Research Plan

Terra North Jersey STEM Fair FAVR:1138

SR-230: *RADIANT: Radiology AI for Detection, Interpretation, And Notification & Triage*

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Background

Radiologists often face heavy workloads, reviewing large volumes of medical images under time pressure. This environment increases the risk of missing subtle lesions or making minor errors (e.g., incorrect laterality in a report). Existing computer-aided detection (CAD) solutions sometimes exacerbate workflow issues by focusing narrowly on a single pathology, lacking integrated reporting features, or failing to triage urgent cases. By developing a robust, multi-pathology detection model, I aim to reduce oversight, streamline the identification of key findings, and improve overall diagnostic efficiencyâwithout requiring radiologists to switch among multiple tools.

Rationale and/or Goals

Primary Goal: Develop a single model that can detect and characterize multiple abnormal findings across different imaging modalities, thereby reducing the reliance on separate, pathology-specific systems.

Hypothesis: A well-structured deep learning model, trained on a diverse dataset, will accurately identify both common and subtle abnormalities, outperforming baseline single-pathology CAD approaches in terms of sensitivity and specificity.

Secondary Objective: Demonstrate that a unified model can yield consistent, high-quality outputs, minimizing common errors in laterality and labeling that arise from juggling multiple software tools.

Vertebrate Subjects

No information provided

Human Subjects

Did you use data obtained by somebody else?	
Did you design a device for human use?	:

No other details given

Results of IRB Review	
Risk Level	
Qualified Scientist Required?	
Risk Assessment Required?	
Minor Assent Required?	not answered
Parental Permission Required?	not answered
Inform Consent Required?	not answered

Experimental Methods [performed by student(s)]

I developed and tested a machine learning model aimed at automatically detecting and characterizing various radiological abnormalities from medical imaging. To do this, I obtained a dataset comprising diverse imaging modalities along with corresponding annotations that identify regions of interest. All work described here was computational.

Data Acquisition & Preprocessing

Dataset Compilation: I collected publicly available and de-identified medical images (e.g., from open-access databases) that included normal and abnormal cases.
Quality Control: I removed low-quality or corrupted images to ensure a consistent dataset.
Image Normalization: I standardized pixel intensities and dimensions across all images for uniform input.
Annotation Alignment: Using the accompanying metadata, I matched images with labels indicating anomalies (e.g., nodules, fractures) or normal findings.
Model Architecture & Training

Base Network Selection: I experimented with state-of-the-art convolutional neural networks and Vision Transformers to identify a suitable backbone for feature extraction.
Multiclass Output Layer: Since I aimed to detect various abnormalities, I configured the final classification layer to output multiple classes, allowing the model to handle multiple pathologies within a single framework.
Training Protocol:
Loss Function: I employed a combination of classification loss (e.g., cross-entropy) and localization loss.
Batching & Optimization: I used standard mini-batch gradient descent or Adam optimization, tuning the learning rate and batch size to minimize overfitting.
Data Augmentation: Techniques such as random rotations, flips, and brightness adjustments were applied to improve generalization.
Validation & Testing

Train-Validation Split: I partitioned the dataset into training, validation, and test sets to ensure unbiased performance metrics.
Performance Metrics: I tracked accuracy, F1-score, sensitivity, and specificity during validation to measure the modelâs ability to identify both common and subtle abnormalities.
Hyperparameter Tuning: I iteratively refined hyperparameters (e.g., learning rate) based on validation metrics until achieving optimal performance.
Final Evaluation: Using the untouched test set, I measured final metrics, including confusion matrices, to confirm the modelâs novelties and robustness.

Data Analysis

After training, I applied the model to the test set and generated predictions for each image. I conducted the following steps to interpret and validate results:

Statistical Summaries: Calculated precision, recall, F1-score, and overall accuracy across different types of pathologies. This helped highlight whether the model performed evenly or struggled with certain categories.
ROC & PR Curves: Plotted Receiver Operating Characteristic (ROC) and Precision-Recall (PR) curves for each class to assess the trade-offs between sensitivity and specificity.
Error Analysis: Examined misclassified or missed cases in detail to identify patternsâsuch as small, subtle lesionsâthat might require further architectural improvements or additional training data.
Cross-Validation of Metadata: Whenever available, I reviewed clinical notes or bounding box annotations to compare predicted labels and locations with ground truth, ensuring consistency in measurement and laterality.

Bibliography

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