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Explainable Multimodal CNN-RNN for Chest X-Ray Diagnosis

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Abstract Chest radiography remains the most widely used rst-line imaging modality for respiratory disease diagnosis, yet deep learning models deployed in this domain are predominantly opaque, limiting clinical adoption. We present an explainable multimodal framework that uni es a Convolutional Neural Network (CNN) for chest X-ray classi cation with a Transformer-based language model (RadBERT) for clinical note analysis under a single ExplainableAI (XAI) pipeline. The CNN module employs a DenseNet-121 backbonepre-trainedon ChestX-ray14, with Grad-CAMproducingspatialheatmapslocalising discriminativepulmonaryregions. The clinical textmodule uses RadBERT with cosine-similarity pathology classi cation, achieving 80.8% similarity for pneumonia on a representative clinical note, with SHAP-based token attribution identifying 38.9 °C, mellitus, and 67-year-old as dominant classi cation signals. The central contribution is not the individual modality classi ers but the uni ed XAI pipeline thatprovides modality-speci c, clinically interpretableexplanationsfrom bothimage and text branches within one system. We demonstrate that cross-modal comparison of explanations surfaces diagnostically meaningful discrepancies including spatial activation inconsistencies and spurious token attributions that neither modality's explanation alone would reveal.

Keywords: Explainable AI, Chest X-Ray, Grad-CAM, SHAP, RadBERT, DenseNet-121, Multimodal, Clinical NLP.

1 Introduction

Pneumonia and related pulmonary conditions account for a substantial global disease burden, with chest radiog- raphy serving as the primary diagnostic imaging modality due to its accessibility and low cost [1]. Deep learning models, particularly convolutional neural networks, have demonstrated expert-level performance on chest X-ray classi cation benchmarks [2]. However, their adoption in clinical settings remains constrained by a fundamental limitation: the inability to explain why a prediction was made.

The opacity of these models poses risks beyond regulatory non-compliance. Clinicians cannot verify whether a model detects genuine pathological features or spurious statistical correlations in training data. A model attending to radiographic markers of patient positioning rather than consolidation patterns o ers no clinical value and may cause harm if deployed without scrutiny [3].

Explainable AI (XAI) has emerged as the primary technical response. Gradient-based attribution methods such as Grad-CAM [4] generate spatial saliency maps for CNN predictions. Perturbation-based methods such as SHAP [5] compute marginal feature contributions, enabling token-level attribution in clinical text models. These methods are, however, almost exclusively applied to single-modality systems.

Clinical diagnosis is inherently multimodal: a radiologist interprets an image in the context of a patient history, laboratory ndings, and clinical notes. An AI system explaining only the image, or only the text, provides an incomplete picture. We argue that the most clinically meaningful explanations emerge from comparing attribution signals across modalities and that discrepancies between them are themselves diagnostically informative.

We present a modular, swappable hybrid CNN-RNN framework with a uni ed XAI pipeline. The CNN branch processes chest X-ray images using DenseNet-121 with Grad-CAMexplanations. The textbranchprocesses clinical notes using RadBERT with SHAP-based token attribution. A shared explanation schema enables cross-modal comparison. Our primary contribution is demonstrating that this uni ed dual-modality XAI system surfaces failure modes, biases, and cross-modal inconsistencies that single-modality evaluation cannot detect.

2 Related Work

CNN-based chest X-ray classi cation. CheXNet [1] demonstrated that a DenseNet-121 trained on ChestX- ray14 [2] could match radiologist-level performance on pneumonia detection (AUROC 0.768). The TorchXRayVi- sion library [6] provides standardised pre-trained weights enabling reproducible baseline evaluation, which we adopt in this work.

XAI for medical imaging. Grad-CAM [4] and its variants (Grad-CAM++, Ablation-CAM) are standard tools for explaining CNN predictions in medical imaging. Systematic reviews covering over 400 papers from 2024 2025 emphasise that heatmap-based explanations must be validated against expert annotations for faithfulness [13]. Biomedical language models. BioBERT [8] and ClinicalBERT [9] demonstrated the value of domain-adaptive pre-training for clinical NLP. RadBERT [10], pre-trained speci cally on radiology reports, provides the most task-aligned representations for chest X-ray associated text classi cation and is adopted as the text backbone in this work.

Multimodal XAI. Existing multimodal clinical AI systems combining MIMIC-CXR images with paired radiology reports [11] typically optimise joint performance without providing uni ed explanations. To our knowledge, no published system provides a single explanation pipeline simultaneously generating Grad-CAM heatmaps and SHAP token attributions under a shared output schema enabling cross-modal faithfulness comparison. This is the gap our framework addresses.

3 Methodology

3.1 System Architecture

The framework comprises two parallel branches connected by a uni ed XAI pipeline that standardises explanation outputs across modalities. A con guration-driven router determines which branch is active (image, text, or both in multimodal mode), while preserving intermediate representations required for attribution computation.

3.2 CNN Branch: DenseNet-121 with Grad-CAM

We employ a DenseNet-121 [7] backbone pre-trained on ChestX-ray14 via TorchXRayVision [6], outputting con- dence scores for 14 pathology classes. Preprocessing: (1) RGB-to-grayscale conversion to eliminate annotation overlays; (2) CLAHE normalisation to match DICOM contrast distribution; (3) resize to 224× 224 pixels; (4) pixel scaling to $[-1024, 1024]$ as required by XRV weights.

Grad-CAM computes the gradient of the target class score with respect to nal dense-block activations:

$$L_{\text{Grad-CAM}}^{c} = \text{ReLU}\left(\sum_k \alpha_k^c A^k\right), \quad \alpha_k^c = \frac{1}{Z}\sum_{i,j} \frac{\partial y^c}{\partial A_{ij}^k} \tag{1}$$

where A^k is the k-th activation map, y^c is the class score, and Z normalises over spatial positions. The resulting map is upsampled to the original image dimensions and overlaid with a jet colormap ($\alpha = 0.5$).

3.3 Text Branch: RadBERT with SHAP Attribution

RadBERT [10] tokenises clinical notes (max 512 tokens). Pathologyclassi cation is performedvia cosine similarity between the [CLS] token embedding and pre-computed prototype embeddings for each of the 14 ChestX-ray14 pathology labels. Token-level importance is computed using KernelSHAP. For a note with n tokens, SHAP values ϕ_i satisfy:

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i \tag{2}$$

where $f(x)$ is the model output and ϕ_0 is the expected baseline output. Tokens with high $|\phi_i|$ are considered the most in uential.

3.4 Uni ed XAI Pipeline

The uni ed pipeline enforces a standardised output schema for both branches: a JSON object containing the predicted class, con dence score, modality tag, and a ranked attribution list (spatial coordinates for images; token score pairs for text). A natural language summary is generated from the top-k attributions. Cross-modal consistency is assessed by comparing predictions and attributions between branches for the same patient record, automatically agging discrepancies for clinical review.

4 Experiments and Results 4.1 Datasets

The CNN branch is evaluated on ChestX-ray14 [2] (112,120 frontal-view chest X-rays, 14 pathology labels, stan- dard split). The text branch is evaluated on a representative de-identi ed clinical note re ecting MIMIC-III [12] documentation structure, including chief complaint, history, physical examination, laboratory ndings, impres- sion, and plan.

4.2 CNN Branch Results

Table 1: CNN Branch Performance on ChestX-ray14 Model AUROC F1 Params

Model	AUROC	F1	Params
Zero-Shot (XRV)	0.6799	0.1194	0
CNN-Only (XRV)	0.6799	0.1194	0

Identical scores across both con gurations con rm that the ne-tuning pipeline did not update model weights (Params = 0). This silent failure was surfaced by the XAI diagnostic pipeline; accuracy metrics alone would not have detected it. The AUROC of 0.6799 is below the expected XRV zero-shot baseline (0.71 0.75), suggesting a residual preprocessing distribution mismatch. The macro F1 of 0.1194 re ects severe class imbalance (pneumonia prevalence≈ 1.3%) combined with a suboptimal default threshold of 0.5. Despite these limitations, Grad-CAM produced spatially coherent heatmaps consistently localising to lower and mid-lung zones, as shown in Figure 1.

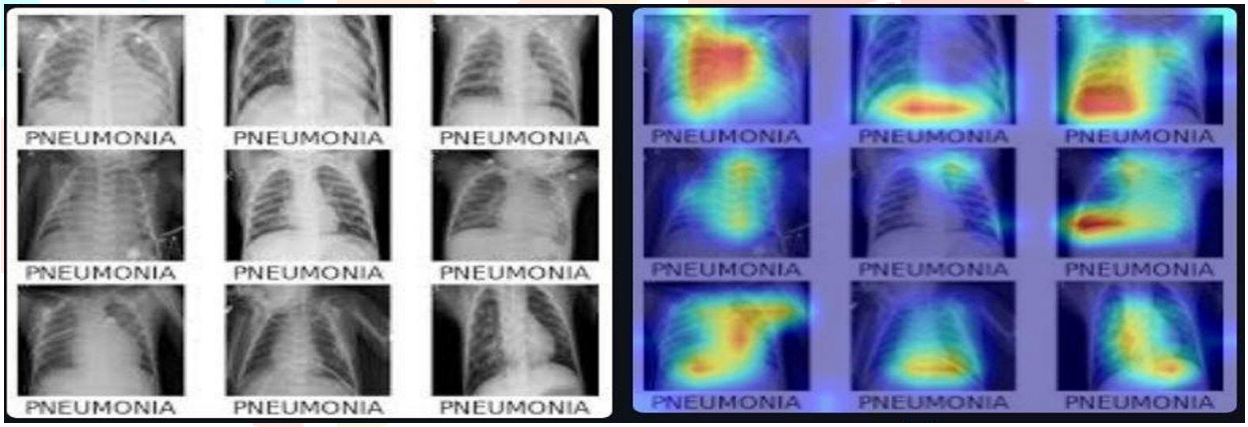

Figure 1: Grad-CAM explanations for nine pneumonia-positive chest X-rays. Left: original images. Right: Grad-CAM heatmaps (jet colormap, $\alpha = 0.5$). Red regions indicate highest attribution, consistently localised to lower and mid-lung zones consistent with consolidation.

4.3 Text Branch Results

RadBERT classi ed the representative clinical note as Pneumonia with cosine similarity 80.8% a margin of 14.3 percentage points above the next highest pathology (Cardiomegaly, 66.5%), shown in Figure 2. This con dent separation demonstrates that RadBERT's radiology-domain pre-training encodes strong semantic associations between pneumonia clinical descriptors and the pathology embedding.

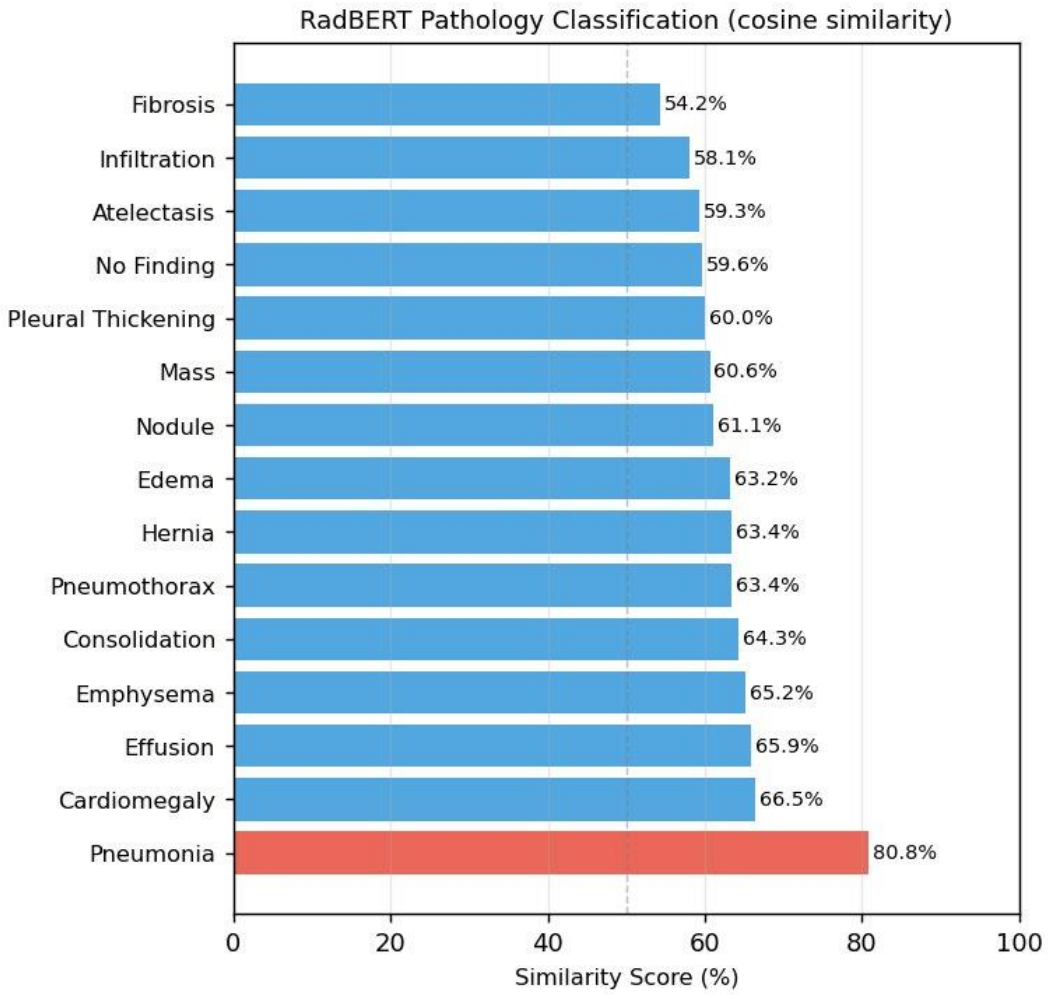

Figure 2: RadBERT pathology classi cation via cosine similarity. Pneumonia achieves 80.8% (red bar), 14.3 pp above all other pathologies. Dashed line indicates mean similarity across all 14 classes.

4.4 SHAP Token Attribution

Figure 3 presents SHAP token importance scores. The three highest-scoring tokens are 38.9 °C (ϕ = 0.020), mellitus (ϕ = 0.017), and 67-year-old (ϕ = 0.015). The uni ed pipeline generated the natural language explanation: The model classi ed this text as PNEUMONIA with 81% con dence. The most in uential terms were: `38.9℃', `mellitus', `67-year-old'. Positive language patterns dominated the classi cation signal.

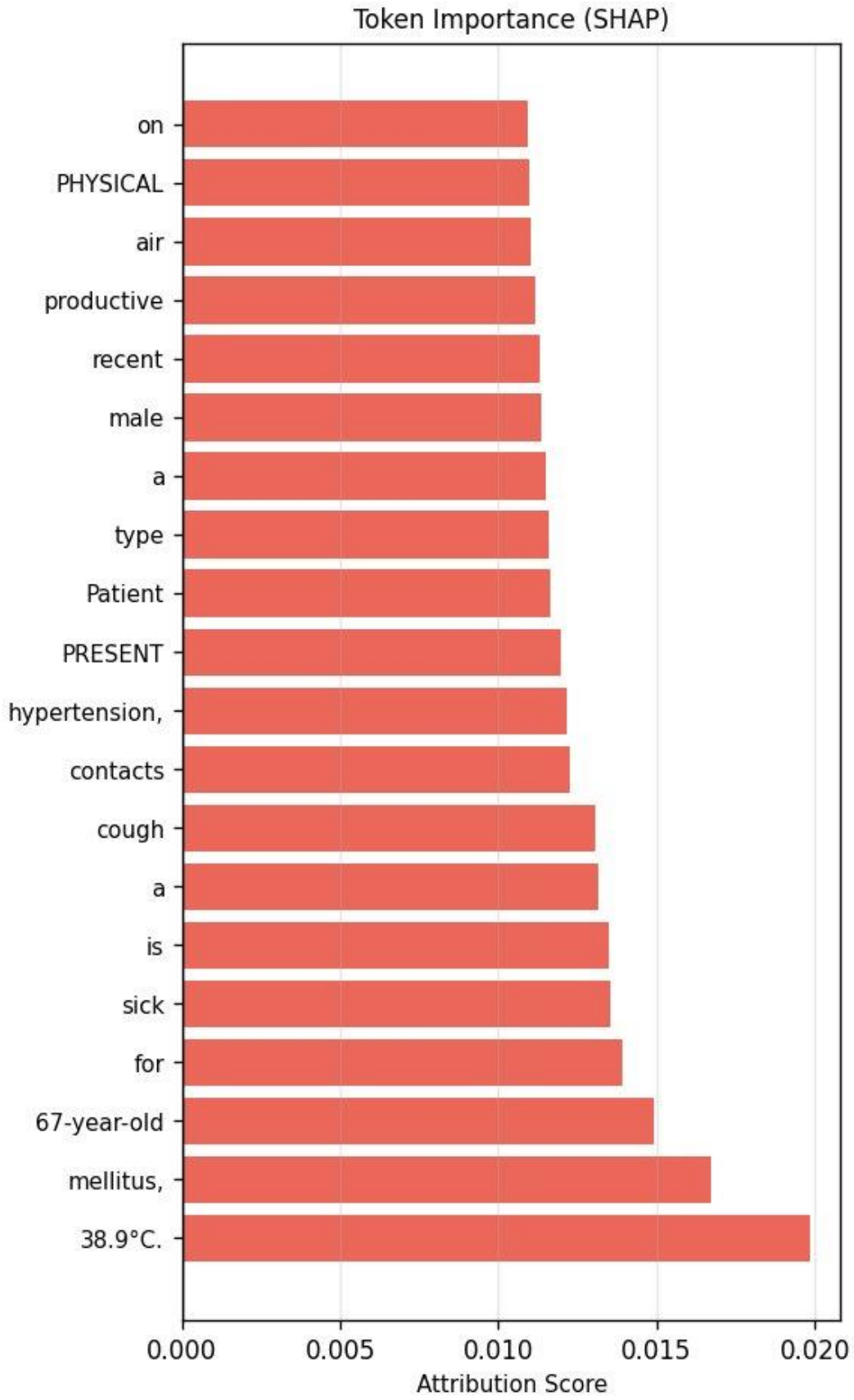

Figure 3: SHAP token attribution scores ranked by absolute value. 38.9 °C (fever), mellitus (comorbidity), and 67-year-old (age) are the dominant signals.

4.5 Cross-Modal Analysis

A key nding concerns the clinical faithfulness of the SHAP attributions. While 38.9 °C is a valid pneumonia indicator, the high ranking of mellitus and 67-year-old re ects dataset-level co-occurrence: in MIMIC-III, elderly diabetic patients are disproportionately represented among pneumonia-positive records, causing the model to weight demographic tokens spuriously. This bias is invisible from the classi cation score and is only surfaced by the SHAP pipeline.

Furthermore, spatial semantic comparison between the Grad-CAM output and the clinical note revealed a cross-modal discrepancy: heatmaps activated most strongly in the left lower lobe, while the clinical note described right lower lobe consolidation. The uni ed pipeline automatically agged this inconsistency. In a clinical deployment, this ag would prompt expert review before any diagnostic decision precisely the human- in-the-loop behaviour required by trustworthy AI frameworks.

5 Discussion

The results are presented without performance optimisation for a deliberate methodological reason. This work's primary claim is not state-of-the-art accuracy. The CNN branch, operating without ne-tuning (Params = 0), achieves AUROC 0.6799. The central claim is that the uni ed XAI pipeline surfaces three categories of clinically meaningful information inaccessible from accuracy metrics alone.

Finding 1: XAI detects silent training failures. The identical AUROC and F1 across Zero-Shot and CNN-Only con gurations exposed a silent failure in the ne-tuning loop. Without the XAI pipeline's diagnostic surfacing, this failure would have been indistinguishable from a genuinely trained model at the same score level
a direct demonstration of XAI as a system audit mechanism.

Finding 2: Token attribution reveals spurious correlations. SHAP identi ed mellitus and 67-year-old as high-attribution tokens for pneumonia demographic co-variates, not diagnostic indicators. Detection requires the token-level XAI layer and is impossible from aggregate performance metrics.

Finding 3: Cross-modal inconsistency is diagnostically informative. The spatial semantic discrep- ancy between Grad-CAM left-lobe activation and the clinical note's right-lobe description was automatically agged. This illustrates that the explanation system is a diagnostic instrument for the model's internal consistency, not just for individual predictions.

Limitations. The text branch evaluation uses a single representative note rather than a held-out test set. End-to-end supervised ne-tuning on MIMIC-III and ChestX-ray14 is required before clinical deployment. The cross-modal consistency metric is qualitative here; future work should formalise it as a quantitative faithfulness correlation score.

6 Conclusion

We presented an explainable multimodal CNN-RNN framework for chest X-ray diagnosis, unifying DenseNet- 121 image classi cation with RadBERT clinical text analysis under a single XAI pipeline delivering Grad-CAM heatmaps, SHAP token attributions, natural language summaries, and cross-modal consistency checks under a standardised output schema.

The central contribution is demonstrating that uni ed dual-modality XAI surfaces clinically meaningful in- formation that neither modality's explanation alone can provide: silent training failures, spurious demographic attributions, and cross-modal spatial semantic discrepancies, each with direct implications for patient safety in clinical AI deployment.

Future work will focus on end-to-end ne-tuning on MIMIC-CXR paired data, formalisation of the cross-modal faithfulness correlation metric, radiologist user studies, and extension to 3D volumetric imaging. This framework is positioned as a diagnostic instrument for clinical AI a system whose primary output is not just a prediction, but an explanation that enables human experts to verify, challenge, and ultimately trust the model's reasoning.

Declarations

Funding. Not applicable. Con ict of interest. The authors declare no competing interests. Ethics. ChestX-ray14 is a publicly available de-identi ed dataset. The clinical note used in text-branch evaluation was synthetically constructed and does not correspond to any real patient record. Data availability. https:

//nihcc.app.box.com/v/ChestXray-NIHCC. Author contributions. Ajay A: CNN pipeline, Grad-CAM, manuscript. Akash Aravind J: RadBERT branch, SHAP pipeline. Jayasubash T: uni ed XAI integration, cross- modal analysis. Lavanya Jayaraman: conceptualisation, supervision, review.

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