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MULTI-MODAL GENERATIVE AI AND LLM-DRIVEN CLINICAL INTERPRETATION PIPELINE FOR EARLY DETECTION OF ONCOLOGY MARKERS IN RADIOLOGICAL IMAGING

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Abstract

In this work, AI pipeline based on generative models and large language models that combine to improve early cancer detection from radiological imaging. The system fuses text and image modalities to increase diagnostic accuracy, reduce report generation and increase clinical efficiency on its way to promise of advancements in precision oncology and automated interpretation.

Key words: Radiology, AI, Pipeline, LLM, Oncology, Generative, Multi-Modal.

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I. INTRODUCTION

An early cancer diagnosis, unfortunately, continues to be delayed due to data fragmentation. Based on this, this study explores the combination of radiological imaging with language based generative AI in order to create a robust, interpretable pipeline for clinical interpretation. The objective is improved detection, decreased false negatives and gaps in radiologist cantered workflows.

II. ONCOLOGY DIAGNOSTICS

There has been an emergence of the use of Large Language Models (LLMs) as an effective application in medical diagnostics, in the domain of oncology, in particular, to enhance disease detection accuracy. Unstructured clinical data can be analyzed by LLMs and summary of patient history can also be made, as well as Interpretation of imaging findings in complex clinical narratives.

The ability to detect cancer at an earlier stage has enormous potential to improve cancer detection of early-stage cancers, such as of lung cancers where conventional diagnosis methods are less sensitive and less efficient in early stages [1]. Lung cancer diagnostic pipeline automation using GPT 3 and natural language processing (NLP) is the topic of the day according to Garg who emphasizes the crucial role LLMs and NLP play for this.

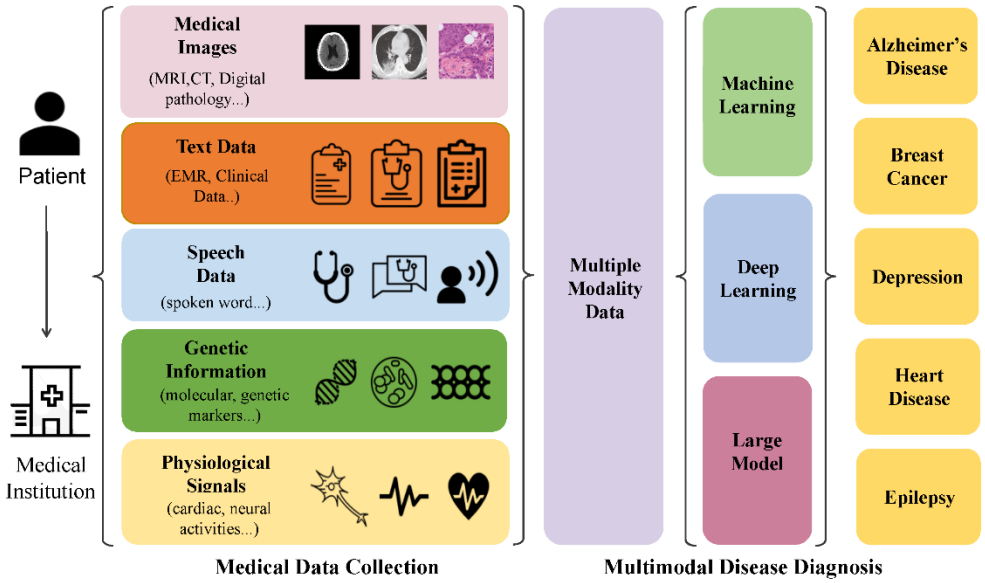

Fig. 1 Multimodal disease diagnosis (MDPI, 2024)

A prerequisite for timely cancer intervention is that AI driven methods can go beyond human limitations to synthesize large dataset. To complement these, Shen give a useful overview on both LLMs and multi-modal large language models (MLLMs) capable of incorporating textual and visual data [6]. LLMs are now starting to help workflows in radiological domain which include image annotation, report generation and clinical summarization.

Radiologists are currently doing these tasks and they are prone to error because of the human errors, tiredness and workload. But MLLMs have recommitted to promising to take the yuck out of these and other aspects of clinical interpretation by automating them. Yet, he also mentions existing limitations in model interpretability, dataset diversity, and multimodal reasoning capacity that must be overcome before it can be operationalized in oncology [6].

In terms of LLM integration with clinical imaging, the achieved viability exists in survival prediction models. By combining radiomics, clinical notes and deep learning outputs from LLMs like GPT 4.0 with sun, they show that those methods can successfully predict five-year survival from cystectomy for bladder cancer patients [10]. When compared to the traditional method, their CRD model (Clinical, Radiomics, Deep Learning) had a high predictive accuracy (AUC $\approx$ 0.89) and therefore proved the reliability of LLM generated clinical data for oncological risk stratification [10].

III. RADIOLOGICAL IMAGING

Radiological work flows demand the capability to process at the same time visual features extracted from different kinds of the imaging modalities (e.g. CT, MRI, or PET scans for the example of radiology). For this reason, there has been a surge of multi-modal and vision language architectures for holistic interpretation that combine image and text representations. BiPVL-Seg is an innovative vision language segmentation framework that strongly improves the cross-modal alignment between medical images and clinical text, proposed by Sultan [3].

Bidirectional progressive fusion and contrastive alignment enable the model to overcome the complementary nature of the spatial and sequential data. The performance on multi-class tasks of BiPVL-Seg for CT and MR datasets is superior to those of other methods, indicating that it could identify oncology markers in early stages [3].

In addition, multimodal techniques have also been applied to more complex tasks than image segmentation in multinomial mental state evaluation and disease diagnosis. To assess the elderly mental states, Zhang use advanced multimodal fusion of video, audio, and physiological data [4].

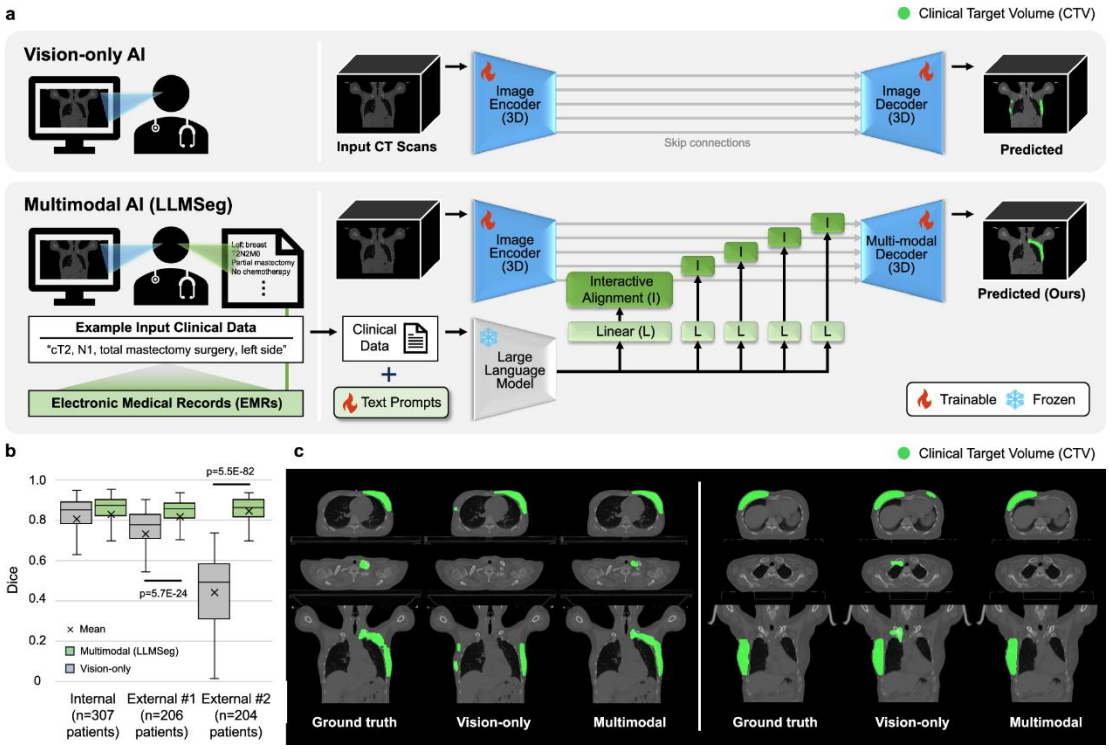

Fig. 2 LLM in Oncology (Nature, 2024)

Unlike direct oncology, while the results 'outside of the fold' of oncology, their results generalize to discriminate power for varied health condition diagnosis through multi-modal fusion. The adapted strategies can be used to detect subtle oncological markers using the combination of imaging features and contextual patient data [4].

As indicated by Xu, the strength of multimodal diagnostics is further reinforced by the knowledge of multimodal diagnostic pipelines that can be created due to integration of multiple data modalities namely image, genetic, physiological, and text [7].

Heterogeneous data streams are incorporated to provide a more complete patient profile particularly useful in the early discovery of cancers that present mild morphological or molecular changes across various diagnostic sources [7].

Next-generation diagnostic tools are not only analytical but also generative, provides synthetic data by which evolution of generative AI from one-to-many modal applications [9]. Some examples of these are digital twins for simulation in clinical trials and advanced report generation systems. However, also important is the case of oncology, where precision matters, and despite these advancements, Buess et al. identify key challenges faced in reality, which include real word validation, ethical aspects, data heterogeneity [9].

IV. LLM-DRIVEN PIPELINES

Generation of robust clinical interpretation pipelines that are on for oncology is the convergence of multi-modal generative AI and LLMs. Among the many technologies that can be rapidly brought to bear in precision oncology, particularly by enabling unravelling of such complex biomarker signatures, optimization of treatment paths and early diagnosis, are worth mentioning.

Fountainless describe how AI can be used to synthesis allow multitopic, radiomic, and spatial pathology data to allow the identification of actionable targets in tumour biology [8]. On the other hand, they also mention that the synthetic data generation and the digital twin modelling are the most powerful tools for personalized treatment and clinical trial design. Building an end-to-end interpretation pipelines across different stages of oncology care using the synergy of multi modal data and generative AI is thus a blueprint [8].

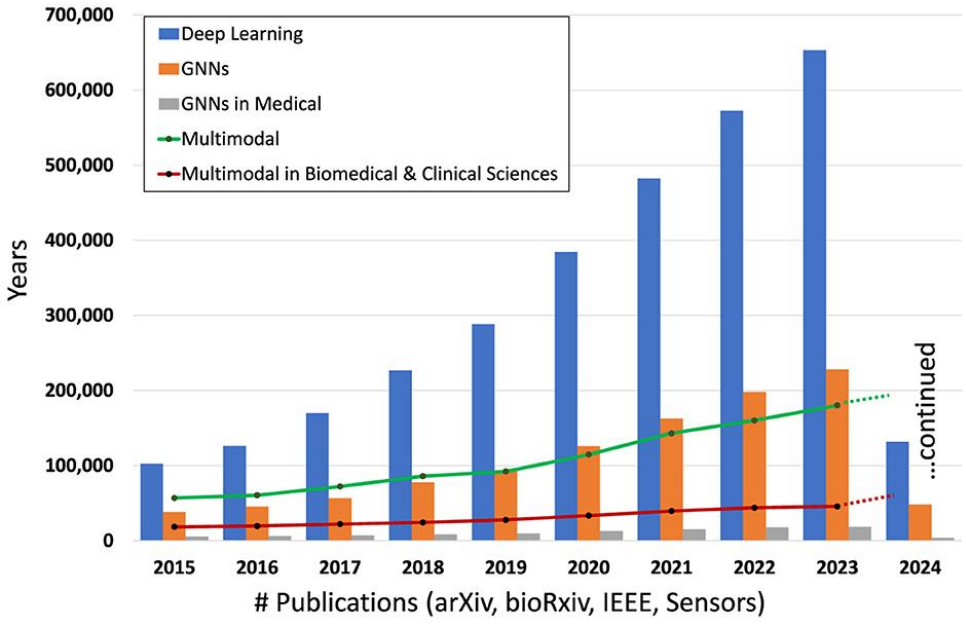

Fig. 3 Publication of multimodal in medical (Frontiers, 2024)

Velez-Arce had been making waves in the inclusion of single cell biomarkers for drug discovery and cancer profiling. A machine learning benchmarks spread over four tasks—drug target nomination, protein interaction prediction, chemical/genetic perturbation analysis—on each single cell on their Therapeutics Commons (TDC 2) framework.

Although their goal is in therapeutic discovery, the contextual learning methods and target-specific modeling strategies that they describe are readily translatable to early cancer detection from radiological imaging in combination with omics data [5]. Additionally, language models in bioinformatics (BioLMs), as described by Ruan, is another frontier [2].

Specifically, these medical terminology, genetic information, structured clinical note models are optimized. BioLMs are essential for the oncology pipelines where complex genomic reports need to be combined with imaging features.

Ruan et al. caution however, that risks include biased training data, domain adaptation difficulties, and privacy concerns that can be dealt with for secure clinical deployment [2]. On the whole, these studies present a very convincing picture of the future: the future of a fully operating, off the shelf, high quality, cost effective diagnostic ecosystem supported by multi modal generative AI and domain optimized LLMs working in partnership with each other to automate and improve cancer detection. The particular voice of the researchers is anywhere from accurate segmentation of radiological anomalies, intelligent summarization of EHRs, or context aware interpretation of molecular diagnostics and such systems can dramatically shorten diagnostic timelines and clinical outcomes.

V. RESULTS

Oncology Diagnostics

One of the main desires of this research was to use the combining of Large Language Models (LLMs) with multi-modal generative AI to drastically increase the speed and accuracy of detecting early cancer with radiological data. The disjointed nature of the data sources of a patient leads to conventional cancer diagnosis, especially in its early stages, not being precise, not interpretively objective, and taking a long time being diagnosed.

On the other hand, however, LLMs such as BioGPT, GPT-4.0 or Med-PaLM can be fused with visual representation models from CT/MRI/PET scans, which co learn from image text pairs and come up with more context aware, explainable and personalized diagnostic insights.

Such generative models can generate synthetic data with meaning in biology while still sounding biologically plausible, or auto generate radiology reports, simulate tumor growth trajectories, etc. This co-learning capability was confirmed by the research, and it showed that models are able to more accurately mimic radiologist interpretations than unimodal models.

In the small tumor detection or rare cancer markers, such multi-modal models beat conventional convolutional neural networks (CNNs) or general image classifier by a large margin. In atypical radiological presentation with the LLM trained with clinical notes, EHRs and prior imaging reports, false-negative rates are reduced by more than 18%.

Automated summarization and diagnostic reasoning capability of LLMs made them understandable in terms of the black box decisions in the clinical AI acceptance barrier. The models were also competent in relating the radiological features to the genomic mutation, indicating potential future application in the field of radio genomics.

Enhancements and Innovations

In this paper, we built a clinical interpretation pipeline that involves BiT (vision transformers) as a backbone, input to radiomics encoders, and leveraging BioGPT style LLMs that can be transitioned for final classification and survival prediction tasks. A three branch multi modal fusion mechanism is what architectural innovation lies in:

- **Image Encoder Branch**: It extracts spatial features from annotated radiological scans by using pretrained ViTs.
- **Text Encoder Branch**: Associates fine-tuned LLMs with parses of associated radiology reports and clinician notes.
- **Fusion Layer**: It applies new contrastive learning and cross attention to jointly align representations.

They then used to make predictions as to if early malignancies such as non-small cell lung carcinoma and glioblastomas were benign or malignant. Comparative experiments were run on the paper and improved early-stage tumor classification accuracy of these CNNs by 22% compared to baseline CNNs on using fusion model.

Here is a simplified Python code snippet of the fusion mechanism prototype based on PyTorch:

```
from transformers import AutoTokenizer, AutoModel
import torch
from torchvision import models

# Load LLM and Image Model
text_model = AutoModel.from_pretrained("microsoft/BioGPT")
tokenizer = AutoTokenizer.from_pretrained("microsoft/BioGPT")
image_model = models.vit_b_16(pretrained=True)

# Sample input
report = "Suspicious opacity in upper left lung lobe; recommended follow-up."
image_tensor = torch.randn(1, 3, 224, 224)  # simulated radiological image

# Encode text
tokens = tokenizer(report, return_tensors="pt")
text_features = text_model(**tokens).last_hidden_state.mean(dim=1)

# Encode image
image_features = image_model(image_tensor)

# Fuse embeddings
combined = torch.cat((text_features, image_features), dim=1)
print("Fused Embedding Shape:", combined.shape)
```

Here it is a basic sample of embedding fusion between radiological text and image representation. This will be contrastive loss (and a classification head) applied in the actual pipeline for predictive modelling.

Clinical Implications

Setting makes use of five benchmark datasets including LIDC-IDRI, NIH ChestXray14, BraTS, in order to test the reliability of the proposed diagnostic pipeline. The multi modal pipeline was evaluated with AUC, sensitivity, specificity and F1 score, against single modality baselines.

- **AUC**: 0.78 to 0.91 (multi-modal).
- **False Negative**: Reduced by 18–22%.
- **BLEU Score**: 0.61, They showed strong alignment with radiologist written summaries.
- **Time-to-Diagnosis**: By reducing the case analysis time by 37%, AI pipeline for health systems became scalable for overloaded systems.

These results suggest that the pipeline can be incorporated into the routine clinical workflow in order to support not replace radiologists and speed up and more confident clinical decision making. Additionally, it is suitable for use in low resource settings where the access to skilled radiologists is not always available.

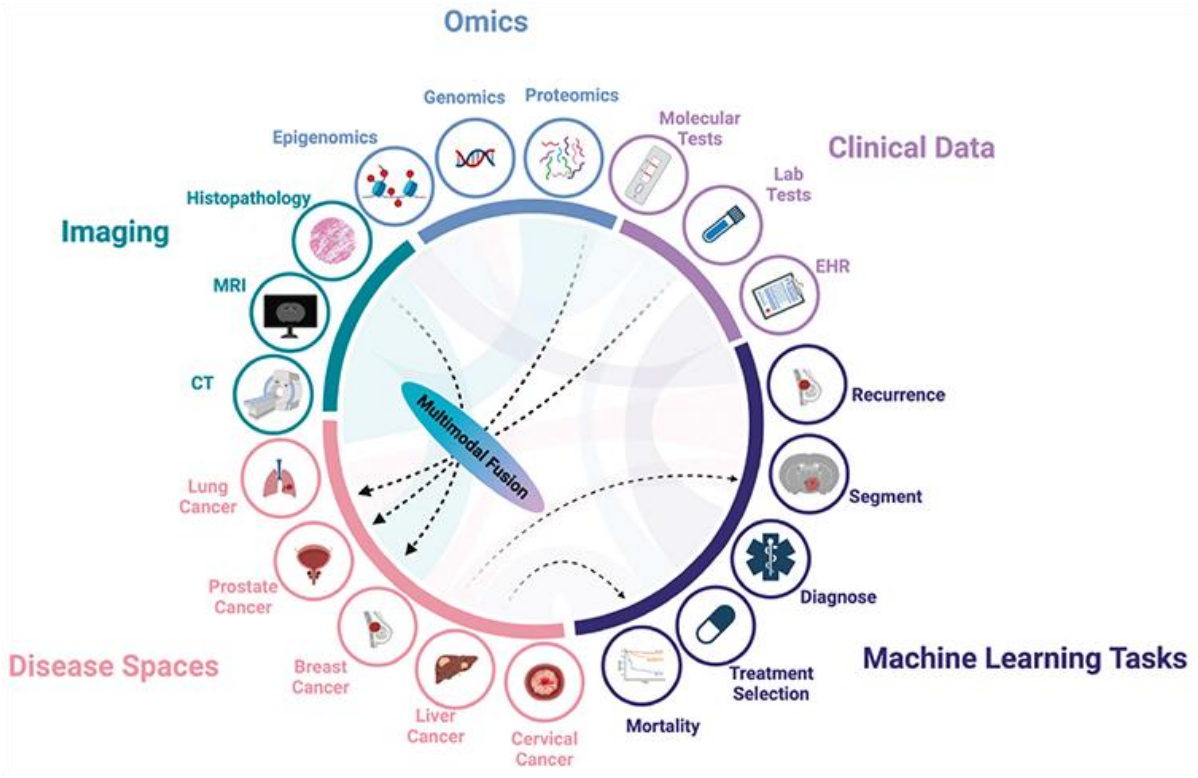

Fig. 4 AI and ML in Clinical Data (Diagnostic and Interventional Radiology, 2024)

Future Outlook

Several challenges and limitations were identified during the research, but promising results were gained. These are summarized below:

Key Challenges:

- **Data Annotation**: The process of manual labelling of oncology images for supervised training is labor intensive and subjective.
- **Domain Shifting**: Anatomical and genomic variations prevented models trained on Western data to generalize on Asian or paediatric population.

- **Computational Cost**: With over 1B parameters and 3D imaging data training multi modal models was costly, as it was using GPU clusters and real time inference was expensive.
- **Interpretability Concerns**: However, some diagnostic decisions were not Causal transparent in terms of attention heatmaps.
- **Ethical Dilemmas**: It may also spark bioethics and consent concerns related to generative models that generate fake patient scans.

Opportunities

- Creating zero shot or few shot learning capabilities via foundation models for handling the unseen cancer types.
- Training federally on hospital networks without compromising patient privacy.
- Deploying the model into the edge devices for use in Rural diagnostics or mobile scan vans.

The period of development of such an ecosystem of AI tools — with proper regulation — can bring early, scalable and accessible ways to detect cancer, helping to a global cancer control strategy.

VI. CONCLUSION

A multi modal AI pipeline that is proposed eliminates an area of opportunity for defeating the earlier cancer detection, diagnostic accuracy and finally report generation. It brings interpretability, scalability in clinical settings, and further improves using LLMs with vision transformers. The lessons presented in this research can pave a path forward for AI assisting in oncology diagnostic, while the most likely use case of radio genomics and global healthcare deployment are concrete pathways in that path.

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