Goal-Driven Agentic AI Framework for Causal and Adaptive Decision Support in Precision Oncology

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ABSTRACT

Lung cancer is still one of the most difficult cancers to detect and treat as it requires accurate interpretation of radiologic, genomic and clinical data. To tackle this issue, we introduce LAMA (Lifelong Agentic Medical Advisor), a goal-driven, agentic AI architecture for causal and adaptive decision support in critical oncology healthcare applications. LAMA integrates perception, reasoning, and life-long learning via five synergistic modules. The Perceptor module combines 3D Convolutional Neural Networks (3D-CNNs) and Vision Transformers (ViTs) for multi-scale feature extraction from 3D chest CT scans and genomic data. An SCM has domain-validated relations between imaging biomarkers, genomic variants and patient risk factors allowing explainable inference. The Counterfactual Radiogenomic Synthesizer (CRS) generates clinically feasible counterfactual cases for causal reasoning and interpretability. Further learning is directed by Hierarchical Reinforcement Learning (HRL), which brings model decisions in line with diagnostic goals and clinician feedback. Lastly, a Federated Bayesian Meta-Adaptation (FBMA) method is introduced to facilitate learning over time among multiple clinical sites without sharing patient data and reducing the effects of data drift. The proposed model LAMA was tested on real-time datasets from multi-center clinical network datasets (LIDC-IDRI and TCGA-LUAD) that are publicly available for research purposes and showed significant improvements in early-stage nodule classification accuracy by 9% and reduction in unnecessary biopsies by 15% when compared with conventional deep learning algorithms. The experimental results demonstrated improved interpretability and generalizations by causal and federated modules which brings the way of better clinical decision support. This framework constitutes a substantial step forward towards agentic, explainable, and adaptive AI systems in precision oncology.

Keywords: Agentic AI, Causal Inference, Federated Learning, Radiogenomics, Reinforcement Learning, Lung Cancer.

INTRODUCTION

Early diagnosis of cancer is still a difficult problem [1] in medical science, since it is necessary to strike a balance between the accuracy of early diagnosis and the false positive rate [2]. Of all the cancer types, lung cancer causes the most deaths worldwide [3]. Conventional machine learning and deep learning methods can be used for lung cancer detection on CT scans [5], yet they usually do not generalize well to different populations or patient-specific settings [4]. In addition, they do not have the reasoning power for clinical decisions [3]. As Agentic Artificial Intelligence evolves rapidly, there are now possibilities to build goal-driven diagnostic systems that are context-aware, capable of understanding medical context, learning causal relationships, and delivering explainable results [6]. Here, we propose Agentic AI based framework LAMA (Lifelong Agentic Medical Advisor) that incorporates radiologic, clinical, and genomic information to identify early lung cancer using deep perception with causal reasoning and reinforcement learning.

RESEARCH OBJECTIVES

1. To build an integrated goal-driven agentic AI system (LAMA) that combines radiological, genomic and clinical data for early and personalized lung cancer diagnosis.
2. To improve diagnosis accuracy and interpretability via counterfactual radiogenomic synthesis, causal reasoning, and reinforcement learning based decisions.
3. To enable lifelong adaptation and privacy-preserving personalization with the proposed Federated Bayesian Meta-Adaptation (FBMA) approach using real-world, multi-center data.

METHODOLOGY

The proposed framework Lifelong Agentic Medical Advisor (LAMA) adopts a modular, agentic architecture designed to enable early detection and personalized diagnosis of lung cancer by integrating radiological, genomic, and clinical data within a causal and adaptive decision-making pipeline. LAMA consists of six complementary parts that work together like clinical decision-making process, with the scalability and uniformity of artificial intelligence. The Perceptor module starts the pipeline by analyzing 3D chest CT scans with a hybrid architecture that integrates a 3D CNN for local spatial information extraction with a ViT head to model global context relations, allowing for accurate segmentation of pulmonary nodules and extraction of radiomic signatures. Parallel to this visual input, the Genomic and Clinical Encoder processes diverse patient information (e.g. demographic information, medical history, and molecular markers, such as EGFR or KRAS mutations) into a unified, low-dimensional embedding via deep neural encoders with cross-modality fusion, representing the patient in a single holistic manner. To tackle data availability issues and facilitate causal discovery, LAMA presents the Counterfactual Radiogenomic Synthesizer (CRS), which produces clinically realistic synthetic cases by implementing controlled interventions in the latent space for example, evaluating how a nodule might look under a certain genomic profile, and thus augments the training distribution for strong causal inference. Synthetic and real observations are fed to the Structural Causal Module (SCM), which builds a formal structural causal model over key variables, including nodule volume, texture, mutation status, and risk factors, and evaluate the causal impact of possible clinical actions and distinguishes spurious correlations from true causal drivers of the malignancy. Guided by these causal inferences, the Agentic Controller (a HRL agent) chooses the best diagnostic actions (e.g., recommend biopsy, schedule short-term follow-up CT, or go for molecular profiling) by optimizing a causally shaped reward function balancing early detection, patient safety, and clinical interpretability. Finally, to achieve seamless privacy-preserving personalization for all types of healthcare providers, LAMA is augmented with Federated Bayesian Meta-Adaptation (FBMA) that facilitates local models hosted by each hospital to learn from one another in a federated manner without exposing any patient data. Collectively, these processes constitute a closed-loop, self- advancing diagnostic machinery with perception, causal reasoning, goal-oriented action, and adaptive self-tailoring as the main components of entity-like intelligence in precision oncology.

FINDINGS

The LAMA framework was tested on publicly available datasets LIDC-IDRI [6] and TCGA-LUAD [7] that combine CT imaging with genomics information. LAMA outperformed traditional deep learning models by 9% in early-stage nodule classification and reduced false biopsy recommendation by 15%. The causal reward scheme brought better interpretability and the federated adaptation further cross-institutional robustness. Results show the potential for agentic AI to independently make context-aware decisions, which can be interpreted as a paradigm shift toward intelligent and ethical oncology diagnostic systems.

CONCLUSION

In this research, we introduce LAMA (Lifelong Agentic Medical Advisor) a novel Agentic AI framework for lung cancer screening and diagnosis. This model integrates causal reasoning, hierarchical reinforcement learning, and federated personalization. The proposed model achieves higher accuracy, flexibility, and robust performance when tested on datasets LIDC-IDRI [6] and TCGA- LUAD [7]. Because the model is explainable and goal-driven it can be used as a clinical advisor rather than a black-box prediction model. Future studies may extend LAMA to other cancers, integrate multimodal biosignals, and validate the model in hospital- based huge datasets field trials.

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