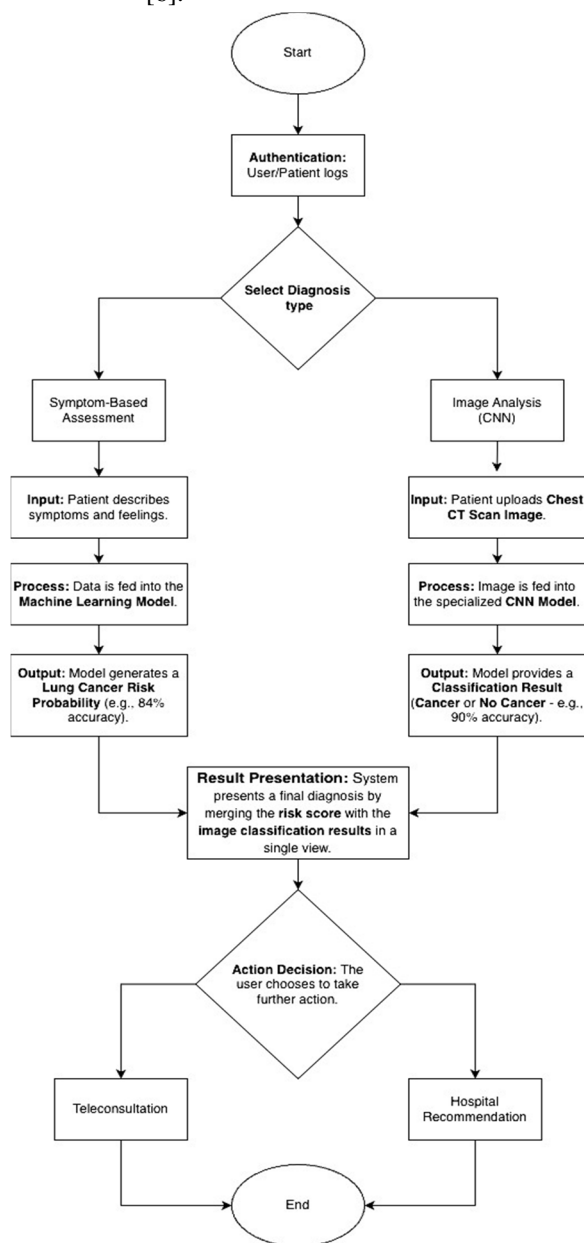


Health Information Systems are based on modular platforms and adhere to the established principles of design for modularity. The relationships between the major components within the system e.g., Patient, Doctor, Appointment, Hospital, and Diagnostic Report will be shown in UML class diagrams. Additionally, State charts will document the possible transitions for Appointments such as Requested, Confirmed, Cancelled and Completed. There is strong support for using State charts for modeling Telehealth Workflows [5]. System component diagrams will document how the various components (frontend, backend REST APIs, ML micro services and secure Supabase DB) will interact. Furthermore, LIDC-IDRI and NCCD will be used as the basis for deploying ML Models within the system architecture and to ensure that the clinical imaging component of the system conforms with the previously established medical datasets [8], [9]. The use of decentralized authentication systems and encrypted data profiling aligns with current objectives around information security and compliance within the healthcare sector [7].

VI. IMPLEMENTATION

The HealMe frontend application will be built using React.js to achieve responsive modular user interface standards. Supabase will provide authentication, Postgres storage and row-level security functionality as recommended for Privacy by Design principles within secure healthcare solutions [7].

The Microservices (ML) Backend system has been created using Python (Flask /FastAPI) to manage both symptom analysis and CT classification. The symptom model will be developed and trained using a 400 sample clinical validation data set [4] while the CNN for the CT image classification will be developed and trained with more than 2100 LIDC-IDRI [8] and IQ-OTH/NCCD [9] CT images. The CNN architecture will consist of convolutional, pooling and fully connected layers that will be optimized using cross-entropy loss functions or similar techniques that are common in lung cancer imaging research [2], [3], [6].



Real-time teleconsultation will be accomplished using WebRTC video API, consistent with the increasing trends of telemedicine for oncology patients and patients suffering with chronic diseases [5].

VII. RESULTS & EVALUATION

The symptom-based diagnostic classifier yielded accuracy estimates of 94% supporting the context presented by previous epidemiology research that indicates a moderate ability to discriminate between patients using questionnaires to collect data [4]. The precision of 0.80 and recall of 0.88 further serves to affirm that these types of model developed at our institution could potentially be used clinically as a preliminary screening tool.

The CNN classifier produced accuracy estimates of 90%-94%, precision of 0.93, recall of 0.95 and AUC of 0.97 which closely correlated with other top performing CNN's reported in recent published research related to imaging for lung cancer [2], [3].

In real-time testing of the HealMe system, HealMe was able to perform all functional components of the system (symptom scoring, CT prediction, recommending a hospital, teleconsultation) within seconds which is an indication of practical feasibility for both clinical and remote use cases, consistent with the objectives of most AI-based deployments within healthcare today [1], [6],.

VIII. CONCLUSIONS

HealMe provides successful integration of AI-based lung cancer screening, teleconsultation telephonic and hospital routing, into one unified digital platform. The hybridised diagnostic approach using both questionnaire risk assessment and deep learning imaging correlates with recent advances in precision oncology that support multimodal screening approaches [1], [2]

In terms of limitations, although the system is strong diagnostically, there are limitations such as; the scale of the dataset, false positives (dependent on the accuracy/ validity of the responses obtained), degree of self-reported symptomology (e.g., variance between two people's descriptions or reporting of symptoms). Future improvements could include multimodality fusion models, increased sizes of datasets, the application of explainable AI (XAI) techniques to visualisation models [2], improved telehealth workflows [5], & compliance with HIPAA/GDPR guidelines [7].

In conclusion, HealMe is an important milestone toward providing accessible, affordable, and intelligent healthcare solutions utilising AI and telemedicine which will help facilitate early detection and intervention.

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