LungVision AI

Ayman Akhras | Kelly Deng | Nathan Luong | Patrick Zhou | Reza Jodeiri

Supervisor: Dr. Mehdi Moradi

McMaster University

Introduction

Chest X-ray (CXR) is the most widely used imaging tool for detecting respiratory and cardiovascular conditions due to its accessibility and affordability

Currently, radiologists interpret chest X-ray images manually, which can be time-consuming, subjective, and prone to diagnostic errors.

Existing AI-driven solutions primarily classify chest X-rays at a general level, but often fail to precisely locate diseases within specific anatomical regions

An ideal AI system should accurately identify diseases, pinpoint their exact anatomical locations, and reliably track changes over time, improving efficiency and diagnostic precision for radiologists.

Methods

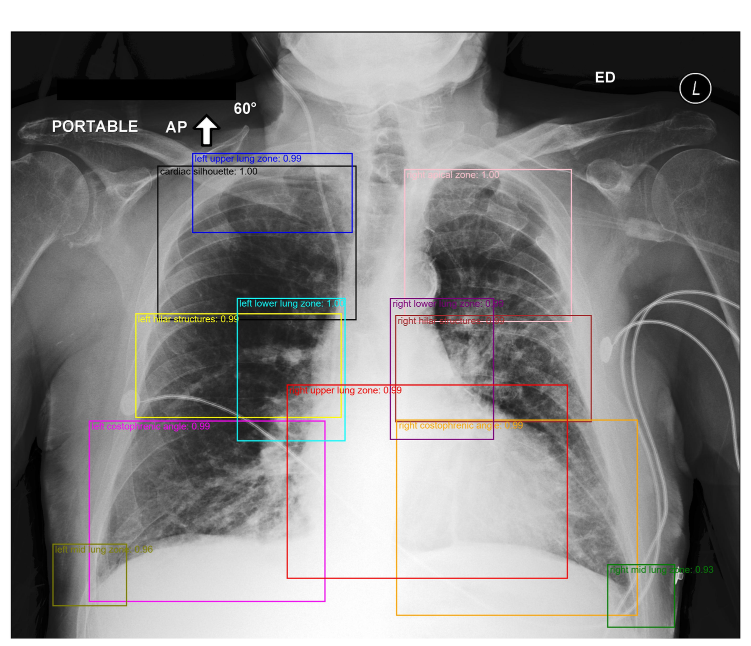
Image Preprocessing → Anatomical Region Detection → Feature Extraction → Disease Classification

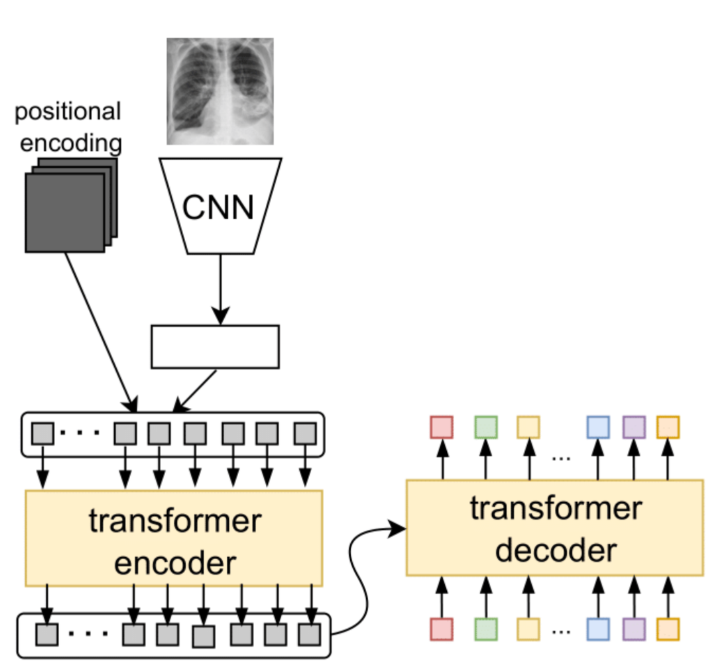
Stage 1: Image Preprocessing

- Converts X-ray images to standardized RGB format and generates tensor representations (pixel_values + mask) for model compatibility
- Prepares data for model input by adding batch dimensions

Stage 2: Anatomical Region Detection

- Employs DETR transformer model to detect and localize 12 anatomical regions with 0.85 confidence threshold
- Converts detected regions from relative coordinates to absolute image coordinates for accurate localization





Stage 3: Feature Extraction:

- Generates a 12x256 dimensional feature matrix where each row represents an anatomical region's learned representations

Stage 4: Disease Classification

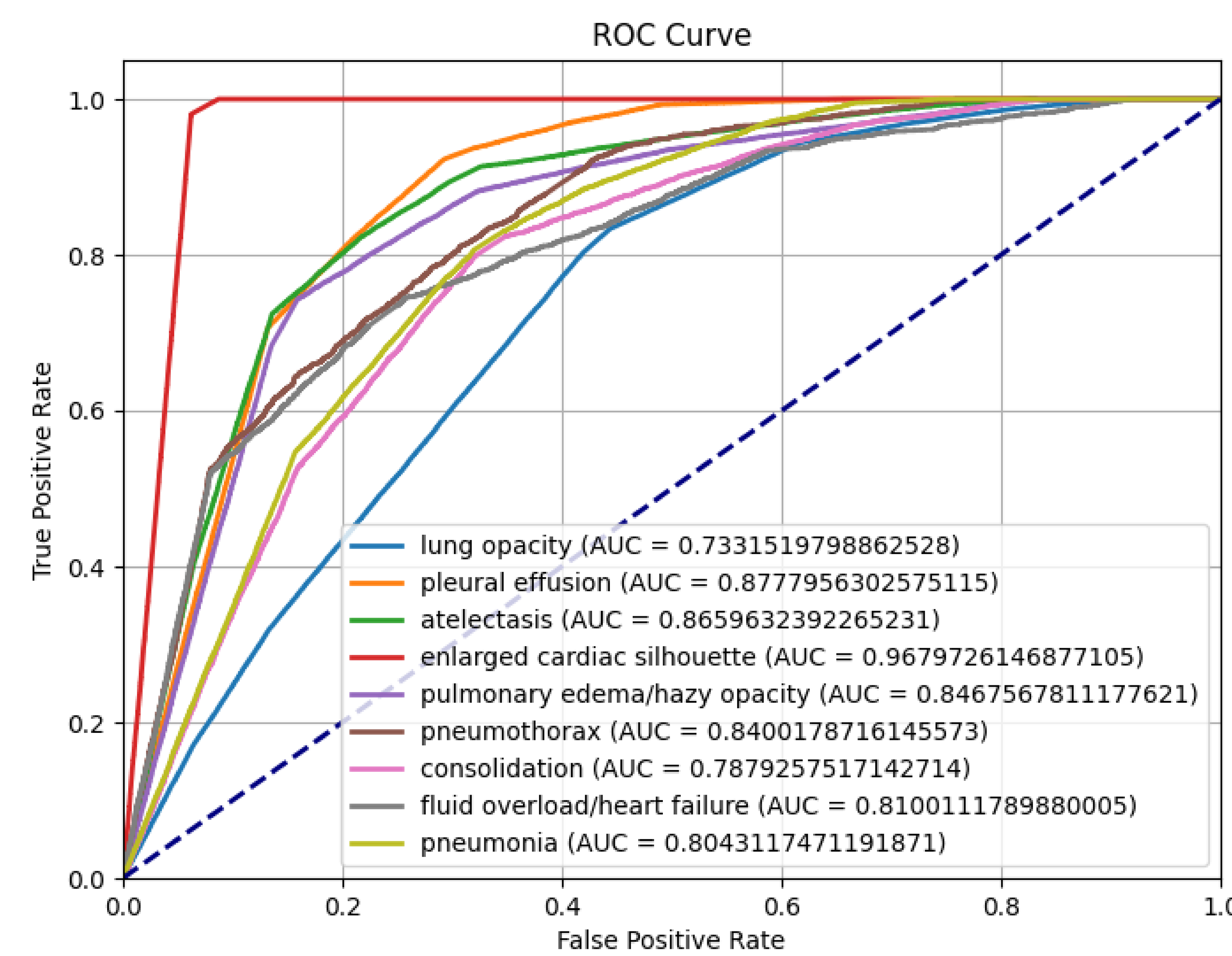
- TransformerNetwork processes 256-dimensional region features through an 8-head attention mechanism and 2-layer encoder to capture relationships between 12 anatomical regions, embedding features into 512-dimensional space before mapping to 9 disease classes

Results

RULZ	RMLZ	RLLZ	RCA	RHS	RAZ
0.984	0.961	0.962	0.818	0.963	0.968
LULZ	**LMLZ**	**LLLZ**	**LCA**	**LHS**	**CS**
0.983	0.964	0.955	0.743	0.960	0.959

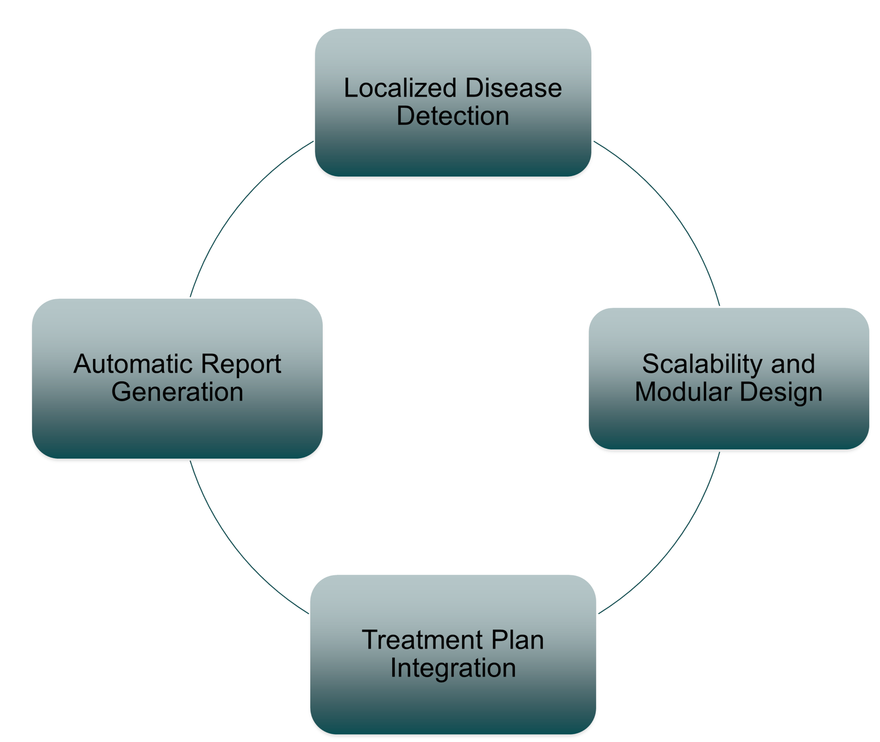
The area under precision-recall curves for the twelve target anatomical regions. The mean average precision (mAP) is 93.5%. For 10 of the 12 regions, the area under ROC curve is at or above 96%, with only right and left costophrenic angle being the exceptions.

Model Evaluation



Accomplishments

- **See What the AI Sees**: system pinpoints diseases with 83% mean accuracy in specific chest regions.
- **Context Matters**: Patient history and metadata from DICOM files help our AI make smarter decisions, reducing bias and providing more personalized analysis
- **From Analysis to Action**: Automatic report generation transforms predictions into structured medical findings ready for clinical review
- **Built to Grow**: Modular design and use of cloud services allows easy addition of new AI models and scaling to handle increasing patient volumes

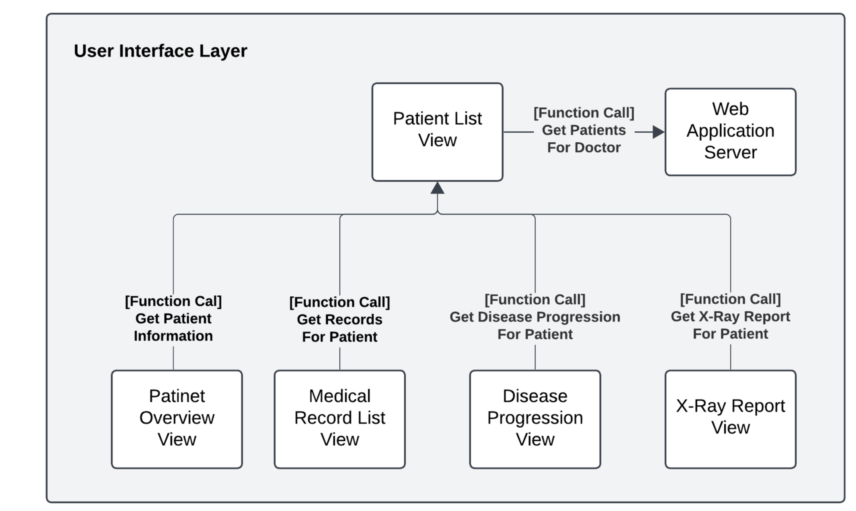


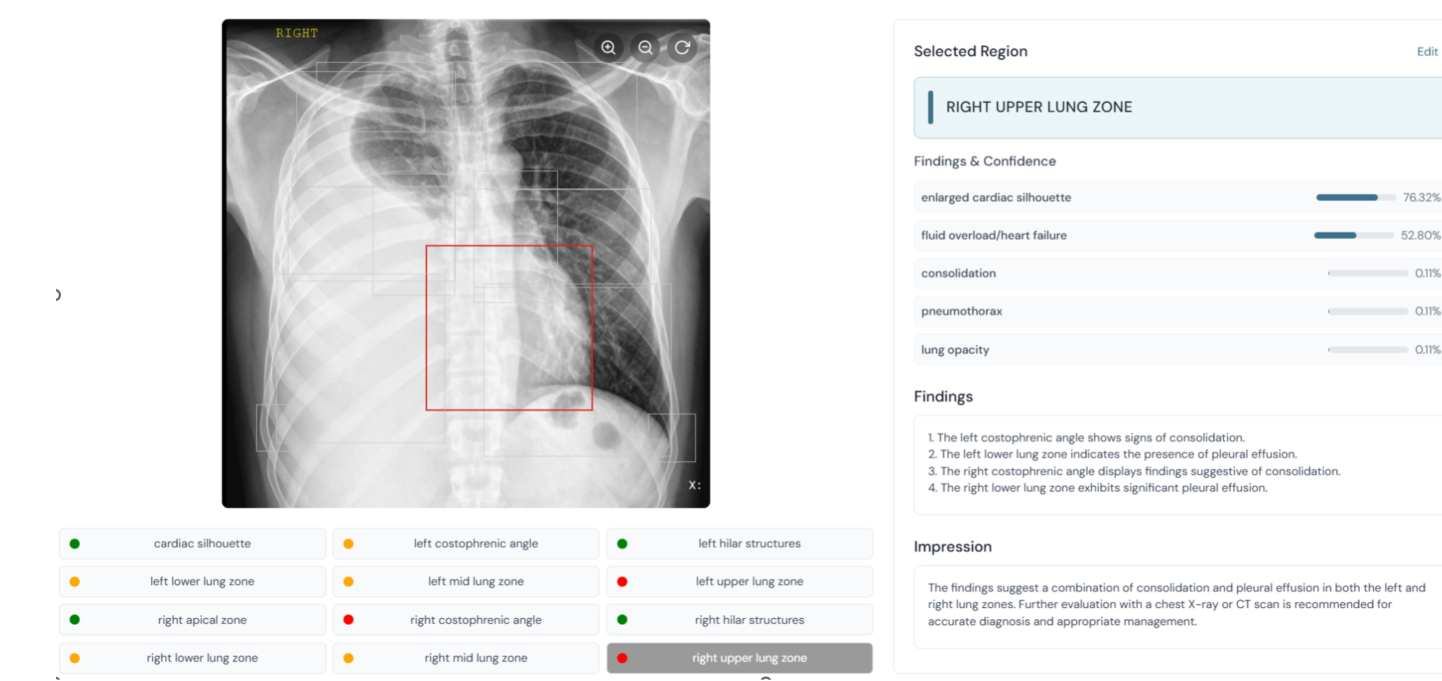
Future Development :

- **Disease Progression**: Implementing longitudinal analysis to monitor disease progression over time, helping clinicians spot subtle changes between examinations
- **Personalized Medicine**: Fine-tuning recommendations by incorporating patient-specific factors such as age, comorbidities, and previous treatment responses
- **Predictive Insights**: Building capabilities to forecast potential disease trajectories based on current findings and similar patient cohorts

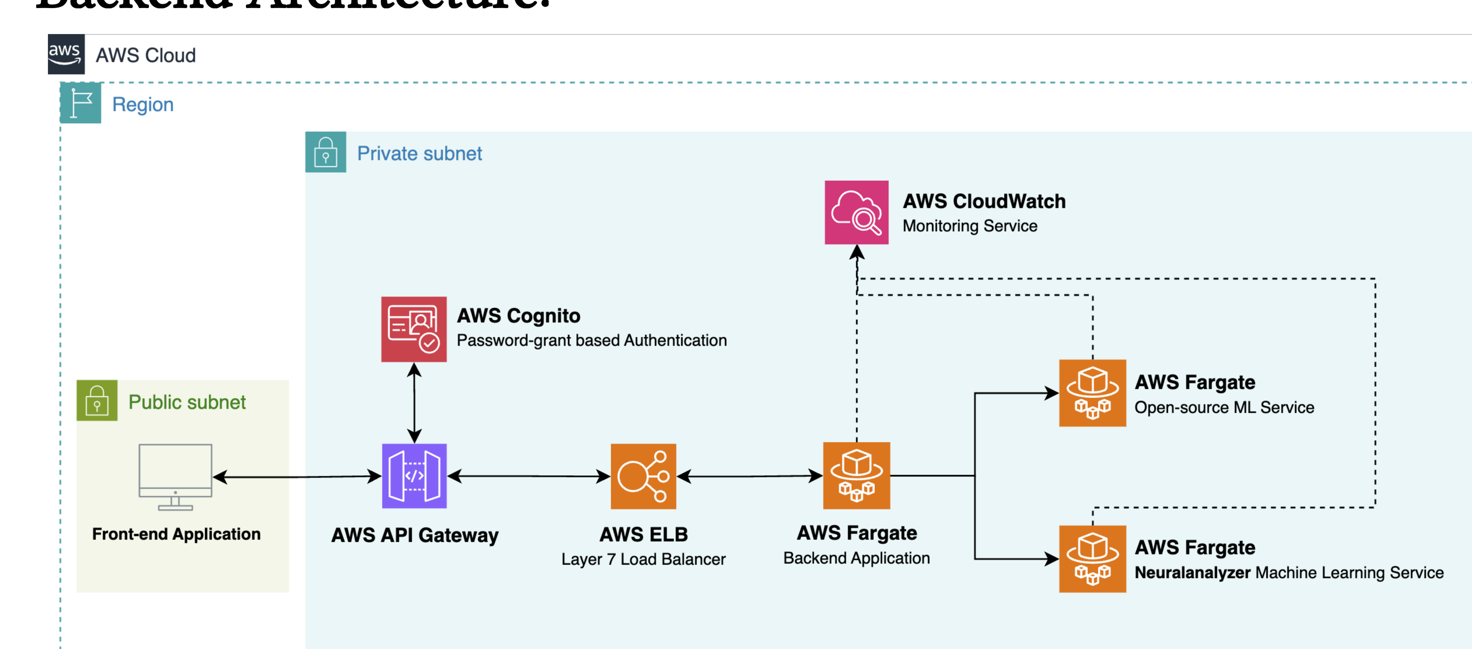
Software Design

Frontend Architecture:





Backend Architecture:



References

[1] Agu, N.N., Wu, J.T., Chao, H., Lourentzou, I., Sharma, A., Moradi, M., Yan, P.,Hendler, J.: Anaxnet: Anatomy aware multi-label finding classification in chest x-ray. In: de Bruijne, M., Cattin, P.C., Cotin, S., Padoy, N., Speidel, S., Zheng, Y.,Essert, C. (eds.) Medical Image Computing and Computer Assisted I Intervention – MICCAI 2021. pp. 804–813. Springer International Publishing, Cham (2021)

[2] Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., Zagoruyko, S.: End-to-end object detection with transformers. In: Vedaldi, A., Bischof, H., Brox, T.,Frahm, J.M. (eds.) Computer Vision – European Conference on Computer Vision(ECCV) 2020. pp. 213–229. Springer International Publishing, Cham (2020)

[3] Falcon, W., The PyTorch Lightning team: PyTorch Lightning (Mar 2019). https://doi.org/10.5281/zenodo.3828935,https://github.com/Lightning-AI/lightning

[4] Johnson, A.E., Pollard, T.J., Berkowitz, S.J., et al.: Mimic-cxr, a de-identified publicly available database of chest radiographs with free-text reports. Scientific data pp. 1–8 (2019)

[5] M. Li, B. Lin, Z. Chen, H. Lin, X. Liang, and X. Chang. Dynamic graph enhanced con- trastive learning for chest x-ray report generation. In CVPR, pages 3334–3343, 2023.

7] H. Nguyen, D. Nie, T. Badamdorj, Y. Liu, Y. Zhu, J. Truong, and L. Cheng. Auto-mated generation of accurate & fluent med-ical x-ray reports. In EMNLP, pages 3552–3569. Association for Computational Linguistics, 2021.