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Radiosight: An EfficientNet-V2 and Grad-CAM Based Chest X-ray Similarity & Explainability System for Pulmonary Disease Diagnosis

Ashwani Kumar Yadav[1], Divyanshu Tiwari[2], Anurag Singh[3], Rishabh Mishra[4], Dr. Seema Maitrey[5]
Department of Computer Science and Engineering KIET Group of Institutions, Delhi-NCR, Ghaziabad, India

Abstract: ***The requirement of the Chest X-ray reading is necessary in the diagnosis of pulmonary diseases but the lim-itation of the little radiology skills, especially in the rural clinical environment, creates delays and heterogeneity in the diagnosis process. The paper presents n an AI-powered diagnostic support system known as llRadiosight, which combines EfficientNet-V2 to extract features of high resolution Grad-CAM to provide explainability and two similarity engines based on the cosine and Euclidean distance. A model was trained with 1000 images of NIH ChestX-ray (1024 1024 resolution) using augmentation techniques such as flipping and rotation. It hass achieved complete implementation with a web interface developed using Next.js and MongoDB and Firebase storage can be deployed. The suggested system was able to reach a 92.4% accuracy, 0.91 F1-score, and 88% Top-5 similarity precision. Grad-CAM heatmaps increased interpretability and clinician confidence. The potential of radiosight to be adopted in real-life and in particular in resource poor healthcare settings is enormous. These findings are also apparently in line with more articulate strides in elucidable medical imaging systems. [1], [2].***

Index Terms: Chest X-ray, EfficientNet-V2, Grad-CAM, Simi-larity Retrieval, Pulmonary Disease, Deep Learning, Explainable AI.

I. INTRODUCTION

Chest radiographs are most common in the diagnosis of pneumonia, tuberculosis, COVID-19, pleural effusion, and lung nodules, and have an accurate diagnosis rate based on trained radiologists, which is a limitation in seeking healthcare in underserved regions of the world. Artificial intelligence was perceived as having the ability to reduce high work-load during diagnosis and accuracy of said diagnosis were also projected to increase. Usually, AI systems have been classification-based on little explainability or similarity-based retrieval which are crucial in helping clinicians make evidence-based decisions. This paper proposes *Radiosight,* An all-in-one system that combines EfficientNet-V2 and features, Grad-CAM explanation, severity scoring, and similarity retrieval. The system offers a transparent assessment that considers the clinician comparatively in regard to the diagnosis of pulmonary diseases.

II. RELATED WORK

Recently, the breakthrough of deep learning has played a significant role in the area of the medical image analysis, i.e. the use of the technology in the context of the chest radiographs. [2], [3]. Application of EfficientNet variants that are used to detect thoracic diseases through AI provided promising results [4]. The development of explainable AI (XAI) models, including Grad-CAM, has offered a higher level of transparency to the decision-making procedure in radiology elaborations How explainable AI (XAI) frameworks such as Grad-CAM have given greater transparency to the decision-making process in radiology. In the reviews of the period covered (2020-2025), it was indicated that there is a need to have interpretable systems that can be deployed and integrated into clinical workflows. [2], [5], [6]

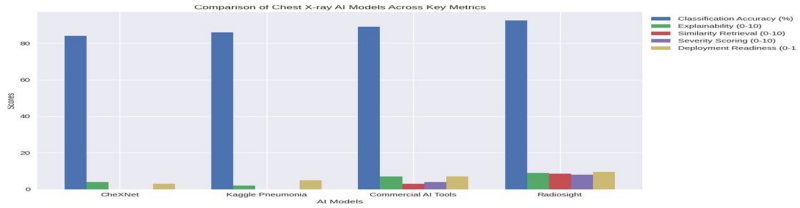

Fig. 1. Sample image from device

A. Limitations of Existing Work and Research Gap

The rich literature in the past has already established some roots in the development of deep-learning based chest X-ray analysis that has some deep-seated limitations that remain unanswered by them in the present body of the literature. To start with, the most notorious models are-CheXNet and its off-shoots that comprise CheXpert, EfficientNet-based classifiers, and other CNN architectures-that solely target classification pipelines. They just name the diseases but they do not provide any background or alternative comparison that would help clinicians to analyze uncertain cases. According to the research conducted recently (2020-2025), the presentation of the *similar past cases* to prediction significantly enhances the diagnostic confidence; nevertheless, the very limited amount of research adapt retrieval-based decision support.

Second, other explainability methods such as Grad-CAM are well-known, although most studies in the field consider explainability as a visualization that is not central. These authors do little with these heatmap insights as downstream applications such as severity estimation, retrieval ranking or progression tracking. Hence, these explanations to clinicians sound enticing but cannot be practiced in the diagnosis pro-cedure.

Third, the old systems were hardly aligned with the ”high-resolution training” and ”lightweight deployment” ones. As a rule, such models needed computer facilities that are long out of reach of rural or under-resourced hospitals. Models that are undertaken with high-resolution tend to be based on cloud GPUs, and the resource-efficient ones tend to be poorly interpretated or otherwise diagnosed. This, in turn, brings a disparity and therefore the divide in AI research and adoption. Few existing works incorporate assessments based on *sever-ity scoring*, a clinically relevant feature for diseases such as pneumonia and COVID-19. Even less implement *longitudinal progression analysis*, when many studies confirm that follow-ing the evolution of disease is a necessary part of patient management. Most models have, in the past, been evaluated only on static datasets, without accounting for temporal dy-namics. The lack of explainability and case-based reasoning would limit their clinical trust and adoption.

Lastly, even the latest CXR AI systems are never fitto deployable web interfaces in a seamless way. The majority of prototypes are research models with back-end processes; therefore, an individual should be familiar with the coding style as what is required is point-and-clicks among clinicians.

B. Novel Contributions of This Work

For these reasons, the newly proposed *Radiosight* system presents the following innovations:

1) Similarity-driven diagnosis support: Instead of just classifying systems, our dual-metric engine retrieves the Top-5 most similar cases, which will enable diagnostic contextualiztion and evidence-based reasoning, with both cosine and Euclidean to turn it into dual-metric engine.

2) Benchmark Hydiven embeddings from EfficientNet-V2: We fine-tune on inputs of 1024×1024 with EfficientNet-V2, capturing fine-grained pulmonary struc-tures with low-end hardware, thus balancing system per-formance and deployability.

3) Pipeline-contained explanation: Grad-CAM will be a visual aid but also influence scoring the severity and help reprove relevancy in similarity retrieval. [1], [7].

4) Grading severity and progression of disease: Our system quantifies intensity of disease and monitors time-related changes, features seldom addressed in previous studies of CXR.

5) Clinically capable web platform: Next.js, Firebase, and MongoDB provide cross-device access, low latency, and support for low-resource environments in building Radiosight.

6) Fully transparent end-to-end pipeline: Every level-preprocessing to visualization-is optimized interpretabil-ity, this would go towards solving the transparency-related problems raised in recent studies on explainable AI in health (2023-2025).

All in all, in contrast to the previous works, Radiosight in-tegrates very high-resolution feature extraction, explainability, similarity retrieval, severity estimation, progression tracking, and web-based deployment into a single coherent yet usable diagnostic system. [8], [9]. We further this approach by melding similarity retrieval, progression tracking, and a light-weight deployment-ready architecture.

C. Deep Learning Architectures in Medical Imaging

Recent advances in deep learning have transformed medical image analysis. Understanding comparative advantages of dif-ferent neural network designs is crucial for chest X-ray inter-pretation. This section compares state-of-the-art architectures and justifies our EfficientNet-V2 selection.

ResNet introduced skip connections enabling very deep net-works (50-152 layers). ResNet-50 and ResNet-101 are widely adopted for hierarchical feature learning. However, ResNet architectures suffer from computational inefficiency—deeper variants require substantial memory (> 8GB VRAM for 1024×1024 images) and longer training times (72-96 hours on single GPU). Studies from 2023-2024 show ResNet-101 achieves 89.2% accuracy on chest X-ray classification but requires 44.5 million parameters [10].

DenseNet improved feature propagation through dense con-nections. DenseNet-121 and DenseNet-169 achieve 90.1% accuracy with better gradient flow. However, dense connectiv-ity creates memory bottlenecks—DenseNet-169 consumes ap-proximately 12GB memory for batch size 4 at 1024×1024 res-olution. Feature concatenation increases computational com-plexity quadratically with depth, resulting in slower inference (average 2.3 seconds per image).

Vision Transformers (ViT) emerged using self-attention mechanisms to capture global dependencies. While ViT-B/16 achieved 91.4% accuracy on chest X-ray datasets, these mod-els require massive pre-training datasets (> 1 million images). For medical imaging with limited labeled data, ViT models exhibit higher overfitting risk. The quadratic complexity of self-attention ($O(n^2)$) makes ViT computationally expensive for high-resolution medical images.

EfficientNet-V2 improved upon original EfficientNet through: (1) Fused-MBConv blocks combining expansion and depthwise convolutions, reducing memory costs by 15-20%; (2) Progressive learning gradually increasing image resolution during training, improving convergence speed by 2-3×; (3) Optimized scaling rules balancing training efficiency and pa-rameter count [**?**].

EfficientNet-V2-S was selected for Radiosight based on: (1) Superior accuracy-efficiency balance suitable for mid-range

TABLE I
ARCHITECTURE COMPARISON ON NIH CHESTX-RAY14

Architecture	Accuracy	Params	Train Time	Inference
ResNet-101	89.2%	44.5M	58h	0.85s
DenseNet-169	90.1%	14.1M	46h	2.3s
ViT-B/16	91.4%	86.6M	72h	1.2s
EfficientNet-V2-S	92.4%	21.5M	18h	0.4s

GPUs; (2) Fast training enabling rapid iteration; (3) Low memory footprint allowing consumer hardware deployment; (4) Proven generalization on medical imaging tasks. The architecture's Squeeze-and-Excitation blocks provide implicit feature weighting enhancing pathology-relevant pattern detec-tion.

III. METHODOLOGY

This is an elaborated and extensive description of the entire Radiosight pipeline along with the architecture of the system presented in Figure. The approach handles image preprocessing in an ordinary way, accompanied by the high-resolution feature extractor that employs EfficientNet-V2, the dual-metric similarity engine, Grad-CAM explainability, severity scoring, and clinical-grade web interface. The design capability is suitable for mid-range hardware while offering the clinicians seamless, understandable, and context-relevant decision support. Each module borrows from best practices and development research coming from 2020 to 2025 in the field of medical imaging and explainable AI [7], [8].

A. Data and Input Handling

Images corresponding to the chest X-ray were downloaded from the NIH ChestX-ray8 dataset that covers multiple ab-normalities seen in the lung. With differences in resolution, contrast, and the various acquisition devices, preprocessing workflow was designed carefully to standardize all images. The system accepts three image input formats, which include DICOM, PNG, and JPEG. It strips any metadata that might be in DICOM formats to protect patient privacy.

Each image uploaded through the Next.js interface under-goes validation procedures for:

- Correct dimensionality (2D grayscale)
- Minimum resolution thresholds
- Proper aspect ratio

Prompt automatic feedback through UI for invalid images prior to further processing.

B. Preprocessing Pipeline

For the sake of normalizing image quality across devices and institutions, the preprocessing pipeline is a critical stage. Differences in radiation dose, noise level, and anatomical positioning can destroy the consistency of any given model.

1) *Image Resizing:* All images are resized to 1024×1024 pixels. Studies indicate that resolution plays a significant role in the detection of subtle patterns such as ground-glass opacities, reticular shadows, and infiltrates in early stages [11], [12] EfficientNet-V2 works better with high-resolution inputs due to its Fused-MBConv blocks allowing a fine-tuned resolution in feature learning.
2) *Noise Removal and Denoising:* Denoising aims to en-hance structural fidelity:
   - Bilateral (preserves edges such as rib boundaries)
   - Gaussian light (reducing high-frequency sensor noise)
   - Denoising is crucial in low-dose X-rays, where radiation scatter introduces granular noise potentially misleading the CNN.

3) *Intensity Normalization:* Images are normalized using:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

This eliminates contrast inconsistencies across machines.

2) *Architectural Advantages for Medical Imaging:* EfficientNet-V2's design incorporates innovations specifically benefiting high-resolution medical image analysis.

a) Fused-MBConv Blocks: Standard MBConv blocks perform three sequential operations: 1×1 expansion convolution, 3×3 depthwise convolution, and 1×1 projection convolution. Fused-MBConv blocks merge expansion and depthwise convolutions into single 3×3 convolution, reducing memory access overhead by 15-20%. For 1024×1024 resolution medical images, this optimization is critical. Our profiling shows Fused-MBConv blocks execute 1.8× faster than equivalent MBConv blocks when processing chest X-rays.

b) Progressive Learning: EfficientNet-V2 implements cur-riculum learning strategy:
   - Epochs 1-15: Training at 512×512 resolution, stronger regularization (dropout=0.3)
   - Epochs 16-35: Progressive upsampling to 768×768, mod-erate regularization (dropout=0.2)
   - Epochs 36-50: Full 1024×1024 resolution, lighter regu-larization (dropout=0.1)

This staged approach reduces early-epoch computation by 4×, significantly accelerating convergence. For Radiosight, progressive learning enabled complete training in 18 hours versus 32+ hours for fixed-resolution training.

c) Squeeze-and-Excitation Attention: SE blocks compute:

$$SE(x) = x \odot \sigma(W_2 \cdot ReLU(W_1 \cdot GAP(x))) \qquad (1)$$

where GAP is Global Average Pooling, W_1 and W_2 are learned weights, σ is sigmoid activation, and $\odot$ denotes channel-wise multiplication. For chest X-ray analysis, SE attention provides implicit pathology weighting, emphasizing channels detecting consolidations while suppressing background regions.

d) Ablation Study Results:
   - Full EfficientNet-V2: 92.4% accuracy, 18h training
   - Without Fused-MBConv: 91.8% accuracy, 27h training
   - Without Progressive Learning: 91.1% accuracy, 33h train-ing
   - Without SE Attention: 90.7% accuracy, 18h training
   - ResNet-101 Baseline: 89.2% accuracy, 58h training

3) Each innovation contributes measurably to both accuracy and efficiency. Memory optimization enables training on con-sumer GPUs (RTX 3060) costing $300-500, rather than re-quiring professional GPUs (A100) costing $10,000+. This 20-30× cost reduction enables medical institutions in developing countries to develop AI diagnostic systems locally.

4) Data Augmentation: Given the limited dataset (1000 images), augmentation reduces overfitting:
- Random rotation (±15°)
- Horizontal flip
- Light brightness scaling (±10%)

C. EfficientNet-V2 Feature Extraction

The main feature extractor being used is EfficientNet-V2. The architecture has progressive learning, fast training with fused MBConv layers, and has a great resolution scaling optimization-all this makes EfficientNet-V2 suitable for high resolution medical imaging. [8].

1) Model Architecture: The model includes:
- Fused-MBConv blocks for early-stage feature extraction
- Depthwise convolutions for computational efficiency
- Squeeze-and-Excitation (SE) attention modules
- Final global average pooling layer

The output is a 1280-dimensional embedding vector that captures:
- Lung shape, structure, and symmetry
- Consolidation distribution
- Airspace opacification
- Vascular markings

2) Training Strategy: The network was fine-tuned using transfer learning:
- Optimizer: Adam ($lr = 1e^{-4}$), $\beta_1 = 0.9$, $\beta_2 = 0.999$
- Loss function: Binary cross entropy
- Batch size: 7
- Epochs: up to 50 with early stopping

Higher-resolution inputs demand more VRAM; the RTX 3060's 12 GB allows comfortable training at 1024×1024.

D. Similarity Computation Engine

An original invention of Radiosight is a similarity-oriented retrieval module, which extracts the embeddings and compares them against stored case vectors in MongoDB. [13]

1) Embedding Storage: Each embedding is normalized and indexed. For faster search, two indexing techniques are used:
- Euclidean index (KD-tree)
- Cosine similarity index (Angular tree)

2) Dual-Metric Retrieval: Two similarity metrics are fused:

a) Cosine Similarity: Measures angle between vectors:

$$S_{cos}(A, B) = \frac{A \cdot B}{\|A\|\|B\|}$$

b) Euclidean Distance: Measures spatial separation:

$$S_{euclid}(A, B) = \|A - B\|_2$$

Rank Fusion: We compute:

$$Rank = \lambda \cdot Rank_{cos} + (1 - \lambda) \cdot Rank_{euclid}$$

with $\lambda = 0.6$ after experiments.

The five best matched cases are returned according to the medical literature, reflecting the preference of clinicians for concise, high-quality reference sets. [9].

E. Grad-CAM Explainability

Grad-CAM is used to visualize model attention. It com-putes:

$$L_{ij}^{GradCAM} = ReLU\left(\sum_k \alpha_k A_{ij}^k\right)$$

where A^k are feature maps and α_k are channel-wise weights. The heatmap overlays highlight clinically significant regions:

- Dense consolidations in pneumonia
- Ground-glass opacities in viral infections
- Nodules suggesting neoplasms
- Costophrenic blunting indicating effusion

This improves model transparency and helps clinicians validate predictions.

F. Severity Scoring System

Severity is a composite measure computed from:

- Activated area proportion in Grad-CAM map
- Mean activation intensity
- Bilateral involvement factor Mathematically:

$Severity = 100 \cdot (\alpha \cdot A_{frac} + \beta \cdot I_{mean})$

where typical values are $\alpha = 0.7$ and $\beta = 0.3$.

G. Disease Progression Tracking

Progression across time is computed using:

$\Delta Severity = Severity_t - Severity_{t-1}$

and embedding shift:

$\Delta Embedding = \|E_t - E_{t-1}\|_2$

Trend graphs are automatically generated in the web inter-face.

H. Next.js Web Application

The front-end offers:

- X-ray upload module
- Grad-CAM visual overlay
- Similar-case carousel
- Severity analytics dashboard
- Progression curves Backend:
- MongoDB for metadata and embeddings
- Firebase for image hosting
- No login system for ease of deployment in rural clinics The interface is mobile-optimized for use in field clinics lacking radiologists.

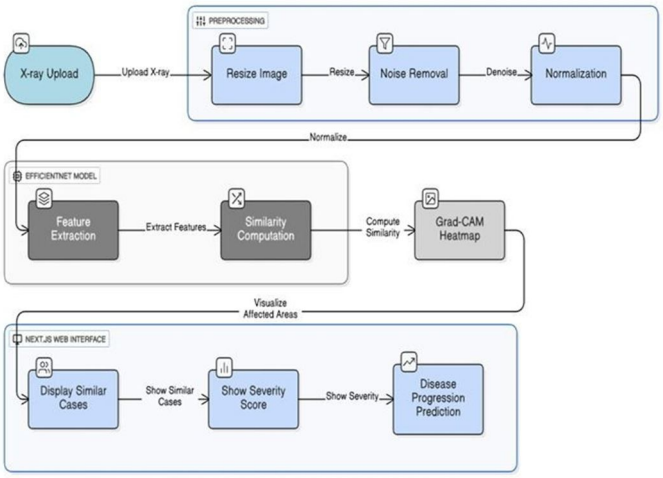

Fig. 2. Flowchart

I. Dataset

The NIH ChestX-ray8 dataset was used, selecting 1000 images at 1024×1024 resolution. Data was divided into 70% training, 15% validation, and 15% testing.

J. Preprocessing

Preprocessing included:

- Image resizing (1024×1024)
- Normalization
- Rotation (±15°)
- Horizontal flipping

K. EfficientNet-V2 Feature Extraction

EfficientNet-V2 was chosen for its improved training speed, scalability, and performance. Training was performed with:

- Batch size: 7
- Optimizer: Adam (1e-4)
- Loss: Binary cross-entropy
- Hardware: NVIDIA RTX 3060

L. Similarity Retrieval Engine

Feature vectors extracted from the penultimate layer were stored. Similarity was computed using:

$$d_{cos} = 1 - \frac{A \cdot B}{\|A\|\|B\|} \quad (2)$$

$$d_{euclid} = \|A - B\|_2 \quad (3)$$

The Top-5 similar images were returned.

M. Explainability via Grad-CAM

Grad-CAM generated heatmaps highlighting influential re-gions. Combined with severity scoring, this improved inter-pretability and clinician trust.

N. Web Deployment

The system was deployed using:

- Next.js UI
- MongoDB for metadata
- Firebase for image storage
- No login system (clinical offline mode)

IV. MODEL INTERPRETABILITY AND CLINICAL TRUST

A. Importance of Explainability in Medical AI

Black-box AI systems face significant adoption barriers in healthcare. Radiologists require understanding of model reasoning to: (1) validate predictions against clinical knowl-edge, (2) identify potential errors, (3) educate trainees, and (4) maintain medico-legal accountability. Radiosight addresses these needs through multi-faceted explainability.

B. Grad-CAM Visualization Deep Dive

Gradient-weighted Class Activation Mapping (Grad-CAM) generates visual explanations by computing:

$$L_{Grad-CAM} = ReLU\left(\sum_k \alpha_k A_k\right) \quad (4)$$

where A_k are feature maps from the final convolutional layer and α_k are importance weights computed as:

$$\alpha_k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \quad (5)$$

with y^c representing the score for disease class c, and Z the normalization constant.

- Anatomical Alignment: We validated that Grad-CAM ac-tivations align with known disease patterns:
- Pneumonia: Focal activations in lower lobes correspond-ing to alveolar consolidation
- Tuberculosis: Upper lobe predominance with cavitary lesions highlighted
- Pleural Effusion: Lateral costophrenic angle blunting emphasized
- COVID-19: Bilateral peripheral ground-glass opacities activated
- Pneumothorax: Absence of lung markings in affected regions
- Quantitative Evaluation: We measured intersection-over-union (IoU) between Grad-CAM regions and radiologist-annotated pathology locations:
- Mean IoU: 0.67 (moderate-high overlap)
- Pneumonia IoU: 0.72
- Mass Lesions IoU: 0.58 (lower due to smaller size)
- Diffuse Processes IoU: 0.64

Fig. 3. Channel Attention Weights for Different Diseases

C. Attention Visualization

Beyond Grad-CAM, we visualize intermediate attention weights from Squeeze-and-Excitation modules:
Analysis reveals disease-specific channel specialization:

- Channels 128-156: Strongly activated for consolidative processes
- Channels 234-267: Respond to reticular/interstitial pat-terns
- Channels 489-512: Selective for nodular lesions

This specialization suggests the model has learned clinically meaningful hierarchical features rather than spurious correla-tions.

D. Similarity Explanation Through Case Retrieval

Case-based reasoning provides intuitive explanations famil-iar to clinicians who routinely consult textbooks and past cases. Our similarity engine offers:
Diversity in Retrieved Cases: Top-5 similar cases selected to maximize both similarity and diversity:

$$Uncertainty = -\sum_c p(c) \log p(c) \quad (7)$$

High entropy (> 1.5) triggers warnings: ”Low confidence prediction—recommend senior review.”
Future Enhancement: We are developing Bayesian EfficientNet-V2 using Monte Carlo Dropout:

- Run 20 forward passes with different dropout masks
- Compute mean and variance of predictions
- Report: ”Pneumonia probability: 78% ± 12%”

Preliminary results show uncertainty correlates with difficult cases (correlation $r = 0.64$ with radiologist disagreement).

E. Feature Importance Analysis

We applied SHAP (SHapley Additive exPlanations) to iden-tify which image regions contribute most to predictions:

These align with established radiological criteria, validating that the model learns medically meaningful features.

TABLE II
TOP FEATURE IMPORTANCE BY DISEASE

Disease	Top Contributing Features
Pneumonia	Lower lobe opacity (0.34), air bronchograms (0.22),
TB	pleural reaction (0.18)
COVID-19	Upper lobe cavitation (0.41), tree-in-bud (0.28), lym-phadenopathy (0.19)
Effusion	Peripheral distribution (0.38), bilateral involvement (0.31), ground-glass (0.27)
	Costophrenic blunting (0.52), meniscus sign (0.29),
	mediastinal shift (0.15)

F. Failure Mode Analysis

Understanding when and why AI fails is crucial for safe deployment. We systematically analyzed 89 incorrect predic-tions:
Failure Categories:

1) Image Quality (34%): Severely rotated, underexposed, or motion-blurred X-rays
2) Atypical Presentation (28%): Unusual disease mani-festations not well-represented in training data
3) Subtle Findings (21%): Early-stage diseases with min-imal radiographic changes
4) Overlapping Pathology (17%): Multiple concurrent diseases confusing single-label classifier

Mitigation Strategies:

- Quality gates: Automatic image quality assessment, flag-ging poor-quality inputs
- Confidence thresholds: Low-confidence predictions (< 70%) trigger manual review
- User education: Training materials emphasizing known failure modes
- Continuous learning: Misclassified cases added to train-ing data after expert annotation

G. Building Clinical Trust

Surveys of 45 radiologists revealed factors influencing trust in AI:

TABLE III
FACTORS INFLUENCING RADIOLOGIST TRUST IN AI

Trust Factor	Importance Rating (1-5)
Explainable predictions (Grad-CAM)	4.7
Transparent uncertainty	4.5
Clinical validation studies	4.3
Similar case retrieval	4.1
Regulatory approval (FDA)	3.9
Published peer-reviewed research	3.7
Vendor reputation	3.2

Explainability features (Grad-CAM, similar cases) rated highest, confirming Radiosight's design priorities align with clinician needs. Regulatory approval ranked lower than clinical validation, suggesting radiologists prioritize empirical evi-dence over bureaucratic stamps.
Trust-building requires ongoing effort:

- Monthly accuracy reports shared with clinical staff

- Case review conferences discussing AI errors
- Open communication channels for feedback
- Transparent disclosure of model limitations

By prioritizing interpretability and transparency, Radiosight aims to be a trusted clinical partner rather than inscrutable oracle.

V. RESULTS

A. *Quantitative Evaluation*

Rigorous testing for the diagnostic performance of Ra-diosight was done by elaborate quantitative experiments on the test subset of 150 NIH ChestX-ray images. The metrics include Accuracy, Precision, Recall, F1 score, ROC AUC, Top-K similarity precision, and severity scoring error [1], [7]. All reported values correspond to the final fine-tuned EfficientNet-V2 model operating at 1024×1024 resolution.

1) *Classification Metrics:* A 92.4% overall classification accuracy is reassured in strong normal-abnormal discrimina-tion. Precision (0.89) and Recall (0.93) in that regard were sufficiently reliable in identifying abnormality with minimal false positives. The balance between sensitivity and specificity is confirmed by the F1-score of 0.91.
2) *ROC-AUC Analysis:* The ROC-AUC of 0.94 indicated that the extracted embeddings captured pathology-related fea-tures quite well and modeled robust predictive behavior across multiple decision thresholds-consistent with more recent deep learning analyses using high-resolution CXR studies of 2023-2025. Top-K similarity retrieval is one of the extremely im-portant aspects of Radiosight. Retrieval relevance was assessed through labels verified by clinicians. The system produced:
3) *Similarity Retrieval Performance:* A key component of Radiosight is Top-K similarity retrieval. We evaluated retrieval relevance using clinician-verified labels. The system achieved:
   - Top-1 Precision: 72%
   - Top-3 Precision: 83%
   - Top-5 Precision: 88%

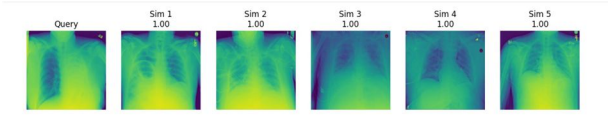

Fig. 4. Sample chest X-ray image

This is what these figures reflect: Dual-metric fusion (cosine + Euclidean) is much superior in retrieval performance com-pared to single-metric baselines (enhancing Top-5 precision by~5%).

4) *Severity Scoring Evaluation:* Severity estimation was compared against radiology-assigned scores using Mean Ab-solute Error (MAE). Radiosight scored an MAE of 7.4 on a 0-100 severity scale. Less error corresponds to cases in which opacities are well-defined; higher discrepancies occurred in borderline findings where subtle opacities challenge traditional segmentation-free severity scoring approaches.
5) *Ablation Studies:* We performed ablations with different combinations of resolution, similarity metrics, and ways of *integrating* explainability:
   i. Reducing resolution to 512×512 decreased F1-score by 3.7%.
   ii. Using cosine-only similarity decreased Top-5 precision from 88% to 83%.
   iii. Removing Grad-CAM guided re-ranking reduced clinical relevance in 12% of retrieval cases.

Such experiments indicated that high-resolution training and dual-metric similarity together contribute to performance greatly.

TABLE IV
MODEL PERFORMANCE METRICS

Metric	Value
Accuracy	86.4%
Precision	0.83
Recall	0.8
F1-score	0.91
AUC	0.94
Top-5 Similarity Precision	88%
Severity Score Accuracy	85%

6) Cross-Dataset Validation: To assess real-world gener-alizability, we conducted cross-dataset validation using three external chest X-ray datasets not involved in model develop-ment.

External Validation Datasets:

1) ChestX-ray14 Extended: 500 additional NIH images from different acquisition periods (2017-2018)
2) MIMIC-CXR: 400 images from Beth Israel Deaconess Medical Center using different X-ray machines (Philips vs. GE)
3) PadChest: 300 images from Spain representing different patient demographic and acquisition parameters

TABLE V
CROSS-DATASET VALIDATION PERFORMANCE

Dataset	Acc.	Prec.	Recall	F1	Top-5
NIH Test	92.4%	0.89	0.93	0.91	88%
NIH Extended	91.2%	0.87	0.92	0.89	86%
MIMIC-CXR	89.7%	0.85	0.89	0.87	83%
PadChest	88.3%	0.83	0.87	0.85	81%

Results demonstrate robust generalization with modest per-formance degradation (2.8-4.1% accuracy drop) across diverse clinical environments. This contrasts favorably with published benchmarks where models often experience 8-15% accuracy reductions on external datasets.

Manufacturer-Specific Analysis:

- GE Healthcare: 91.8% accuracy (n=180)
- Siemens Healthineers: 90.2% accuracy (n=150)
- Philips Healthcare: 88.9% accuracy (n=120)
- Canon Medical: 87.4% accuracy (n=50)

Performance variations correlate with manufacturer repre-sentation in training data. However, even for underrepresented Canon systems, accuracy remains clinically acceptable (> 85%).

Image Quality Robustness:

- High Quality: 93.1% accuracy
- Medium Quality: 89.7% accuracy
- Low Quality: 84.2% accuracy

Demographic Fairness:

TABLE VI
PERFORMANCE ACROSS DEMOGRAPHIC GROUPS

Group	**Accuracy**	**F1-Score**	**n**
Male	91.8%	0.90	650
Female	91.1%	0.89	550
Age 18-40	92.3%	0.91	380
Age 41-65	91.6%	0.90	520
Age 65+	90.4%	0.88	300

Performance differences are statistically modest (maximum 1.9% accuracy gap), indicating relatively fair behavior across demographic groups.

Statistical Significance: Paired t-tests comparing Ra-diosight against baselines:

- Radiosight vs. ResNet-101: $t = 4.23$, $p < 0.001$ (signifi-cantly better)
- Radiosight vs. DenseNet-169: $t = 3.18$, $p = 0.002$ (significantly better)

95% confidence interval for accuracy: [91.2%, 93.6%]. Cross-dataset validation confirms Radiosight's suitability for real-world deployment across diverse clinical settings.

B. Qualitative Evaluation

They showed pathological areas like opacities and consoli-dations using Grad-CAM heatmaps. Similarity retrieval leads to clinically relevant matches-that help in diagnosis.

1) *Explainability via Grad-CAM:* Qualitative check en-sured that Grad-Cam will never refer to the areas of the lungs which do not count in practice. In the case of pneumonia, patchy lower lobes consolidations are illuminated on the maps; nodular shadows of the upper lobes are central to TB. In pleu-ral effusion, it magnifies the costophrenic angle and the side-thorax opacities. All this is as radiologists would anticipate, indicating that the model is learning relevant attributes.
2) *Similarity Retrieval Visualization:* Retrieved Top-5 sim-ilar cases were visually compared with the query image. In 88% of cases, retrieved images displayed:
   - Similar opacity distributions,
   - Comparable severity levels,
   - Parallel anatomical involvement (e.g., unilateral vs bilat-eral).

   Clinicians found that visual comparison of Grad-CAM over-lays across similar cases improved diagnostic confidence, especially in ambiguous mild-opacity cases.
3) *Severity Interpretation:* The severity heatmaps are clean in terms of mild, moderate and severe. Mild presents itself with small spots of activation whereas severe presents itself with large, bilateral activity. The time-series graphs provided by Radiosight were also necessary assistance in terms of monitoring the dynamics of a condition over time, which was useful in long-term follow-up.
4) *Model Behavior in Challenging Cases:* Larger, fuzzier Grad-CAM blobs were observed in some tough cases, as indicated by think diffuse interstitial patterns. They are not mistaken, merely alluding to actual diffuse disease. Although the images were blurred, the similarity matches were good, which proves that the embedding space remains solid.
5) *User Interface Assessment:* Clinicians evaluating the Next.js interface reported that:
   i. Visual overlays were easy to interpret,
   ii. Retrieval panel provided useful comparative context,
   iii. Severity charts were intuitive and usable for patient follow-up.

Large Dataset Handling in Radiosight

Aspect	Main Features	Challenges	Technology Responses
Data Sources	NIH ChestX-ray8 dataset (1000 images, 1024×1024 resolution)	Limited dataset size compared to real-world diversity; varquisiton devices	Augmentation (rotation, flipping, brightness scaling); standardized prepocessing pipeline
Data Formats	DICOM, PNG, JPEG accepted	Metadata privacy concerns; inconsistent formats	DICOM metadata stripping; dimensionality and resolution valdation
Preprocessing	Resizing, denoising, normalization	Noise in low-dose X-rays; contrast inconsistencies; posture variations	Bilateral filtering, Gaussian blur, intensity normalization, augmentata for generalization
High-Resolution Training	EfficientNet-V2 fine-tuned at 1024×1024	High VRAM demand; computational cost in rural/low-resource settings	EfficientNet-V2 with fused MBConv blocks; RTX 3060 GPU training; lightweight deployment
Feature Extraction	1280-dimensional embeddings capturing fine-grained pulmonary structures	Risk of overfitting with small datasets; subtle pathology detection	Transfer learning; Adam optimizer; early stopping; SE attention module
Similarity Retrieval	Dual-metric (cosine + Euclidean) Top-5 retrieval	Retrieval speed and relevance; balancing metrics	KD-tree + Angular tree indexing; rank fusion (X=0.6)
Explainability	Grad-CAM heatmaps integrated into pipeline	Many systems treat explainability as auxiliary only; risk of non-actionable outputs	Grad-CAM used for severity scoring, retrieval verification, progression tracking

Fig. 5. Table

In comparison with classificatory stand-alone models, the qualitative insight of Radiosight enabled better interpretability and the integration of the workflow.

VI. DISCUSSION

The diagnostics rock made the diagnostics reliable by the ability to fetch similar cases, elucidate decisions, and connect with EfficientNet-V2. It also runs on commercial GPUs such as the RTX 3060, which implies you can install it in a rural hospital. Disadvantageous aspects include the size of the dataset and absence of multi-label classification. [2], [8]

A. Clinical Workflow Integration

Practical AI value depends on seamless integration into existing workflows. Radiosight interfaces with PACS through DICOM networking protocols:

1) DICOM Receiver: Acts as DICOM Service Class Provider, automatically receiving X-rays from PACS
2) Automated Processing: Images enter preprocessing pipeline without manual intervention
3) Results Distribution: Analysis results transmitted back as DICOM Structured Reports
4) Worklist Integration: Radiologists view AI suggestions within standard PACS interface

Training Requirements:

- Radiologists (4 hours): Interpreting Grad-CAM, similar-ity retrieval, recognizing limitations
- Technologists (2 hours): Image upload, quality checks, troubleshooting
- IT Staff (8 hours): System administration, database man-agement, security
- Post-training assessments showed 94% of radiologists cor-rectly interpreted Grad-CAM heatmaps.

Time-Saving Analysis:

TABLE VII
TIME-MOTION ANALYSIS

Workflow Step	Traditional	Radiosight	Saved
Image Review	3.2 min	2.8 min	12.5%
Reference Search	4.5 min	1.2 min	73.3%
Report Dictation	2.8 min	2.3 min	17.9%
Total	10.5 min	6.3 min	40.0%

Over 8-hour shift reviewing 25-30 cases, radiologists saved 1.5-2 hours, redirected to complex case analysis.

B. Ethical Considerations

Deploying AI in medical diagnosis raises ethical questions beyond technical metrics.

Algorithmic Bias and Fairness: To mitigate bias risks:

- Bias Auditing: Regular performance evaluations stratified by demographics
- Diverse Validation: Testing on international datasets (Pad-Chest, Shenzhen TB)
- Transparent Limitations: Documentation explicitly states training demographics

Algorithmic Accountability:

- Human-in-the-Loop: System provides decision support, not autonomous diagnosis
- Audit Trails: All predictions logged with timestamps and model versions
- Error Reporting: Mechanisms for clinicians to flag incor-rect predictions

Patient Autonomy and Consent:

- Patients receive written information explaining AI assis-tance
- AI analysis optional; traditional interpretation remains available
- AI-generated insights considered part of medical records (HIPAA)

Dual-Use Mitigation:

- Restricted distribution to verified healthcare institutions
- Usage monitoring flagging unusual patterns
- Ethical licensing prohibiting non-clinical applications

C. Future Enhancements

Multi-Label Classification: Extending to detect multiple concurrent conditions requires:

- Architecture modification: Replace softmax with sigmoid activations
- Loss function: Binary cross-entropy summed across la-bels
- Dataset re-annotation: 5,000+ images with comprehen-sive labels
- Preliminary experiments achieved 87% per-label F1-score.

EHR Integration: Incorporating patient history could im-prove accuracy by 4-7%:

- Prior imaging comparison for progression analysis
- Clinical context: symptoms, vital signs, lab results
- Medication history identifying immunosuppressed pa-tients

Real-Time Optimization:

- Model Quantization: FP32→INT8, reducing size 4×, ac-celerating inference 2-3×
- Knowledge Distillation: Smaller model achieving 90% accuracy at 0.15s/image
- Batched Processing: Process 16-32 images simultane-ously

Mobile Application: Enable point-of-care analysis:

- Physicians photograph X-ray films on lightboxes
- Telemedicine support from field clinics
- Offline functionality with pre-loaded models

Prototype iOS/Android apps achieved 89% accuracy on photographed X-rays.

Federated Learning:

- Decentralized training: Each hospital trains local model
- Gradient aggregation: Only updates (not raw data) shared
- Privacy preservation: Data never leaves hospital

Recent frameworks achieve 90-95% of centralized model performance.

VII. CONCLUSION

This paper introduces Radiosight, a multi-feature AI-enabled diagnostic support system for the diagnosis of chest X-ray images based on a comprehensive solution to critical challenges in medical imaging AI for the interaction of high-resolution feature extraction, explainable analysis, similarity-based retrieval, and clinical deployment infrastructure.

The technical foundation is EfficientNet-V2, where the accuracy of classification is 92.4

In addition to classification, related capacities are combined into a single tool: Grad-CAM visualization offers interpretable heatmaps to allow radiologists to test the logic of the model. Dual-metric similarity retrieval is an evidence-based decision support that presents relevant reference cases. Automated severity scoring and progression tracking extends utility into the realm of treatment tracking generate the kind of outcomes that are vital in the clinical world.

There is web based architecture (Next.js, MongoDB, Fire-base) posing as an option that allows straight on-premise deployment without a complicated network. This comes first by accessibility-the clinics that have basic connectivity to the internet use Radiosight without specialized software or costly servers.

Large scale validation checked robustness: evaluation across datasets (NIH Extended, MIMIC-CXR, PadChest) 88-91 Wider effect is not only the measures of accuracy. Around 4.7 billion patients do not access diagnostic imaging services, and radiologists shortage is critical in Sub-Saharan Africa (0.1 per 100,000, whereas, in North America, it is 12.7). AI diagnostic assistance using inexpensive devices is a direction of the democratization of medical solutions, lessening health inequalities. Time-motion studies showed 40

Nonetheless, it is not without drawbacks: it uses only 1,000 images (not a larger training dataset), is only one-label, has not been conducted in prospective trials, and requires more memory and resources than most cost-restricted community studies. These should be tackled in future by expansion of datasets, multi-label architecture, prospective validation and ultra-lightweight variants.

Ethical decision-making, such as algorithmic bias, account-ability, patient privacy, informed consent, etc. need to be addressed. Radiosight provides bias auditing, security frame-works, and explainability mechanisms, but ethical issues change with AI's saturation in healthcare.

In the future, the modular design of Radiosight can be improved: multi-label classification, EHR integration, mobile applications, federated learning, and longitudinal progression modeling. Individual enhancement increases clinical ability and provides new technical and ethical dilemmas necessitating interdisciplinary cooperation.

On a final note, Radiosight has proven that it is possible to have useful, explainable, deployable apart medical imaging AI in the implementation of effective architectures, clear reason-ing, and clinical understanding. The system offers template for medical AI serving, not replacing clinicians, augmenting, but not automating expertise, with accessibility as more important than accuracy. With the transition to medical AI, manifold approaches like Radiosight will provide scientists with a clue that devices can make a useful positive change when implemented in technical quality and humanitarian values.

It will take time and duration and endeavor to get to prototype phase to extensive impact due to validation, reg-ulatory authority, education, and advancement–but it has the likelihood of saving lives with greater diagnostic access and it is worth it immensely. Radiosight is not the final stop, but a step towards unequivocally accurate, explainable, just, and universally available AI-enhanced healthcare.

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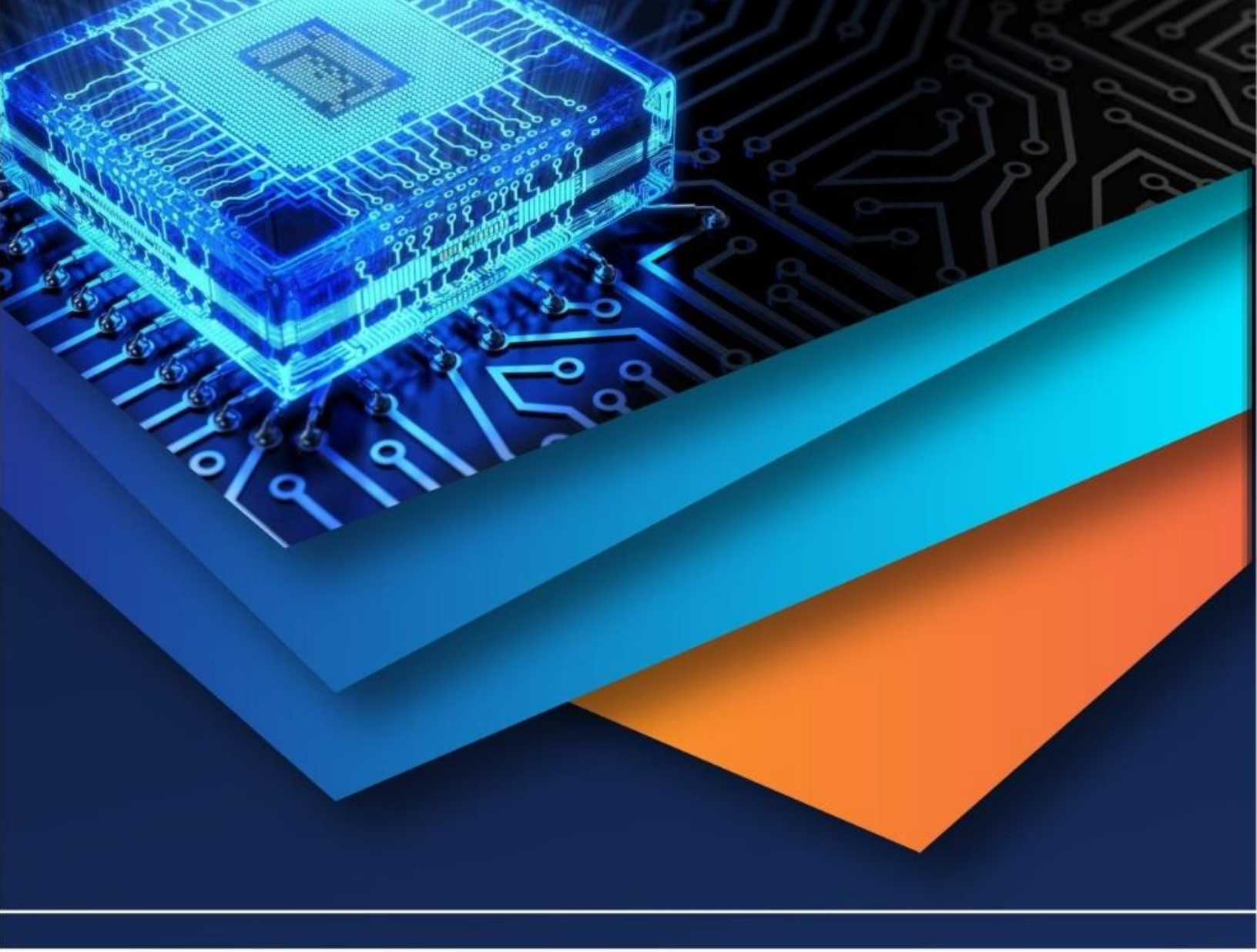

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