Evaluating GPT-4o mini for Diagnostic Prediction, Description and Localization in Medical Imaging

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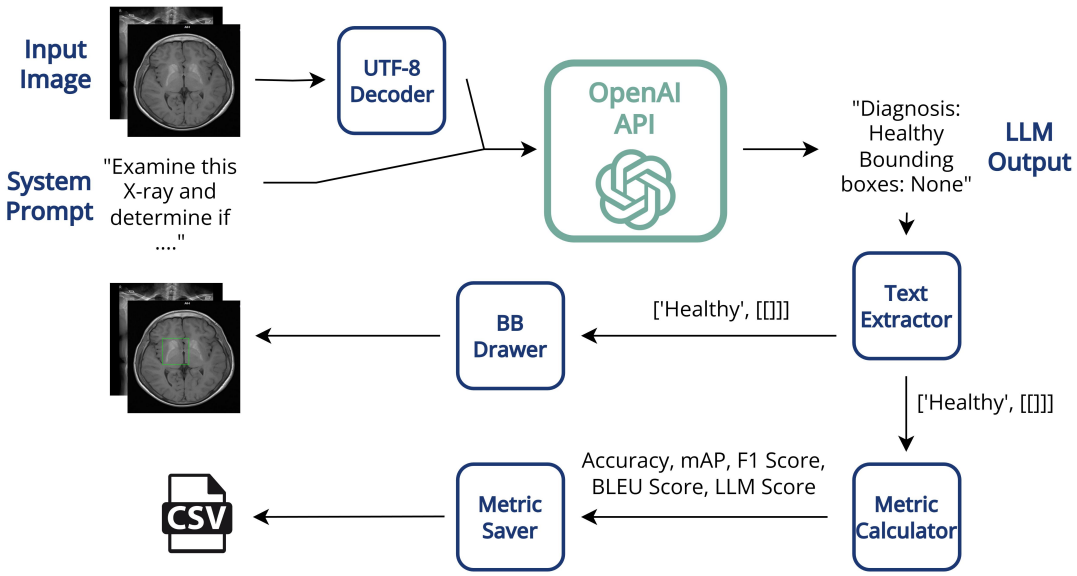
Introduction

🚀 **Motivation**: Large language models (LLMs) have shown surprising capabilities across text, image, and multimodal tasks.

🛠️ **Method**: We applied GPT-4o mini to Chest X-rays and MRI brain slices using multimodal prompts and evaluated its outputs across classification, localization, and captioning tasks.

🎯 **Goal**: Assess the viability of zero-shot LLM-based analysis for clinical imaging without domain-specific fine-tuning.

Methodology



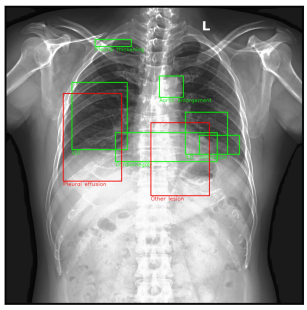
Results

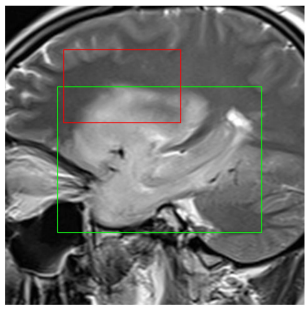
Accuracy	F1- Healthy	F1 Unhealthy	mAP@50:95	mAP@50:95	mAP@50:95
30.00%	14.63%	40.67%	0.00%	0.00%	0.00%

Results for Chest X-Ray Experiments

BLEU-1	BLEU-2	LLM Score	mAP@50:9	mAP@50:95	mAP@50:95
10.80%	1.96%	9.23%	0.80%	0.04%	0.00%

Results for Brain Slice Experiments





Analysis

🧠 **Model Misalignment**: GPT4-o mini is not trained on medical image datasets, limiting its ability to extract clinically relevant visual features.

📉 **Below Random Performance**: Evaluation metrics (e.g., accuracy, mAP, F1) were worse than random guessing, suggesting no meaningful pattern recognition.

🖼️ **Poor Visual Grounding**: The model failed to identify disease regions, often producing bounding boxes that were random or unrelated to pathology.

🌀 **Hallucinated Descriptions**: Text outputs included plausible-sounding but incorrect or irrelevant medical terms, highlighting limitations in factual consistency.

💾 **No Fine-Tuning**: Using the model in a zero-shot setting, without domain-specific adaptation, resulted in generic or misaligned responses.

⚙️ **Prompting Limitations**: Even carefully engineered prompts could not reliably elicit correct classification or localization behavior from the model.

Conclusion

🚧 **Limitation**: Zero-shot inference, though convenient, cannot replace specialized architectures trained on medical datasets.

📉 **Key Insight**: General-purpose LLMs, even with multimodal capabilities, are currently unsuitable for diagnostic imaging without domain-specific training.

🔭 **Future Work**: Incorporate medical vision-language models (e.g., BioViL, Med-PaLM) or fine-tune on labeled datasets like CheXpert or BraTS.

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