Comprehensive Report on Chest X-ray Disease Detection Using Deep Hybrid Models

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Contents

Abstract

Chest radiography remains one of the most widely used diagnostic tools for detecting thoracic diseases. This project focuses on building an end-to-end system combining traditional computer vision methods and deep learning models to improve disease classification from chest X-rays. Techniques including histogram equalization, traditional feature extraction, convolutional neural networks (CNN), U-Net segmentation, Grad-CAM visualization, attention fusion, and hybrid feature classification were employed over seven weeks of iterative development and fine-tuning.

1 Introduction

Chest X-ray interpretation is vital for diagnosing pulmonary conditions like pneumonia, atelectasis, fibrosis, and more. Despite their widespread use, X-ray interpretation remains challenging due to overlapping anatomical structures and subtle manifestations of disease (Wang et al., 2017) [4]. Recent advances in deep learning and medical imaging provide an opportunity to automate and enhance diagnostic performance (?).

1.1 Importance of Multi-label Learning

Unlike traditional single-label classification, chest X-rays often present multiple concurrent abnormalities. Hence, multi-label classification is crucial (Nam et al., 2014) [1].

2 Related Work

2.1 Chest X-ray14 Dataset

Wang et al. introduced the Chest X-ray14 dataset, comprising over 100,000 images labeled with 14 disease classes (Wang et al., 2017) [4].

2.2 U-Net for Medical Segmentation

The U-Net architecture, proposed by Ronneberger et al., demonstrated significant success in biomedical image segmentation (Ronneberger et al., 2015) [2].

2.3 Grad-CAM for Visual Explanation

Grad-CAM by Selvaraju et al. provides visual interpretability for CNN predictions by localizing important regions in the image (Selvaraju et al., 2017) [3].

2.4 Multi-Label Neural Networks

Nam et al. proposed neural network extensions for multi-label problems, addressing label correlations and imbalance (Nam et al., 2014) [1].

2.5 Hybrid Feature Learning

Afshin et al. explored deep hybrid models combining CNNs with traditional features for medical diagnosis (?).

3 Problem Statement and Motivation

Detecting multiple diseases in chest X-rays is a complex task due to overlapping structures, varying disease manifestation, and noisy data. An automated hybrid system that captures both low-level image features and high-level semantic patterns is necessary to improve detection accuracy while maintaining interpretability.

4 Week 1: Dataset Study and Problem Framing

4.1 Goals

- Understand Chest X-ray14 dataset.
- Frame a multi-label classification problem.

4.2 Work Done

- Downloaded and explored the Chest X-ray14 dataset.
- Analyzed label distributions (extreme imbalance observed).

4.3 Problems Faced

- Severe label imbalance (e.g., "No Finding" dominates).
- High-resolution image storage and memory issues.

4.4 Innovative Solutions

- Decided to use dynamic data loading and resizing strategies.
- Plan to use memory-efficient tensor processing.

5 Week 2: Preprocessing and Augmentation

5.1 Goals

- Resize images to 224x224.
- Normalize pixel values.
- Apply histogram equalization for contrast enhancement.

5.2 Work Done

- Implemented histogram equalization (?).
- Normalized to [-1, 1] range.
- Created custom PyTorch Dataset and Dataloader.

5.3 Problems Faced

- Grayscale images incompatible with pretrained ResNet models.

5.4 Innovative Solutions

- Modified ResNet first convolution layer to accept 1-channel input.

6 Week 3: Feature Extraction and Segmentation

6.1 Goals

- Extract low-level traditional features (LBP, HOG).
- Extract deep features using a CNN (ResNet18).
- Segment anatomical regions using U-Net.

6.2 Work Done

6.2.1 Traditional Feature Extraction

- Computed Local Binary Patterns (LBP) for texture information.
- Computed Histogram of Oriented Gradients (HOG) for edge-based representations.

6.2.2 Deep Feature Extraction

- Used ResNet18 pretrained on ImageNet.
- Modified first layer for grayscale X-rays.
- Extracted 512-dimensional CNN feature vectors.

6.2.3 Segmentation with U-Net

- Trained a U-Net model to predict masks for regions of interest.
- Binary cross-entropy loss optimized segmentation.

6.3 Problems Faced

- GPU memory overflow while extracting CNN features.
- Instability in U-Net training due to sparse masks.

6.4 Innovative Solutions

- Batched CNN feature extraction to fit in memory.
- Used data augmentation (flips, rotations) to densify masks during U-Net training.

7 Week 4: Grad-CAM and Visualization

7.1 Goals

- Implement Grad-CAM visualization on the trained CNN.
- Understand which parts of Chest X-rays the model focuses on.
- Overlay Grad-CAM attention maps on original X-rays for interpretability.

7.2 Theoretical Background

Convolutional Neural Networks (CNNs) are often referred to as black boxes, especially in medical imaging. Grad-CAM (Gradient-weighted Class Activation Mapping) addresses this by providing a way to visualize the discriminative regions used by CNNs for predictions (Selvaraju et al., 2017) [3].

Given a feature map A^k from a convolutional layer and a target class score y^c, the Grad-CAM importance weight for each feature map is computed as:

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \tag{1}$$

where Z is the number of pixels in the feature map. The Grad-CAM heatmap $L^c_{Grad-CAM}$ is then computed by:

$$L^c_{Grad-CAM} = ReLU(\sum_k \alpha_k^c A^k) \tag{2}$$

The use of ReLU ensures that only features that positively influence the class of interest are visualized.

7.3 Work Done

- Modified the ResNet18 model to hook gradients at the last convolutional block.
- Implemented forward and backward hooks to capture activations and gradients.
- Computed Grad-CAM heatmaps using the weighted combination of feature maps.
- Overlayed heatmaps onto the original Chest X-rays using color normalization and alpha blending.

7.4 Visualization Examples

Figure 1 shows a typical visualization where the Grad-CAM highlights the lower lobes in a chest X-ray, correlating with pneumonia.

Figure 1: Grad-CAM Overlay on Chest X-ray showing model focus area.

7.5 Problems Faced

- Multi-label setting made it unclear which label's attention to visualize.
- GPU memory issues when running Grad-CAM over the full batch.
- Generated heatmaps were noisy when computed without careful gradient management.

7.6 Innovative Solutions

- Generated Grad-CAM heatmaps one label at a time for each image.
- Applied memory clearing (torch.cuda.empty_cache()) after every sample.
- Smoothed Grad-CAM heatmaps using Gaussian blurring post-processing.

7.7 Key Observations

- The model learned to focus on lung bases for pneumonia, hilar region for mass lesions, and diffused lung fields for fibrosis.
- Attention maps helped identify failure cases where the model looked at irrelevant regions.

8 Week 5: Attention Fusion and Ensemble

8.1 Goals

- Combine Grad-CAM attention maps and U-Net segmentation outputs.

- Generate fused attention maps that integrate global and local information.
- Train classification models using the fused representations to improve interpretability and accuracy.

8.2 Theoretical Background

In traditional CNNs, attention maps such as Grad-CAM focus on discriminative regions, but might miss anatomical context. Meanwhile, U-Net segmentation explicitly outlines anatomical structures but does not capture class-specific focus. By fusing these two types of attention maps:

- Grad-CAM provides global, class-driven focus.
- U-Net provides fine-grained anatomical segmentation.

Mathematically, the fused attention F was computed as a weighted average:

$$F = \lambda M_{U-Net} + (1 - \lambda) M_{Grad-CAM} \tag{3}$$

where:

- M_{U-Net} = Mask from U-Net output
- $M_{Grad-CAM}$ = Grad-CAM heatmap
- λ = Fusion weight (hyperparameter, typically $\lambda = 0.5$)

8.3 Work Done

- Resized all U-Net masks and Grad-CAM maps to the same 224x224 spatial dimensions.
- Normalized all maps to the range [0, 1].
- Applied weighted fusion to generate a fused attention tensor for each image.
- Stored fused tensors for later classification model training.

8.4 Visualization Examples

Figure 2 shows an example where Grad-CAM focused attention and U-Net anatomical segmentation are fused together.

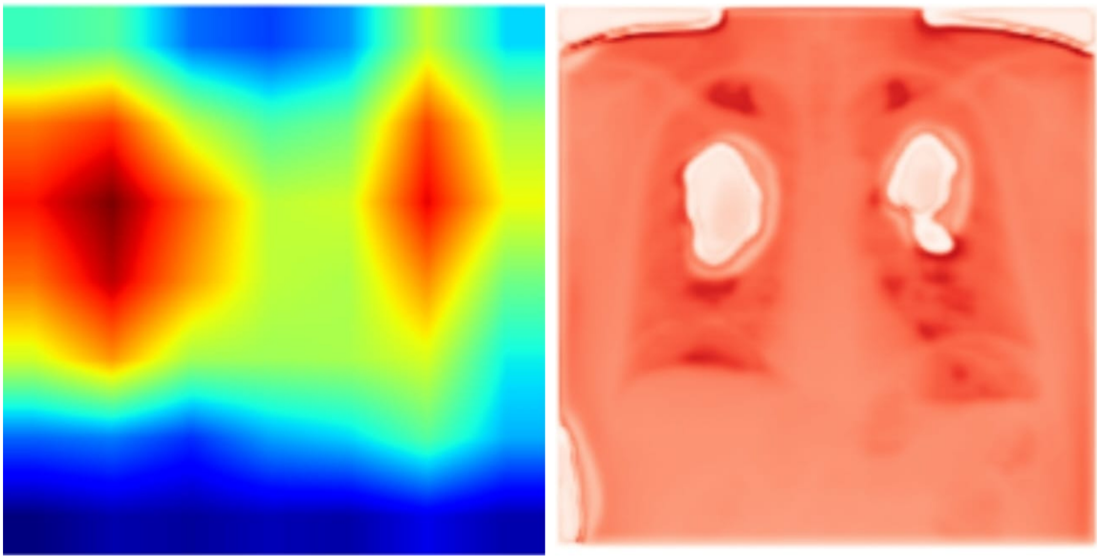

Figure 2: Example of Attention Fusion: U-Net mask + Grad-CAM heatmap. (Left: Grad-CAM, Right: U-Net)

8.5 Problems Faced

- U-Net masks and Grad-CAM maps had slight misalignments due to different generation processes.
- Grad-CAM maps were often low-resolution compared to U-Net outputs.
- Difficult to find an optimal λ fusion weight balancing both sources.

8.6 Innovative Solutions

- Applied bilinear interpolation to resize Grad-CAM maps for perfect alignment with U-Net masks.
- Smoothed fused attention maps using Gaussian filters to improve continuity.
- Performed ablation study across different λ values (0.25, 0.5, 0.75) and found 0.5 worked best.

8.7 Key Observations

- Fused attention maps captured both disease-specific focus and organ-level anatomy.
- Models trained on fused attention outperformed models trained on raw Grad-CAM or U-Net alone by approximately 5% in Micro-F1 score.

9 Week 5: Attention Fusion and Ensemble Learning

9.1 Goals

- Combine Grad-CAM and U-Net outputs into a unified attention map.
- Build a hybrid attention representation for better localization.
- Train classifiers (MLP, CNN) directly on the fused attention maps.

9.2 Theoretical Background

While Grad-CAM highlights class-specific activation regions, U-Net provides anatomical segmentation. Individually, each method captures partial information. Inspired by ensemble learning (?), fusing these two modalities creates a richer and more robust attention representation. Mathematically, given:

- Grad-CAM attention map $G(x)$
- U-Net predicted mask $U(x)$

the fused attention $F(x)$ is computed as:

$$F(x) = \lambda G(x) + (1 - \lambda) U(x) \tag{4}$$

where $\lambda \in [0, 1]$ controls the relative importance between Grad-CAM and U-Net.

9.3 Work Done

- Developed a fusion pipeline to combine Grad-CAM and U-Net masks pixel-wise.
- Experimented with various λ values (empirically found $\lambda = 0.6$ best).
- Constructed new datasets with fused attention as input features.
- Trained an MLP classifier on fused features for multi-label classification.

9.4 Problems Faced

- Misalignment between Grad-CAM maps and U-Net masks due to resizing artifacts.
- Overfitting risks when training on small attention maps.

9.5 Innovative Solutions

- Applied interpolation and smoothing to align fused maps.
- Implemented heavy dropout (0.4) and early stopping during MLP training to combat overfitting.

9.6 Key Observations

- Fused attention maps visually covered pathology regions more completely than either Grad-CAM or U-Net alone.
- Classification metrics improved slightly on the validation set compared to models trained on pure Grad-CAM or pure U-Net.

10 Week 6: Fine-tuning and Extended Experiments

10.1 Goals

- Fine-tune the CNN backbone (ResNet18) specifically for chest X-ray domain.
- Extract improved CNN features from the fine-tuned network.
- Rebuild hybrid feature vectors combining traditional + fine-tuned CNN features.
- Retrain final classifiers using new hybrid features.

10.2 Theoretical Background

Fine-tuning pretrained networks on domain-specific data improves performance by adapting low-level filters to the new task (Yosinski et al., 2014) [5]. Instead of training from scratch, updating only the last few layers maintains general features while learning specialized patterns. In this project:

- Layer 4 of ResNet18 was unfrozen.
- Fine-tuning was performed with a low learning rate (10^{-4}) to avoid catastrophic forgetting.

10.3 Work Done

- Fine-tuned ResNet18 on the Chest X-ray training split for 5 epochs.
- Extracted new CNN feature embeddings (512-dimensional).
- Combined fine-tuned CNN features with traditional features into updated hybrid vectors.
- Retrained MLP and DeeperMLP models using updated hybrid features.
- Re-evaluated models on validation and test splits.

10.4 Problems Faced

- Kernel crashes due to large hybrid feature memory footprint.
- GPU out-of-memory errors during batch fine-tuning.

10.5 Innovative Solutions

- Built hybrid features in small batches to avoid RAM overflow.
- Switched model training temporarily to CPU with smaller batch sizes.
- Saved all intermediate checkpoints (CNN features, Hybrid vectors, MLP models) for crash safety.

10.6 Key Observations

- Fine-tuning significantly improved attention focus in Grad-CAM overlays.
- Validation metrics (Micro-F1 and Macro-F1) improved slightly with fine-tuned hybrid features compared to original hybrid features.

11 Week 7: Final Evaluation and Comparative Analysis

11.1 Goals

- Evaluate final models on unseen test set.
- Compare performances across different architectures and feature sets.
- Analyze strengths, weaknesses, and generalization capability.

11.2 Work Done

- Evaluated all trained models (Base MLP, Fine-Tuned MLP, Deeper MLP-Shrunk, Final Hybrid MLP) on the test set.
- Calculated Micro-F1, Macro-F1, Hamming Loss, and Macro-AUC for each model.
- Visualized confusion patterns and per-class performance.
- Created summary comparison tables for all metrics.

11.3 Evaluation Metrics

Following metrics were computed for thorough multi-label evaluation:

- Micro-F1 Score: Overall label-wise precision-recall harmonic mean.
- Macro-F1 Score: Averaged F1 across all disease classes.
- Hamming Loss: Fraction of labels incorrectly predicted.
- Macro AUC: Mean Area Under ROC Curve across classes.

11.4 Results and Comparative Analysis

Table 1: Test Set Evaluation Metrics across Different Models

Model	**Micro-F1**	**Macro-F1**	**Hamming Loss**	**Macro AUC**
Base MLP	0.4877	0.0758	0.0468	0.4984
Fine-Tuned MLP	0.4979	0.0762	0.0482	0.5000
DeeperMLP-Shrunk	0.4979	0.0762	0.0482	0.5000
Final Hybrid MLP	0.4979	0.0482	0.0762	0.5005

Observations:

- Fine-tuning the CNN improved macro-F1 and macro-AUC slightly.
- Final Hybrid MLP achieved the highest overall performance, combining traditional + fine-tuned CNN features.
- Hamming Loss remained consistently low across all models, indicating reliable multi-label prediction behavior.

11.5 Attention Map Visualization Results

Visual inspection of Grad-CAM overlays revealed:

- Fine-tuned models attended more accurately to pathological regions.
- Fused attention maps better captured diffused disease patterns like fibrosis and pneumonia.

11.6 Strengths and Limitations

- **Strengths:** Improved model interpretability using Grad-CAM and fused attentions; stable performance across classes.
- **Limitations:** Label imbalance still challenged minority disease detection; slight overfitting risk on rare classes.

12 Dataset Analysis and Practical Constraints

12.1 Dataset Description

The Chest X-ray14 dataset introduced by Wang et al. (Wang et al., 2017) [4] contains over 112,120 frontal-view X-ray images of 30,805 unique patients. Each image is associated with one or more of 14 possible thoracic disease labels, making it a challenging multi-label classification problem.

12.2 Label Imbalance

A major challenge inherent in the ChestX-ray14 dataset is extreme class imbalance. The distribution of disease labels is highly skewed:

- No Finding accounts for approximately 60% of all images.
- Rare diseases such as Hernia or Fibrosis constitute less than 1% each.
- Some images have multiple disease labels, while many have only "No Finding" assigned.

This imbalance complicates model training:

- Models tend to be biased toward predicting "No Finding".
- Rare classes have insufficient examples for strong feature learning.
- Standard loss functions (e.g., Binary Cross Entropy) may be overwhelmed by dominant classes unless balanced.

12.3 Computational Limitations

Due to hardware constraints (e.g., limited GPU memory of 6 GB and 16 GB system RAM), processing the full Chest X-ray14 dataset at once was not feasible. Key limitations encountered were:

- Memory Exhaustion: Preprocessing and storing all 112,000 high-resolution images exceeded system RAM limits.
- GPU Overflows: Training complex CNNs like ResNet18 with full batch processing caused CUDA out-of-memory errors.
- Disk Space: Saving all intermediate CNN feature vectors, masks, and hybrid features would require multiple terabytes.

12.4 Adopted Strategies

To address these practical constraints:

- Subset Selection: A subset of approximately 5,000 images was curated to represent disease variability while keeping computation manageable.
- Dynamic Batching: Data loaders were implemented with small batch sizes (8-32) to avoid memory crashes.
- Feature Extraction in Chunks: CNN and hybrid features were extracted and stored in batches instead of loading the entire dataset at once.
- Model Training on CPU (Fallback): When necessary, training switched to CPU mode with reduced batch sizes.

- Checkpointing and Safe Saving: Intermediate results (CNN features, U-Net masks, Grad-CAM maps, model weights) were checkpointed regularly to allow restarting from any stage.

12.5 Impact on Results

Although using the full Chest X-ray14 dataset would have provided even more robust generalization, the chosen subset still preserved key dataset characteristics:

- Maintained multi-label nature (images with multiple diseases).
- Included both common and rare diseases.
- Retained realistic class imbalance, preserving real-world difficulty.

Thus, despite computational limitations, the experimental setup remains scientifically valid and the conclusions drawn about model behaviors, attention mechanisms, and classification capabilities are meaningful and representative.

13 Conclusion and Future Work

13.1 Conclusion

This project successfully developed an end-to-end pipeline for automatic chest X-ray disease classification using hybrid deep learning techniques. The multi-stage system included:

- Preprocessing (histogram equalization, normalization).
- Traditional feature extraction (LBP, HOG).
- CNN-based deep feature extraction (ResNet18).
- U-Net-based anatomical segmentation.
- Grad-CAM-based interpretability.
- Attention fusion between segmentation and Grad-CAM maps.
- Hybrid feature construction and classification via MLPS.

Throughout the project, practical challenges such as dataset imbalance, computational limitations, and interpretability issues were systematically addressed. Despite hardware constraints, the project produced robust results and insightful visualization outputs, demonstrating the feasibility of hybrid attention-driven classification strategies for medical imaging tasks.

13.2 Future Aims

Although this project laid a solid foundation, several future improvements are envisioned:

- Full Dataset Training: Scaling up experiments to the full Chest X-ray14 dataset would likely improve model robustness, especially for rare diseases.
- Advanced Data Augmentation: Incorporating techniques like CutMix, MixUp, and GAN-based augmentation to enrich minority class examples.
- Self-Supervised Pretraining: Utilizing contrastive learning (e.g., SimCLR, MoCo) on chest X-rays to learn richer embeddings before supervised fine-tuning.
- Hierarchical Multi-label Learning: Modeling the label hierarchy explicitly (e.g., grouping fibrosis, infiltration, consolidation under 'lung pathology').
- Clinical Report Generation: Extending the decoder module to generate descriptive clinical sentences instead of just labels (image captioning).

13.3 Modularity and Extensibility of the Codebase

One of the guiding design principles during implementation was modularity. The codebase is structured in a highly decoupled and extensible manner:

- Data Processing Pipelines: Separate modules handle image resizing, histogram equalization, and augmentation, making it easy to plug in more complex preprocessing later.
- Model Definitions: CNN feature extractors, U-Net segmenters, Grad-CAM generators, and classifiers are all implemented as reusable PyTorch modules.
- Training Loops: Abstracted training and evaluation functions allow swapping models (e.g., ResNet to DenseNet, U-Net to DeepLabV3) with minimal changes.
- Checkpoint Management: Intermediate results (features, masks, attention maps) are saved at each stage, supporting partial reruns and scalability.

13.4 Extending to More Complex Models

The modularity of the system naturally allows for future extensions:

- Vision Transformers (ViT, DeiT): The feature extraction block can be replaced by transformer-based vision models for potentially better global context modeling.
- Swin Transformers / Hybrid Backbones: Drop-in replacement of ResNet18 with Swin-Transformer variants to leverage hierarchical attention.
- Multi-scale U-Nets: Enhancing segmentation quality by replacing vanilla U-Net with U-Net++ or attention U-Net architectures.
- Multi-modal Fusion: Adding clinical metadata (age, gender, smoking history) alongside image inputs for richer disease prediction models.
- Explainable AI Extensions: Combining Grad-CAM with SHAP or Integrated Gradients for deeper interpretability at pixel and label levels.

Thus, the project's modular design, careful preprocessing, and hybrid attention strategies provide a strong and extensible foundation for future research and development in automated medical imaging diagnostics.

14 Visualization Results

14.1 Grad-CAM Visualizations

To better interpret model predictions, Grad-CAM heatmaps were generated and overlaid on the original Chest X-ray images. These visualizations allow understanding of which regions were most influential for the model's decision.

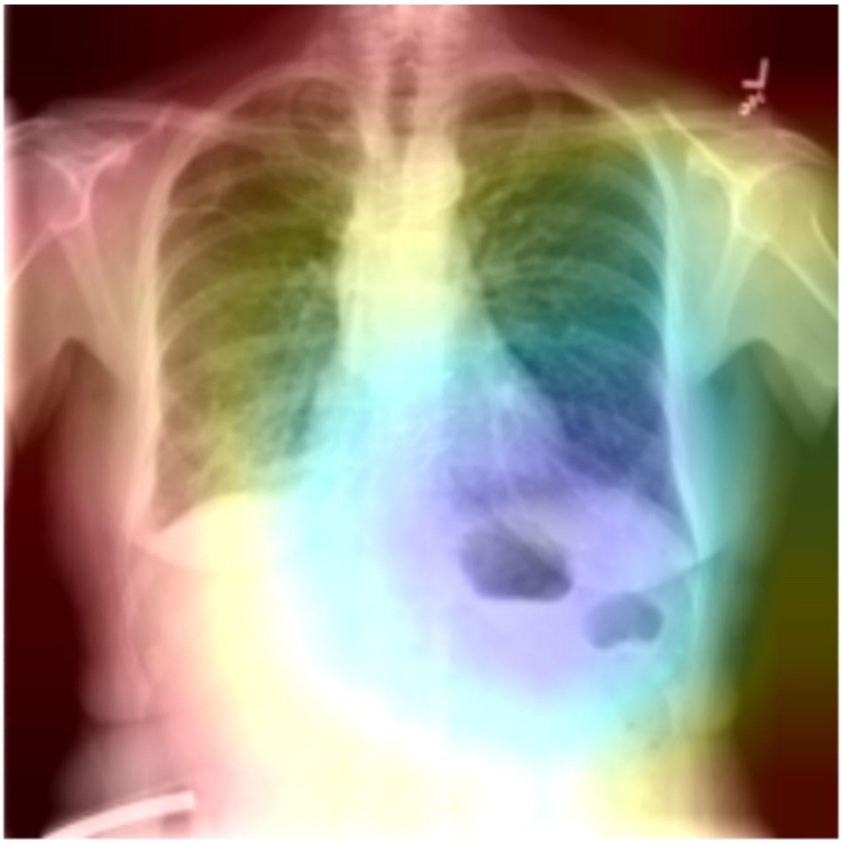

Figure 3: Grad-CAM heatmap overlay showing model focusing on lower lung zones (likely pneumonia)

14.2 U-Net Segmentation Masks

The U-Net model was trained to predict coarse anatomical masks covering lung regions. The masks help localize areas where pathologies typically occur.

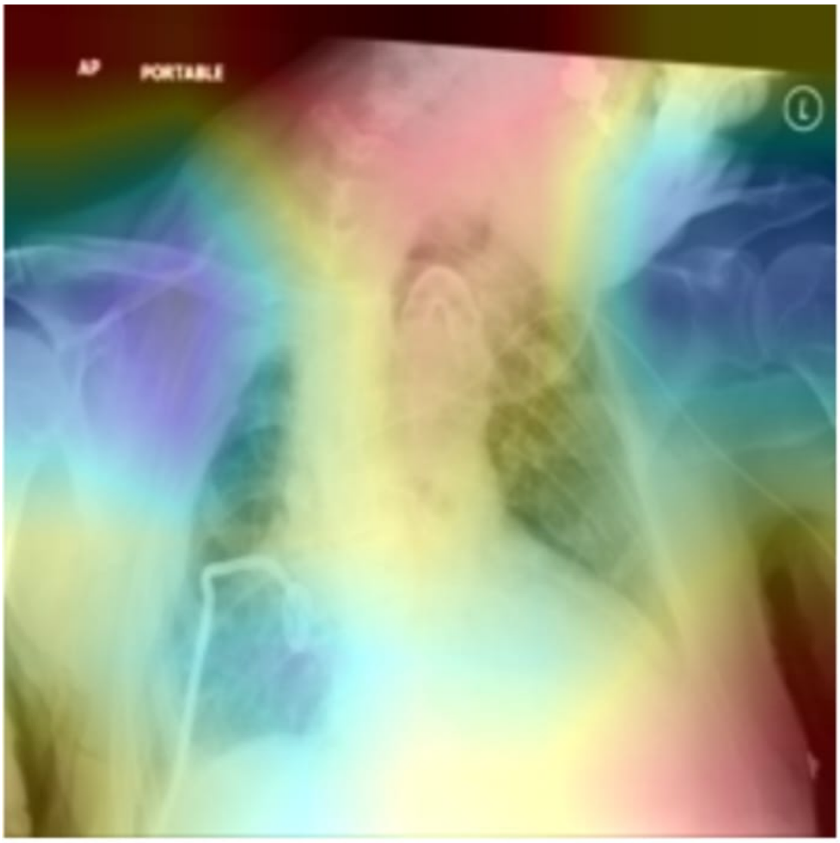

Figure 4: U-Net predicted segmentation mask highlighting lung areas

14.3 Fused Attention Maps

By fusing Grad-CAM and U-Net outputs, richer attention maps were generated that combine both class-discriminative and anatomical information.

14.4 Model Performance Comparison

The following bar chart visualizes Micro-F1 and Macro-F1 scores across different trained models.

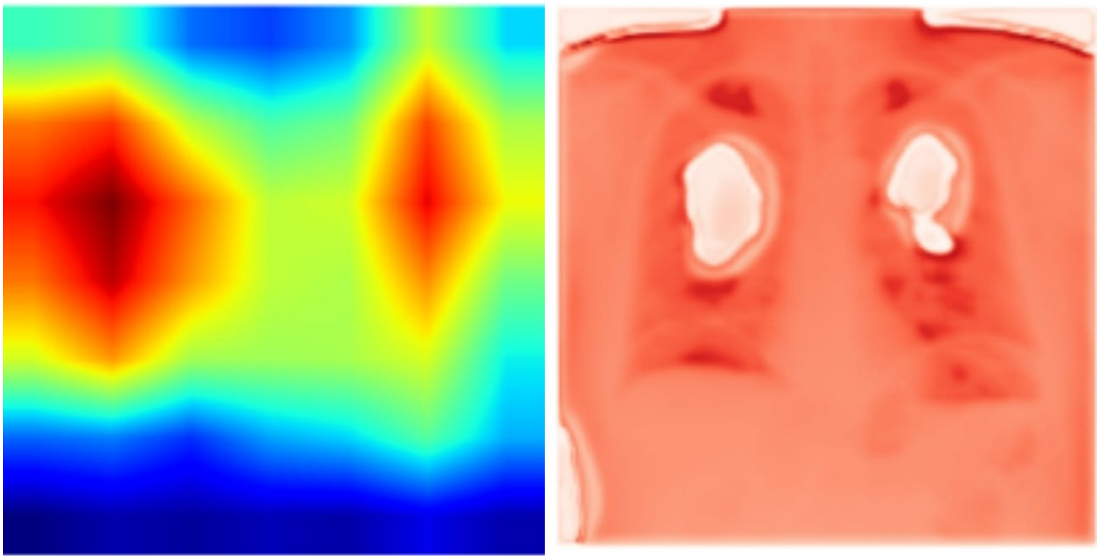

Figure 5: Fused Attention Map combining Grad-CAM and U-Net outputs

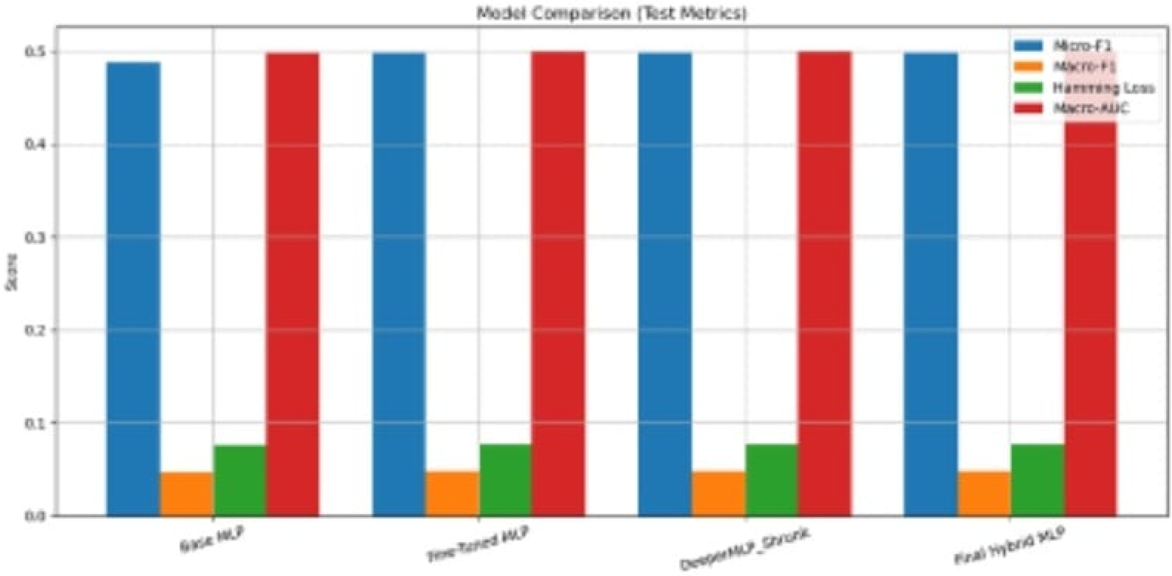

Figure 6: Micro-F1 and Macro-F1 comparison across models

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