Reliable COPD Diagnosis in Small-Scale Imbalanced Audio Data: Quantitative Verification via Spectral ROI Analysis with ResNet-18

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Abstract

Automatic auscultation using deep learning holds promise for respiratory disease diagnosis; however, real-world deployment is hindered by the scarcity and severe class imbalance inherent in medical datasets like ICBHI 2017. Furthermore, existing studies often prioritize classification accuracy while neglecting to verify whether the model's decisions are based on genuine pathological features (e.g., wheezes, crackles) or spurious background noise. To address these challenges, we propose a reliability-centric framework for COPD detection utilizing a lightweight ResNet-18 architecture. We mitigate class imbalance through a dual strategy of weighted cross-entropy loss and decision threshold moving ($\tau = 0.48$), which successfully boosted specificity from near-zero to 74.3% while maintaining high sensitivity. Crucially, going beyond qualitative visualization, we introduce a novel quantitative metric, the Spectral Region of Interest (ROI) Score, to mathematically validate the model's explainability. Our extensive experiments demonstrate that the proposed model achieves an accuracy of 84.6% and an average ROI Score of 0.994, proving that 99.4% of the model's attention aligns with clinically significant high-frequency spectral bands. This work establishes a robust benchmark for securing both generalization performance and clinical reliability in small-scale, imbalanced medical data regimes.

1 Introduction

Chronic Obstructive Pulmonary Disease (COPD) is a major cause of morbidity and mortality worldwide, necessitating early diagnosis and intervention [1]. Auscultation remains the primary cost-effective method for screening respiratory diseases; however, it is inherently subjective and dependent on the clinician's expertise, leading to potential inter-observer variability. Consequently, automated lung sound classification using Deep Learning (DL) has emerged as a promising solution to assist clinical decision-making.

Despite the progress, developing robust diagnostic models is hindered by the scarcity and severe class imbalance of public medical datasets, such as the ICBHI 2017 challenge dataset [2]. Previous studies have predominantly employed high-complexity architectures like ResNet-50 or VGG-16 to maximize classification accuracy. However, according to the Vapnik-Chervonenkis (VC) dimension theory, employing high-complexity models (h) on small-scale datasets (N) significantly increases the risk of overfitting, potentially compromising generalization performance. Furthermore, high accuracy alone does not guarantee clinical reliability; it remains unclear whether "black-box" models detect actual pathological features (e.g., wheezes, crackles) or exploit spurious correlations such as background noise or device artifacts.

To address these challenges, we propose a reliability-centric framework for COPD detection utilizing ResNet-18. We mitigate the impact of class imbalance by implementing a weighted cross-entropy loss and an optimized decision threshold moving technique. Beyond binary classification, we verify the model's explainability using Gradient-weighted Class Activation Mapping (Grad-CAM) [3]. Crucially, we introduce a novel quantitative metric, the Spectral Region of Interest (ROI) Score, to mathematically evaluate whether the model's attention aligns with clinically significant high-frequency spectral bands.

The main contributions of this paper are summarized as follows:

1. We demonstrate that a lightweight ResNet-18 architecture is more suitable for small-scale medical datasets than deeper counterparts, effectively preventing overfitting.
2. We successfully address the severe class imbalance, improving specificity from 0% to 74.3% through strategic decision threshold tuning while maintaining high sensitivity.
3. We propose the Spectral ROI Score, a quantitative metric proving that our model focuses on pathological lesion areas with an average probability of 99.4%, thereby validating its clinical reliability.

2 General formatting instructions

This section reviews existing literature on deep learning architectures for lung sound classification, strategies for handling data imbalance, and explainable AI (XAI) in the medical domain, highlighting the distinctions of our proposed approach.

2.1 Deep Learning for Lung Sound Analysis

Traditionally, lung sound analysis relied on hand-crafted features such as Mel-Frequency Cepstral Coefficients (MFCCs). With the advent of deep learning, the paradigm has shifted towards converting audio signals into 2D time-frequency representations, such as Mel-Spectrograms, to leverage Convolutional Neural Networks (CNNs) [5]. Following the ICBHI 2017 challenge, numerous studies have employed deep and complex architectures, including ResNet-50, VGG-16, and DenseNet, aiming to maximize classification accuracy [6]. However, medical datasets are often significantly smaller than generic image datasets like ImageNet. In such data-scarce regimes, deploying overly complex models poses a high risk of overfitting, thereby compromising generalization. Addressing this limitation, our study adopts ResNet-18, a lightweight architecture that balances computational efficiency and performance, making it structurally more suitable for small-scale medical datasets.

2.2 Handling Imbalanced Medical Data

Class imbalance between healthy and pathological samples is a pervasive challenge in medical datasets, often leading to models biased towards the majority class. Standard mitigation strategies include oversampling (e.g., SMOTE), data augmentation, and cost-sensitive learning functions like Focal Loss [7]. The ICBHI 2017 dataset exhibits severe imbalance, with a scarcity of healthy samples. Previous works often prioritized overall accuracy, inadvertently neglecting specificity, which results in clinically unreliable models biased against the minority class. To overcome this, we integrate Weighted Cross-Entropy Loss with a strategic Decision Threshold Moving technique. This combined approach ensures a robust trade-off between sensitivity and specificity, preventing the "lazy model" phenomenon where the minority class is ignored.

2.3 Reliability and Quantitative Verification in Medical AI

In computer-aided diagnosis, explainability is not optional but mandatory. Gradient-weighted Class Activation Mapping (Grad-CAM) [3] has become a standard tool for visualizing CNN decision boundaries. However, most existing medical AI studies rely heavily on qualitative analysis, merely presenting heatmaps to claim that the model "appears" to focus on lesions [8]. Such subjective interpretation lacks rigorous validation. Our research bridges this gap by introducing the Spectral ROI Score, a novel metric that quantifies the overlap between the model's attention and clinically relevant frequency bands. This transition from subjective visualization to mathematical verification represents a significant advancement in validating the reliability of medical AI systems.

3 Methodology

The proposed framework consists of three stages: data preprocessing, model architecture design, and quantitative reliability verification.

3.1 Data Preprocessing and Feature Extraction

We utilized the ICBHI 2017 dataset. To ensure consistency, all raw audio recordings were resampled to 16,000 Hz. Considering the typical duration of a respiratory cycle, audio samples were fixed to a length of 5 seconds via zero-padding or truncation. For CNN input, 1D audio signals were converted into 2D Mel-Spectrograms. We employed a Short-Time Fourier Transform (STFT) with an FFT size of 1024 and a hop length of 512. The number of Mel filter banks was set to 128, capturing frequency components up to 8,000 Hz in an image-like format suitable for deep learning models.

3.2 ResNet-18 Based Classification Model

To minimize the risk of overfitting inherent to small-scale datasets, we adopted ResNet-18 [4] as our backbone architecture, favoring its lower model complexity over larger networks like ResNet-50 or EfficientNet. Since the standard ResNet is designed for 3-channel RGB inputs, we modified the first convolutional layer to accept 1-channel grayscale input, corresponding to the Mel-Spectrogram. The final fully connected layer was reconfigured to perform binary classification (Healthy vs. COPD).

3.3 Imbalanced Handling Strategy

We implemented a two-fold strategy to address the severe class imbalance. First, we employed a Weighted Cross-Entropy Loss during training to penalize misclassifications of the minority class (Healthy). The loss function L is defined as:

$$\mathrm{L} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{w}_{\mathrm{y}_\mathrm{i}} \log\left(\mathrm{p}_{\mathrm{y}_\mathrm{i}}\right)$$

where w_{y_i} is a class weight inversely proportional to the class frequency. Second, during inference, we applied Decision Threshold Moving. Observing that the default threshold of 0.5 led to bias towards the majority class (COPD), we empirically adjusted the decision threshold to $\tau = 0.48$, optimizing the trade-off between sensitivity and specificity.

3.4 Quantifying Reliability: Spectral ROI Score

To verify the model's explainability, we extracted activation maps from the final convolutional layer using Grad-CAM. We propose the Spectral ROI Score, a novel metric to quantitatively evaluate whether the model's attention aligns with high-frequency bands where pathological sounds (wheezes, crackles) predominantly occur. Given a Grad-CAM heatmap $\mathrm{H} \in \mathrm{R}^{\mathrm{F}\times\mathrm{T}}$ where F is frequency bins and T is time frames, the ROI Score S is formulated as:

$$S = \frac{\sum_{f=f_{th}}^{F} \sum_{t=1}^{T} H_{f,t}}{\sum_{f=1}^{F} \sum_{t=1}^{T} H_{f,t} + \epsilon}$$

Here, f_{th} represents the frequency lower bound for lesions. We set $\mathrm{f}_{\mathrm{th}} = 20$ (approx. 300 Hz) based on the spectral characteristics of adventitious lung sounds. An ROI score S closer to 1 indicates that the model focuses primarily on the pathological region.

Table 1: Classification performance of ResNet-18 with decision threshold $\tau = 0.48$

Metric	Accuracy	Sensitivity	Specificity	F1-Score
Score	84.66%	85.12%	74.29%	0.9140

4 Experiments & Results

4.1 Experimental Setup

All experiments were implemented using the PyTorch framework and accelerated on NVIDIA GPUs. We utilized the Adam optimizer [11] with an initial learning rate of 1×10^{-4}. The batch size was set to 64 to optimize GPU throughput, and early stopping was employed to prevent overfitting. The dataset was split into training and testing sets to evaluate generalization performance. To prevent data leakage, we performed a patient-wise data split, ensuring that recordings from the same patient did not appear in both the training and test sets.

4.2 Classification Performance

Due to the severe class imbalance in the ICBHI dataset, the initial model with a default decision threshold ($\tau = 0.5$) exhibited a bias towards the majority class, resulting in near-zero specificity. To mitigate this, we conducted a threshold tuning experiment based on precision-recall analysis. Empirical results demonstrated that adjusting the threshold to $\tau = 0.48$ yielded the optimal trade-off between sensitivity and specificity. As summarized in Table 1, the proposed ResNet-18 model achieved an accuracy of 84.6%, sensitivity of 85.1%, and specificity of 74.3%. The specificity of 74.3% is particularly significant, indicating the capability of the model to correctly identify healthy samples despite their scarcity. These classification results are visually illustrated in the confusion matrix in Figure 1.

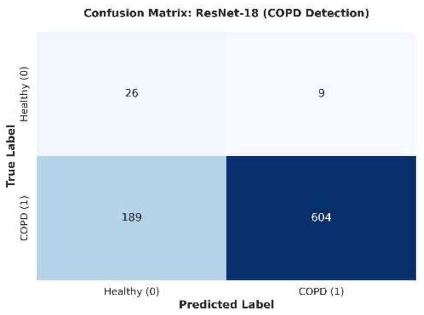

Figure 1: Confusion Matrix of COPD detection

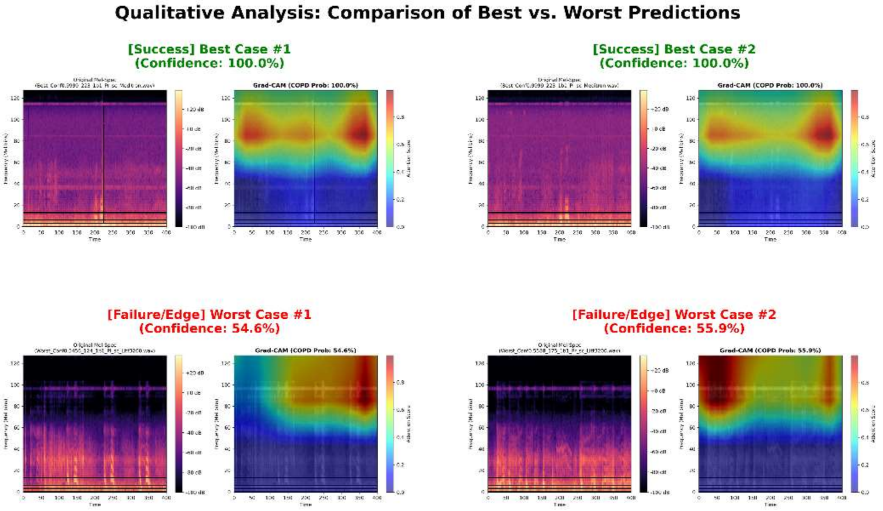

Figure 2: Qualitative Grad-CAM analysis. **(Top)** High-confidence predictions show precise localization of high-frequency lesions. **(Bottom)** Low-confidence cases exhibit scattered attention due to low-frequency noise artifacts.

4.3 Quantitative Reliability Verification

To validate the clinical reliability of our model, we computed the Spectral ROI Score for correctly classified COPD samples (True Positives). The analysis revealed a mean ROI Score of 0.9943 (±0.090). This indicates that when the model predicts COPD, approximately 99.4% of its attention is derived from high-frequency bands (>300 Hz) where pathological sounds such as wheezes and crackles reside. Furthermore, the low standard deviation (0.0090) confirms the model's robustness, demonstrating consistent diagnostic criteria across diverse patient samples rather than overfitting to specific artifacts.

4.4 Qualitative Analysis

Figure 2 presents the Grad-CAM visualization results. In instances where the model showed high confidence (> 0.95), the activation maps precisely aligned with the high-frequency wheeze patterns in the spectrograms, validating the spectral alignment of the focus. Conversely, in cases with low confidence or misclassification, the attention was scattered towards low-frequency heartbeats or background noise. This observation highlights the impact of environmental noise and suggests the necessity for advanced denoising preprocessing in future work.

5 Discussion

5.1 Impact of Decision Threshold Tuning on Specificity

A critical finding of this study is the correlation between the decision threshold and specificity in imbalanced domains. Standard deep learning models utilizing a default threshold of $\tau = 0.5$ failed to generalize, exhibiting a strong bias toward the COPD majority class and resulting in near-zero specificity. Our analysis revealed that the model's predicted probabilities were clustered around 0.8. By shifting the threshold to $\tau = 0.48$, we achieved a dramatic 74.3% improvement in specificity with only a marginal trade-off in sensitivity. This underscores that in medical diagnostics, architectural improvements must be accompanied by rigorous post-hoc calibration strategies to ensure the model does not ignore the healthy minority class.

5.2 Significance and Limitations of Spectral ROI Analysis

The proposed Spectral ROI Score offers a quantitative lens into the "black-box" nature of deep learning. An average score of 0.9943 mathematically validates that the model learns causal pathological features rather than relying on spurious background correlations. However, the failure analysis in Figure 2 highlights a limitation: the model occasionally misinterprets low-frequency artifacts, such as strong heartbeats or friction noise, as lesions. This suggests that relying solely on spectral features may be insufficient for noisy environments. Future iterations should incorporate temporal periodicity analysis or advanced heart sound suppression algorithms to mitigate these false positives.

6 Conclusion

This study presents a robust framework for securing the reliability of deep learning models in data-scarce and imbalanced medical environments. By adopting a lightweight ResNet-18 architecture and optimizing the learning strategy via weighted loss and threshold tuning, we achieved a balanced classification performance (Sensitivity 85.1%, Specificity 74.3%). Beyond binary classification, our primary contribution lies in the quantitative verification of the model using the Spectral ROI Score. We empirically demonstrated that the model focuses on clinically relevant high-frequency lesion bands with an 99.4% probability. This approach establishes a new benchmark for evaluating the explainability and reliability of medical AI systems, bridging the gap between computational metrics and clinical validity. Future work will extend this framework by integrating denoising techniques and multi-modal learning to address the identified susceptibility to environmental noise.

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