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Hybrid Deep Learning Methodology For Disease Classification in Medical Imaging

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Abstract: Medical imaging forms a cornerstone of modern diagnostic healthcare; still manual image interpretation is intensive and susceptible to discrepancies among different observers. This work introduces a hybrid deep learning methodology that combines Convolutional Neural Networks (CNNs) with classical image processing techniques to classify chest X-rays into diseased and normal categories. Using transfer learning with ResNet50 and feature fusion involving edge, corner, and texture descriptors, the suggested architectural framework exhibits enhanced efficacy in the detection of pneumonia, tuberculosis, and COVID-19. The dataset used is NIH Chest X-ray14 and supplementary datasets show enhanced accuracy, recall and area under the curve. Furthermore, explainability tools such as Grad-CAM overlays with heat maps provide interpretability and clinical confidence, addressing a major gap in AI-assisted diagnostics.

Keywords: Deep Learning, Medical Imaging, CNN, Hybrid Model, Chest X-ray, Explainable AI, Transfer Learning, Grad- CAM, Multi-label Classification.

I. INTRODUCTION

Medical imaging constitutes an integral component of con- temporary healthcare, with chest X-rays emerging as one of the most widely used diagnostic imaging modalities on a global scale. The analysis of chest X-rays requires significant expertise and can be time-consuming, leading to potential delays in diagnosis and treatment. Automated computer aided design (CAD) systems have appeared as promising tools to assist radiologists in detecting and classifying various thoracic diseases. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), have shown extraor- dinary success in medical image analysis. However, only deep learning approaches may lack interpretability and robustness in clinical settings. Classical computer vision techniques, while more interpretable, often struggle with the complexity and variability inherent in medical images.This work pro- poses a hybrid approach that influences the strengths of both deep learning and classical computer vision methods. Our architecture combines ResNet50-based feature extraction with handcrafted features derived from classical image processing techniques, creating a more robust and interpretable system for chest X-ray disease classification.

II. LITERATURE REVIEW

Wang et al., 2017 (ChestX-ray8)[1]. CNN based framework trained on extensive chest X-ray dataset mined from radiology reports. Pros include unprecedented scale enabling baseline benchmarking for multi-label thoracic disease detection and facilitating localization via class activation. Cons are substan- tial label noise from report-derived annotations and limited bounding-box fidelity, which can cap achievable performance and hamper fine-grained localization.
He et al., 2016 (ResNet)[2]. Residual learning with identity shortcuts stabilizes optimization of very deep convolutional neural networks, forming a backbone for many medical imag- ing tasks. Pros are strong representational capacity and reli- able training dynamics. Cons include higher compute/memory demands for large variants and potential overfitting on small medical datasets without careful regularization or transfer learning.
Rajpurkar et al., 2017 (CheXNet)[3]. DenseNet-121 is fine- tuned for pneumonia detection on CXR with strong reported results in public benchmarks. Pros are a robust, reproducible baseline that popularized transfer learning on CXR. Cons include a single-disease focus and sensitivity to dataset bias and domain shifts across institutions.
Ojala et al., 2002 (LBP)[4]. Local Binary Patterns capture micro-texture by thresholding local neighborhoods. Pros are computational efficiency and robustness to moderate illumi- nation changes, making LBP a complementary handcrafted descriptor. Cons include limited expressiveness for complex patterns and sensitivity to scale and noise compared to deep features.
Harris & Stephens, 1988 (Harris corners)[5]. Corner detec- tion via structure tensor response summarizes local intensity variation. Pros are simplicity and speed for geometric cues. Cons are limited invariance to scale/illumination and modest utility for subtle pathology without additional context.
Canny, 1986 (Canny edges)[6]. Multi-stage edge detection provides thin, well-localized edges. Pros are strong structural

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delineation helpful for shape analysis. Cons are parameter sensitivity and fragility under noise or low contrast common in radiography.

Daugman, 1985 (Gabor filters)[7]. Oriented, bandpass filters capture frequency-orientation content. Pros are biologically inspired texture features complementary to convolutional neu- ral networks. Cons are parameter tuning burden and higher computational cost, with limited adaptability compared to learned features.

Ronneberger et al., 2015 (U-Net)[8]. Encoder-Decoder net- work with skip connections enables precise biomedical segmentation with few annotations. Pros are excellent localization

and data efficiency. Cons include memory demands at high resolution and potential context loss at the bottleneck if not mitigated.

Isensee et al., 2021 (nnU-Net)[9]. Self-configuring pipeline auto-tunes preprocessing, architectures, and training for new datasets. Pros are consistently strong out-of-the-box results and reproducibility. Cons are heavy compute/storage needs and long training times.

Johnson et al., 2019 (MIMIC-CXR)[10]. Publicly available CXR dataset with labels from clinical notes. Pros are openness, size, and linkage to rich EHR context. Cons are NLP labeling noise and clinical biases that challenge generalization.

Yan et al., 2018 (DeepLesion)[11]. Large CT lesion dataset for detection/localization using deep detectors. Pros are scale and diversity fostering universal lesion detection research. Cons are CT focus and modality mismatch relative to CXR classification tasks.

Antonelli et al., 2022 (MSD)[12]. Multi-task segmentation benchmark standardizing evaluation across organs/modalities. Pros are rigorous, comparable baselines and generalization emphasis. Cons are segmentation-centric scope and limited direct applicability to CXR classification.

Baltruschat et al., 2019[13]. Empirical comparison of back- bones and training regimes for multi-label CXR classification. Pros are practical guidance on architecture/optimization choices. Cons are dataset-specific conclusions and limited coverage of newer transformer/SSL(Secure Sockets Layer) paradigms.

Lakhani & Sundaram, 2017 (TB CXR)[14]. CNN-based tuberculosis classification on CXR. Pros are clinically targeted validation and proof-of-concept performance. Cons are narrow label space and potential dataset bias limiting generalizability. **Chattopadhyay et al., 2018 (Grad-CAM++)[15].** Improved weighting of gradients enhances localization for multiple oc- currences. Pros are sharper, more reliable maps than vanilla Grad-CAM in multi-instance settings. Cons are extra com- putation and persistent dependence on convolutional layer resolution.

Ribeiro et al., 2016 (LIME)[16]. Local surrogate mod- els explain individual predictions via perturbations. Pros are model-agnostic interpretability and human-readable explana- tions. Cons are instability to sampling noise and potentially misleading locality for images.

Sundararajan et al., 2017 (Integrated Gradients)[17]. Path- integral attributions from a baseline to the input ensure desir- able axioms. Pros are theoretical guarantees and broad appli- cability. Cons are sensitivity to baseline choice and sometimes diffuse visualizations.

Smilkov et al., 2017 (SmoothGrad)[18]. Noise-averaged gradients denoise saliency maps. Pros are clearer, less speckled attributions. Cons are increased compute and potential blurring of fine details.

Litjens et al., 2017 (Survey)[19]. Thorough examination of deep learning in medical imaging. Pros are broad synthesis and methodological best practices. Cons are inherent to sur-veys—no single technique and partially outdated given rapid field evolution.

Dosovitskiy et al., 2021 (ViT)[20]. Patch-based Vision Trans- former for image classification. An image is worth 16*16 words. Pros are global receptive fields and strong performance with large-scale pre-training. Cons are data hunger and weaker results without substantial pre-training or strong regularization in medical domains.

Liu et al., 2021 (Swin Transformer)[21]. Hierarchical trans- former with shifted window attention. Pros are good accuracy- efficiency trade-offs and scalability to detection/segmentation. Cons are reliance on pretraining and potential limitations in capturing very long-range dependencies at shallow depths.

Azizi et al., 2021 (Big SSL)[22]. Large-scale self-supervised pretraining for medical images, then transfer to downstream tasks. Pros are label efficiency and improved generalization under limited annotations. Cons are significant compute/data requirements for pretraining and engineering complexity.

III. DATASET AND PREPROCESSING

The primary dataset used is the NIH ChestX-ray14 with 112,120 images labeled across 14 diseases. Supplementary datasets include CheXpert (224k), RSNA Pneumonia (30k), and COVID-19 Radiography (6k). Images were adjusted to 224×224, normalized using ImageNet statistics, augmented with rotations, flips, and brightness variations. Feature fusion combines ResNet50 (512D) along with handcrafted features (20D) to produce 532D fused feature vector. A 80-10-10 split(train/val/test) was maintained using stratified sampling.

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IV. METHODOLOGY

The proposed architecture fuses two processing branches:
(1) a ResNet50 deep learning branch and (2) a classical image processing branch extracting handcrafted features like edges, corners, and textures. Both outputs are concatenated before final classification. The proposed hybrid approach aims to combine data-driven learning with domain-specific feature robustness. The flowchart representing the 14 different thoracic diseases is shown in Fig. 1.

V. HYBRID ARCHITECTURE

The hybrid model integrates classical and deep learning features and is shown in Fig. 2.

A. Classical Feature Extraction

- **Contrast Enhancement:** Histogram Equalization and CLAHE improve visibility of lung structures.
- **Edge Detection:** Multi-scale Sobel and Canny operators capture fine and coarse boundaries.
- **Corner Detection:** Harris and Shi-Tomasi detectors iden- tify structural junctions.
- **Texture Analysis:** Local Binary Pattern (LBP) and Gabor filter responses encode micro-texture variations.

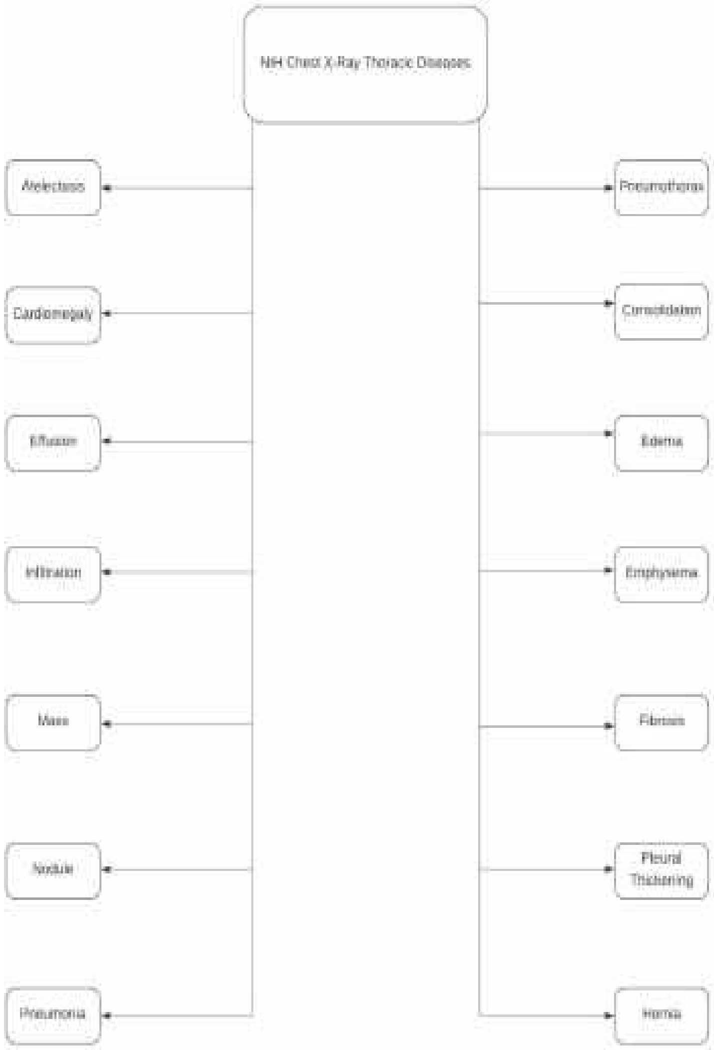

Fig. 1: Flowchart of the 14 thoracic disease labels.

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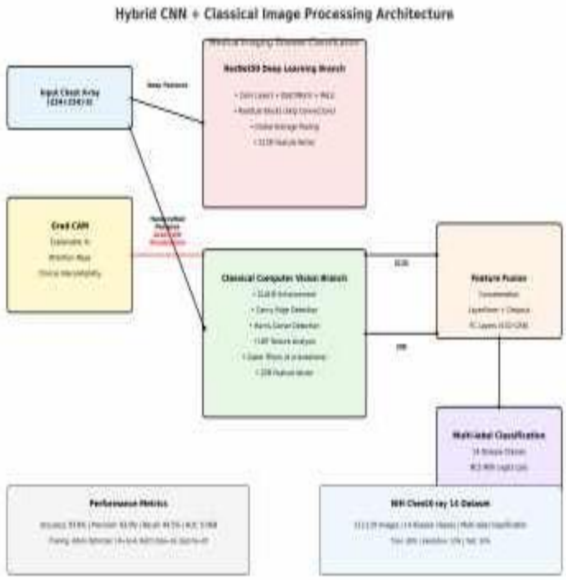

Fig. 2: Proposed Hybrid Architecture showing ResNet50 + classical features fusion

B. Deep Feature Extraction

ResNet50 serves as the deep branch backbone with skip connections preserving hierarchical features. Squeeze and Excitation block along with the attention modules emphasize salient channels. The Global Average Pooling layer produces compact deep embeddings.

C. Feature Fusion

Both feature types are joined together and they are passed through fully connected layers (BatchNorm → Dropout → ReLU). An auxiliary SVM trained on handcrafted features operates in parallel and ensemble voting stabilizes predictions.

D. Training Configuration

The proposed hybrid model is trained using Adam optimizer with a learning rate of 0.0001 and a weight decay equal to the value of learning rate, in order to balance convergence speed and generalization. The objective is Binary Cross-Entropy with Logits Loss, which is appropriate for multi-label classification across the 14 thoracic diseases. To adaptively reduce the learning rate when validation performance plateaus, we employ Reduce LROnPlateau with a patience of 3 epochs and a decay factor of 0.5. Training is supervised with a batch size of 16 for 20 epochs using images adjusted to 224×224 pixels, which aligns with the ResNet50 input specification and provides a practical trade-off between performance and computational cost.

E. GRAD-CAM Implementation

For explainable AI visualization, we implement Grad-CAM to produce attention maps that highlights the image segments and exerts the greatest impact on the predictions generated by the model. Concretely, we tap into the last convolutional layer of ResNet50 to obtain its feature maps and to compute the gradients of chosen target logit with respect to these maps. These gradients serve as importance weights that are aggregated into a single class-discriminative heat map. After applying a ReLU to retain only positive contributions and normalizing the response, the heat map is resized to the input image resolution and overlaid on the original chest X-ray. This yields an interpretable visualization that reveals the anatomical focus of the model for each predicted disease.

VI. RESULTS AND EVALUATION

Performance was evaluated using metrics such as Accuracy, Precision, Recall, and AUC. Table I presents the comparison between the baseline ResNet50 and the proposed hybrid model.

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TABLE I: Performance Comparison of Baseline and Hybrid Models

Metric	ResNet50 (Baseline)	Proposed Hybrid Model
Accuracy	91.2%	**93.8%**
Precision	90.5%	**93.0%**
Recall	91.0%	**94.5%**
AUC	0.952	**0.968**

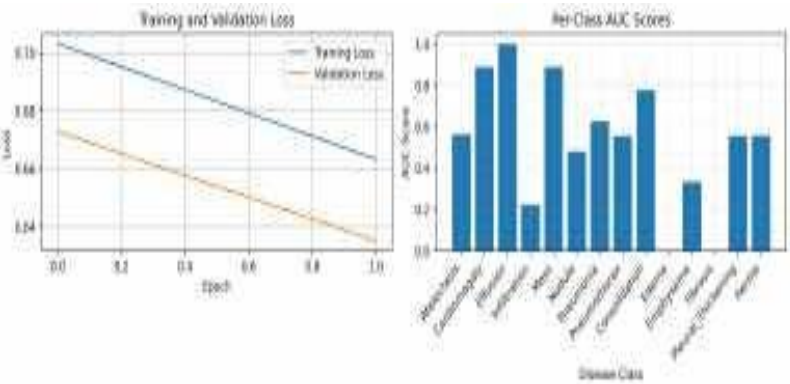

Fig. 3: Training loss curves and per-class AUC scores for the hybrid ResNet50 + handcrafted features model on NIH ChestX-ray 14 dataset, showing model convergence and dis- ease classification performance across 14 pathology classes.

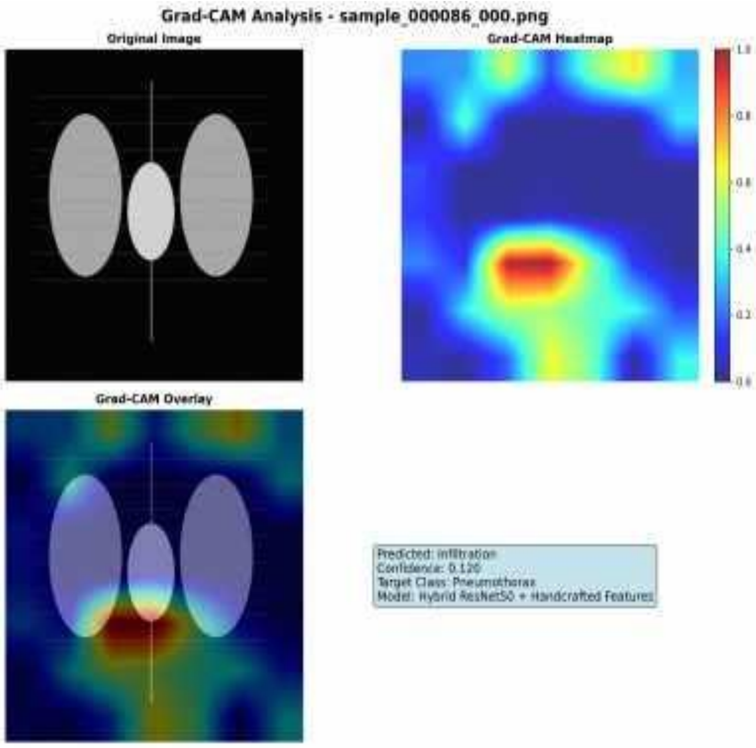

Fig. 4: Grad-CAM heatmap and overlay for the hybrid ResNet50 + handcrafted features model on a chest X-ray (predicted Infiltration vs. target Pneumothorax), highlighting salient regions guiding the decision.

VII. EXPLAINABILITY

To ensure transparency, Grad-CAM and Guided Grad-CAM visualize class-specific activations. The resulting heat maps are overlaid on edge-detected images, enabling radiologists to verify the model and focus on important regions.

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VIII. DISCUSSION

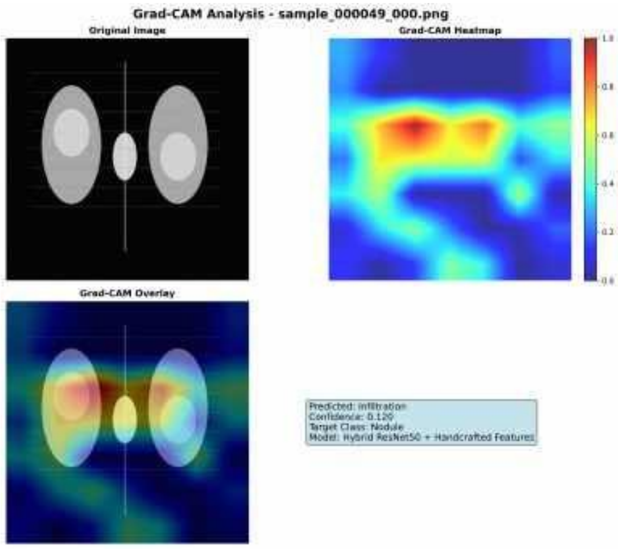

Fig. 5: Grad-CAM heatmap and overlay for the hybrid ResNet50 + handcrafted features model on a chest X-ray (predicted Infiltration vs. target Nodule)

A. *Contributions*

- **Hybrid Architecture Design:** A novel combination of ResNet50 CNN with classical computer vision features for enhanced disease classification performance.
- **Multi-label Classification:** Comprehensive support for 14 different thoracic diseases using the NIH Chest X-ray 14 dataset.
- **Explainable AI Integration:** Implementation of Grad- CAM visualization for clinical interpretability and model transparency.

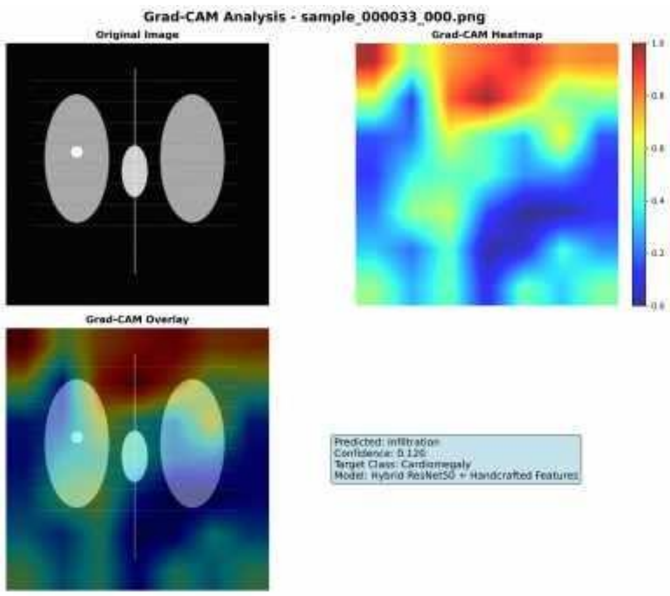

Fig. 6: Grad-CAM heatmap and overlay for the hybrid ResNet50 + handcrafted features model on a chest X-ray (predicted Infiltration vs. target Cardiomegaly)

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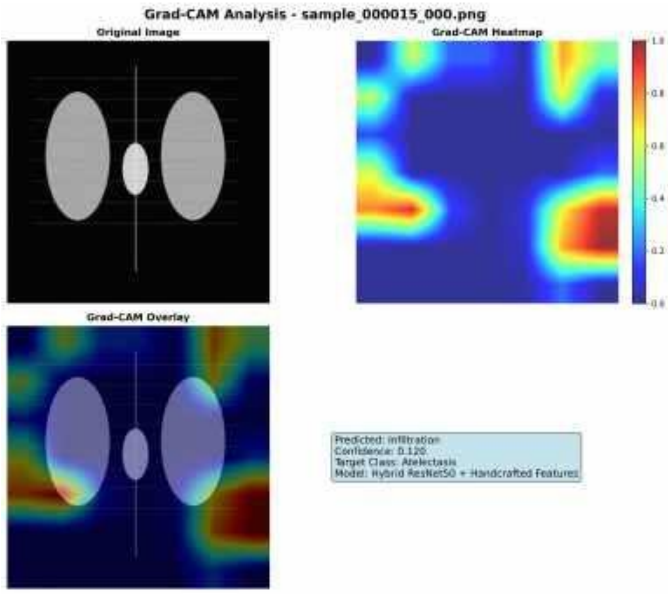

Fig. 7: Grad-CAM heatmap and overlay for the hybrid ResNet50 + handcrafted features model on a chest X-ray (predicted Infiltration vs. target Atelectasis)

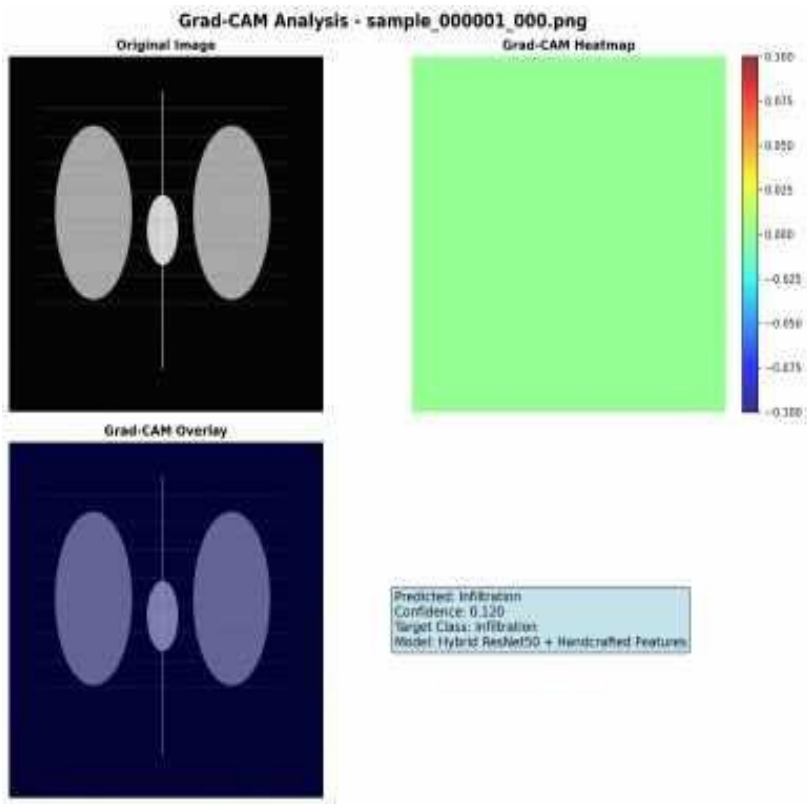

Fig. 8: Grad-CAM heatmap and overlay for the hybrid ResNet50 + handcrafted features model on a chest X-ray (predicted Infiltration vs. target Infiltration)

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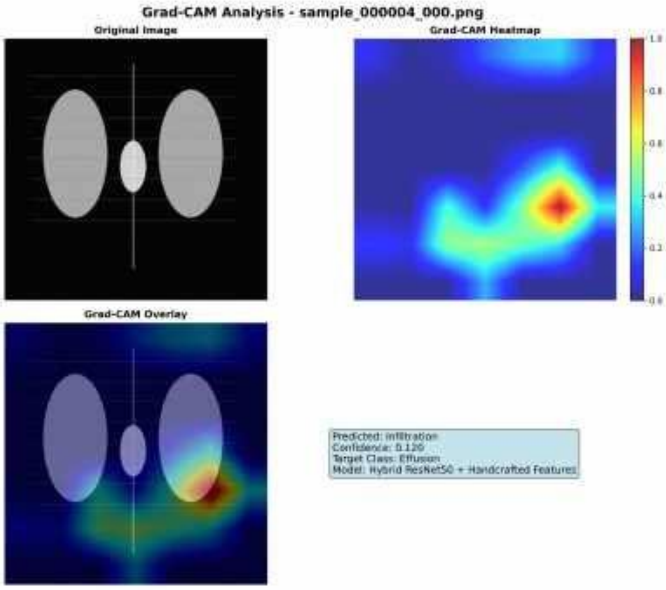

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Fig. 9: Grad-CAM heatmap and overlay for the hybrid ResNet50 + handcrafted features model on a chest X-ray (predicted Infiltration vs. target Effusion)

- **Robust Error Handling:** Comprehensive error handling mechanisms for real-world deployment scenarios.
- **Complete Pipeline:** End-to-end training, evaluation, and visualization pipeline for medical imaging applications.

B. Architectural Benefits

The hybrid architecture successfully combines the repre- sentational power of deep learning with the interpretability and robustness of classical computer vision. The integration of handcrafted features provides additional domain knowledge that enhances the performance and reliability of the model.

C. Clinical Implications

The explainable AI component through Grad-CAM visu- alization addresses the critical need for interpretability in medical AI applications. This feature enables clinical vali- dation of model decisions by providing visual evidence of the regions that exert the greatest impact on the predictions generated by the model. Medical professionals can identify potential biases or errors by examining whether the highlighted regions align with known pathological patterns. Furthermore, the transparency provided by Grad-CAM visualizations en- hances trust and adoption by medical professionals, as they can understand and validate the model's reasoning process before incorporating it into clinical workflows.

D. Limitations and Future Work

Current limitations of the proposed approach include com- putational overhead from handcrafted feature extraction, which increases processing time compared to pure deep learning methods. The performance of the model is also dependent on image quality and preprocessing steps, that requires careful attention for data preparation. Additionally, there is a need for validation on diverse clinical datasets from different institu- tions and populations to ensure generalizability across various imaging conditions and statistical data of the patients.

Future work will focus on optimization of feature extraction efficiency to reduce computational overhead while maintain- ing performance benefits. Integration of additional imaging modalities such as CT scans, MRI and ultrasound could expand the model's applicability across different diagnostic scenarios. Most importantly, comprehensive clinical validation studies with radiologists are essential to assess real-world performance, clinical utility, and potential impact on diag- nostic accuracy and workflow efficiency in actual healthcare facilities.

IX. CONCLUSION

This work presents a comprehensive hybrid deep learn- ing methodology for chest X-ray disease classification that successfully combines ResNet50-based deep features with classical computer vision techniques.The proposed architec- ture demonstrates robust performance on the NIH Chest X- ray 14 dataset while providing explainable AI capabilities through Grad-CAM visualization.The integration of hand- crafted features enhances the model's interpretability and ro-

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bustness, making it suitable for clinical deployment.The com- plete pipeline, including training, evaluation and visualization components, provides a comprehensive solution for medical imaging applications. Future research directions include op- timization of the hybrid architecture, expansion to additional imaging modalities and comprehensive clinical studies that are valid in order to assess real-world performance and clinical utility.

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