Summer Internship 2024

<<Interpret-CXR >>

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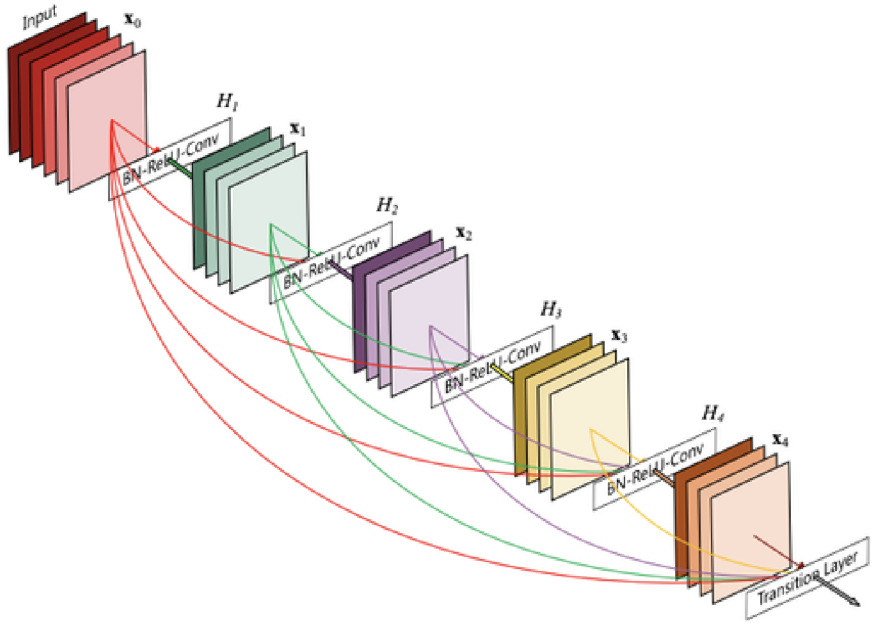
Existing Approaches

DenseNet



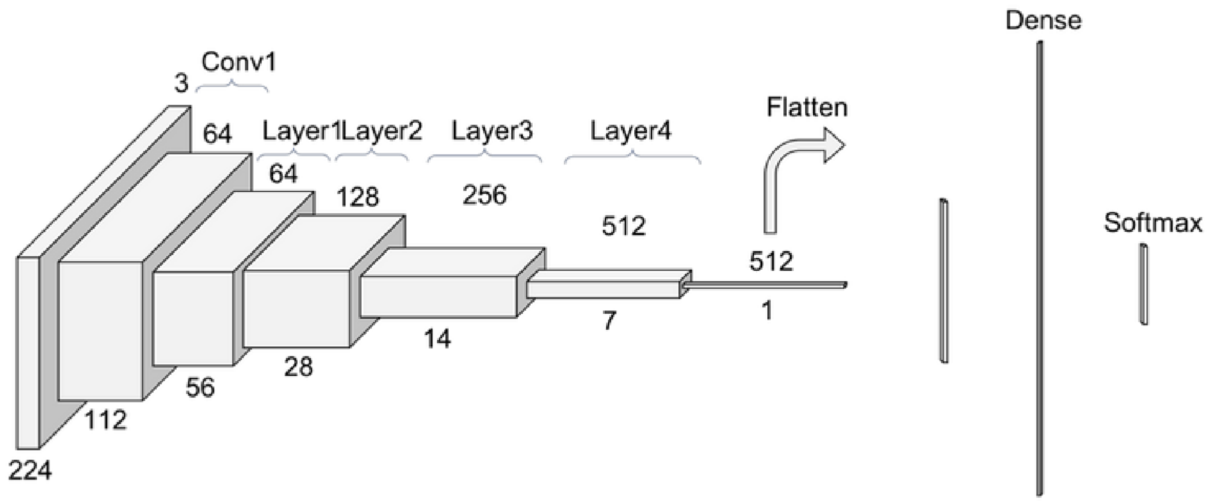
This is a complex network that improves on the basic CNN by connecting each layer to every other layer in a feed-forward fashion.

This helps the model retain information from earlier layers and reduces the problem of vanishing gradients.

Training: It starts from scratch without any prior knowledge. The images are resized and normalized. It uses Adam optimizer and focuses on minimizing binary cross entropy loss.

Performance: It typically performs well early in training, showing strong ability to generalize from the data.

ResNet



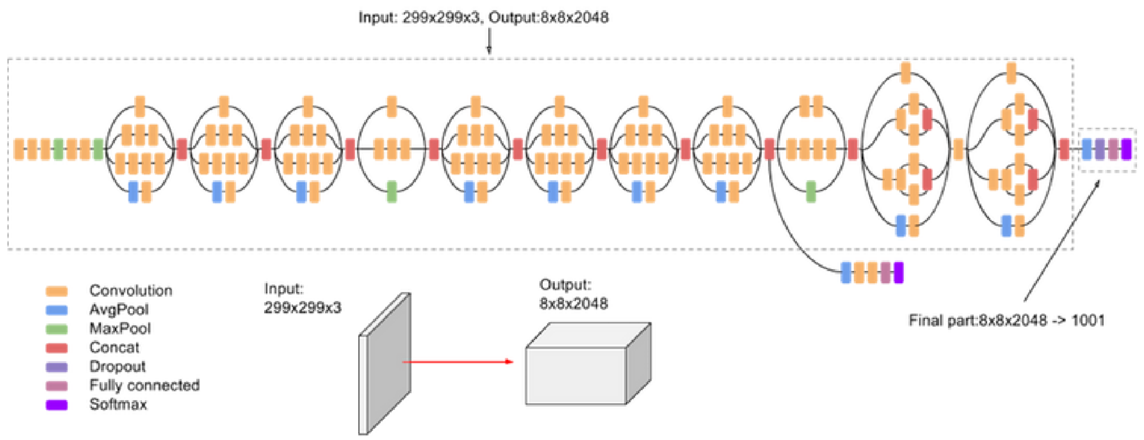
This network uses a special setup called "residual learning" to help deeper networks learn better.

It helps to solve the problem where adding more layers to a network doesn't improve its performance.

Training: Begins with a model already trained on a different dataset (ImageNet), which helps it to start with a good understanding of image features. It is fine-tuned by adjusting many of its layers specifically for the task of analyzing X-rays.

Performance: Specific layers are gradually unlocked and trained further to refine its predictions.

InceptionV3



Known for its efficiency and depth, InceptionV3 processes images through various-sized filters simultaneously within the same layer. This allows it to capture details at multiple scales.

Training: Similar to ResNet50, it starts with pre-trained ImageNet weights. It includes stages where the model is gradually adapted from general image recognition to specific X-ray analysis tasks.

Performance: After initial training, more layers are unfrozen and trained to better adapt to the CXR analysis.

Ensemble

This technique combines the outputs of multiple models to make a final decision. By doing this, it leverages the strengths and mitigates the weaknesses of individual models.

Simple CNN Networks

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Literature Survey

Literature Review

Reference	Dataset used	Merits	Demerits
Few-shot Structured Radiology Report Generation Using Natural Language Prompts	• MIMIC-CXR-JPG v2.0.0, which is derived from the MIMIC-CXR dataset	• Data Efficiency • Standardization • Clinical Accuracy • Scalability	• Dependency on Pre-trained Models • Resource Intensity • Clinical Accuracy • Scalability
Vision Transformer and Language Model Based Radiology Report Generation	• Indiana University Chest x-Ray dataset (IU X-Ray)	• State-of-the-Art Performance • Domain Adaptability • Avoidance of Spatial Bias • End-to-End Model	• Computational Intensity • Data Requirement • Lack of Inductive Bias
Attention based automated radiology report generation using CNN and LSTM	• The Indiana University CXR dataset • MIMIC CXR dataset	• Hybrid Approach • Enhanced Accuracy • Scalability • Assistance to Medical Professionals	• Complexity in Training and Implementation • Overfitting Risks • Dependence on High-Quality Data • Interpretability
Automatic Radiology Report Generation based on Multi-view Image Fusion and Medical Concept Enrichment	• CheXpert • Indiana University Chest X-ray (IU CXR)	• Advanced Feature Representation • Contextual and Semantic Accuracy • State-of-the-Art Performance • Potential for Practical Application	• Complexity in Model Training and Deployment • Dependence on High-Quality, Large-Scale Data • Potential for Bias • Interpretability Issues

Literature Review

Reference	Dataset used	Merits	Demerits
Deep learning in generating radiology reports: A survey	• MIMIC-CXR • IU-CXR • ChestX-ray14 • PadChest • DDSM • PIER	• Enhanced Diagnostic Efficiency • Consistency and Coverage • Clinical Accuracy • Scalability	• Dataset Limitations • Complexity in Model Training • Potential for Bias and Errors
Deep learning approaches to automatic radiology report generation: A systematic review	• Not Disclosed	• Enhanced Efficiency • Scalability • Consistency and Availability	• Data Imbalance and Complexity • Lack of Large-Scale, Diverse Datasets • Evaluation Metrics • Interpretability and Trust

Summary

- Reporting chest X-rays is time-consuming and challenging due to complex medical data, different writing styles, and errors in free text.
- To automate this process, we a method that uses a language-image model to link chest X-rays with corresponding textual reports.
- This model can be trained using various deep learning architectures such as CNNs (Convolutional Neural Networks), ResNet (Residual Networks), DenseNet (Densely Connected Convolutional Networks), or other advanced deep learning techniques

THANK YOU