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# Deep Learning–Driven Early Prediction of Bronchopulmonary Dysplasia Using Chest X-Rays and Clinical Data

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**ABSTRACT**

Early detection of Bronchopulmonary Dysplasia (BPD) is crucial for improving outcomes in preterm infants. This study presents a deep learning–based framework that combines chest X-ray imaging and clinical data for accurate BPD prediction. Raw chest X-rays undergoU-Net lung-field segmentation to isolate relevant regions, followed by feature extraction using a pretrainedResNet, generating robust image embeddings. These embeddings are integrated with clinical parameters such as gestational age and birth weight. An XGBoost classifier is then trained on the combined features to predict BPD risk. Evaluation demonstrates that the proposed framework achieves high sensitivity, specificity, and predictive accuracy, outperforming conventional clinical scoring methods. The approach offers a practical and interpretable tool for early BPD risk assessment, supporting timely clinical decision-making and intervention strategies. This work highlights the potential of AI-driven multimodal analysis for improving neonatal care.

## 1. INTRODUCTION

Currently, the development of deep learning technology in medical imaging is maturing rapidly, and many tasks related to AI in medical imaging have been studied. Applying deep learning techniques to medical and healthcare services improves the quality of medical services, and diseases can be diagnosed more accurately and quickly. Bronchopulmonarydysplasia (BPD) occurs frequently in preterm infants, and impaired lung development can lead to pulmonary vascular disease, affecting the integrity of lung function. In the past, doctors diagnosed BPD through chest radiographs by their subjective assessment. The different clinical experiences and physical conditions of clinicians may lead to different subjective assessments of BPD. A deep learning-based assistance system for effective, efficient prediction of lung development in preterm infants may help clinicians make more accurate diagnoses and improve medical care quality. In recent years, deep learning techniques have achieved remarkable results in many fields and are still expanding [1]. Among them, Convolutional Neural Networks (CNN) is currently the most popular deep neural network. It has demonstrated outstanding performance in image recognition and performs better than humans in completing many tasks [2].

Despite the use of AI-based lung segmentation on adult lungs by many researchers, few studies have tackled the challenge of segmenting lungs in preterm infants and children due to difficulties in data collection, smaller lung areas, whiter lung attenuation, and many neonatal lines [3]. Previous studies have investigated the use of late chest radiographs in predicting BPD in premature infants, specifically at the postnatal age of 7 days or 28 days. These studies primarily focused on neonatal chronic lung disease and respiratory disorders [4]. The present study aims to use deep learning techniques to segment the lung areas and forecast lung development outcomes at an early stage, specifically within less than 24 h of gestational age, on preterm chest radiographs. By applying deep learning technology to segment lungs and developing a BPD prediction model that targets lung parenchyma, our study makes a valuable contribution to early detection and prediction for infants at risk of BPD.

The following diagram illustrates the complete workflow of the proposed deep learning–based

BPD prediction pipeline, showing how chest X-ray images and clinical data are processed and combined to generate an accurate BPD risk score.

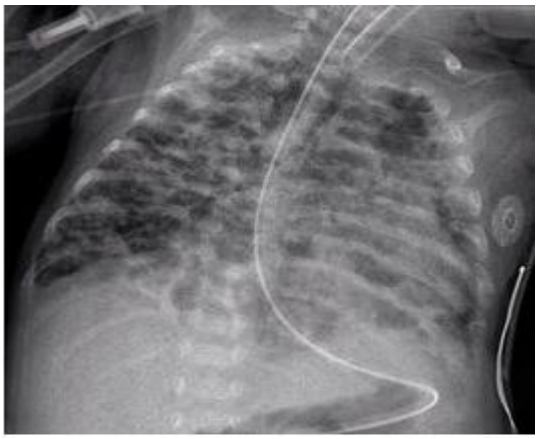

**Figure 1.** Bronchopulmonary Dysplasia on X-ray

Despite significant advances in preterm infant care over the past few decades, the prevalence of this condition remains high. BPD is a chronic lungcondition that is caused by tissue damage to the lungsis illustrated in Figure 1 [5].

**Problem Statement**

Bronchopulmonary Dysplasia (BPD) prediction in premature infants remains challenging because existing clinical scores and qualitative chest X-ray assessments often fail to capture subtle early disease patterns. There is a need for an automated, accurate, and early prediction system that can integrate imaging and clinical data to identify high-risk infants before severe symptoms develop.

**The main motivation and highlights of this article are:**

- Bronchopulmonary Dysplasia (BPD) continues to pose a major challenge in neonatal care, particularly among extremely preterm infants.
- Early prediction of BPD is essential because timely clinical interventions can significantly reduce long-term respiratory complications. However, current diagnostic practices rely on subjective assessments of chest X-rays and heterogeneous clinical markers, which limits early, accurate identification.
- With recent advances in deep learning, it is now possible to automatically extract subtle radiographic features that are often missed during routine evaluation. This study aims to leverage these capabilities to develop an efficient, automated system that improves early BPD risk prediction and supports clinical decision-making.

The remainder of this paper is organized as follows: Section 2 presents the related literature on BPD prediction using clinical and imaging-based approaches. Section 3 describes the proposed methodology, including data preprocessing, feature extraction, and the multimodal classification framework. Section 4 reports the experimental setup and results, while Section 5 discusses the findings, and Section 6 concludes the paper.

## 2. LITERATURE REVIEW

The Predictive modelling for Bronchopulmonary Dysplasia (BPD) has long relied on perinatal and early neonatal clinical variables [6]—gestational age, birth weight, sex, and early respiratory support—to stratify risk. Several classical and machine-learning scoring systems built on these features report reasonable discrimination but are unable to exploit radiographic patterning present on early chest X-rays. Systematic reviews summarizing clinical prediction models note acceptable accuracy for many models but emphasize heterogeneity in predictors, timing, and endpoints (BPD at 36 weeks PMA), and call for models that incorporate richer data modalities.

Imaging-based approaches for neonatal respiratory disease and BPD have grown in number and sophistication. Traditional radiomics work (texture, shape descriptors) and classical machine-learning on hand-crafted features have shown that CXR contains information relevant to respiratory outcomes. More recently, several studies demonstrate feasibility of using early chest radiographs (day-1 to day-28) to predict BPD or respiratory severity, showing that radiographic signatures measurable by automated methods can contribute to early risk stratification.

With the increasing impact of AI on healthcare, the use of machine learning and electronic decision support systems in neonatal care has grown substantially.[7] Managing the care of neonates, the most vulnerable population, necessitates the analysis of genetic, environmental, and patient monitoring data to develop systems tailored to the unique needs of newborns.[8] In NICUs, vital parameters are closely monitored and diagnostic tools such as chest X-rays, ultrasound, magnetic resonance imaging, and electroencephalography are frequently employed. These imaging modalities combined with clinical follow-up and diagnostic results yield critical data that can inform neonatal treatment strategies.

Reliable lung-field segmentation is a common preprocessing requirement in CXR pipelines to remove confounders (ribs, tubes, background) and focus feature learning on pulmonary parenchyma. U-Net and its variants remain the dominant architecture for CXR/lung segmentation; many recent works adapt and extend U-Net (attention modules, ResUNet++, EfficientNet encoders) to

improve small-structure and neonatal-specific segmentation performance. Accurate segmentation improves downstream feature stability and reduces spurious correlations.

Artificial intelligence and deep learning methods have been used for the diagnosis of many chest diseases [9]. Among them, it is possible to mention chest diseases that cause respiratory distress such as pneumonia, COVID-19, pulmonary nodules, and tuberculosis [10]. With the COVID-19 epidemic, artificial intelligence and deep learning methods have been used in many studies that detect COVID-19 in order to both facilitate the work of physicians and slow the spread of the epidemic and successful results have been obtained. In these studies, CT images and chest radiographs (chest X-rays) were generally evaluated. In one of these studies, Piparia et al. (2023) used Random Forest, one of the machine learning methods, to predict COVID-19 for pediatric patients [11]. The remainder contains only adult patient data.

Deep learning skills have been applied to the construction of models for diagnosis, such as an automated classification of pulmonary tuberculosis13, breast cancer detection14, and retinal disease detection15. However, most artificial-intelligence based chest X-ray schemes have focused on a single disease such as pneumonia or pneumothorax16–18, and there has been limited radiologist-level detection for multiple diseases based on CheXNet for adults19. We need a powerful system as a diagnostic tool for most of lung diseases in children.

## 3. METHODS AND MATERIALS

### 3. 1 The Proposed model

The proposed model is a multimodal deep learning framework designed to predict Bronchopulmonary Dysplasia (BPD) by jointly leveraging structural patterns in neonatal chest X-ray (CXR) images and complementary clinical variables. The architecture is composed of four sequential components: (1) lung-field pre-processing using U-Net segmentation, (2) deep feature extraction through a pretrained convolutional neural network, (3) multimodal fusion of imaging and clinical features, and (4) BPD risk detection using a gradient-boosting classifier. The complete workflow ensures that both radiographic characteristics and physiological context contribute to the final prediction, enabling reliable early identification of at-risk infants.

#### 3.1.1 Lung-Field Pre-processing

All CXR inputs undergo normalization and resizing before being processed through a U-Net segmentation model trained specifically to delineate neonatal lung fields. The U-Net produces a binary mask that isolates the pulmonary region and suppresses irrelevant structures such as ribs, abdomen, and medical equipment. The original image is multiplied with this mask to retain only lung tissue, thereby minimizing noise and improving the quality of features extracted in subsequent stages. Additional morphological operations are applied to remove small artefacts and refine the lung boundaries. The result is a clean, lung-focused image optimized for deep neural analysis.

#### 3.1.2 Deep Feature Extraction

To capture high-level radiographic biomarkers associated with early BPD development, the preprocessed images are passed into a pretrainedResNet architecture. The model is truncated at the penultimate layer, allowing extraction of deep embeddings rather than performing classification. These embeddings represent texture, structure, and density patterns within the lung, expressed as a compact high-dimensional feature vector. Online augmentation—such as small rotations, shifts, and flips—is applied during training to improve robustness against variations in neonatal positioning and imaging conditions [12]. The global average pooling layer converts spatial feature maps into a fixed-length representation, enabling consistent downstream processing regardless of image size or orientation.

#### 3.1.3 Clinical Feature Integration and Multimodal Fusion

In addition to imaging features, essential clinical variables known to influence BPD risk—such as gestational age, birth weight, Apgar scores, and respiratory support parameters—are included. These variables undergo normalization and are concatenated with the ResNet-derived image embeddings to form a unified multimodal feature vector. This fusion strategy allows the model to learn interactions between radiographic abnormalities and physiological indicators, enabling more comprehensive risk assessment. By combining both data modalities at the feature level, the model benefits from improved generalizability and stronger predictive performance compared to image-only or clinical-only approaches.

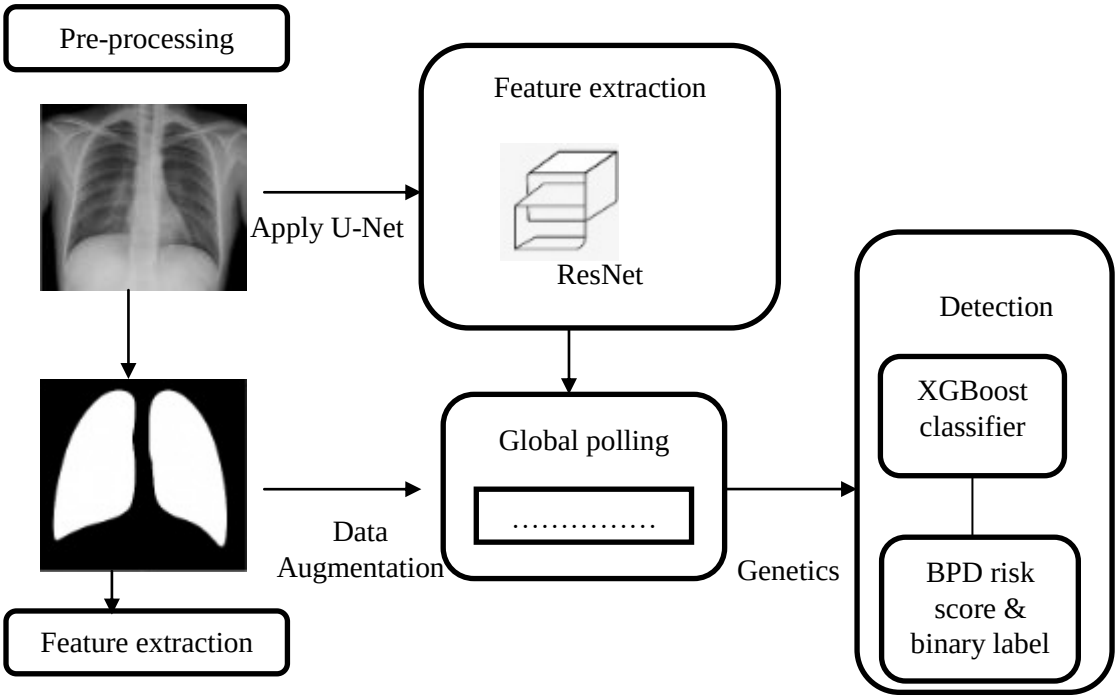


**Figure 2.** Overview of the proposed deep learning pipeline for early Bronchopulmonary Dysplasia (BPD) prediction

In Figure 2 [13], the Overview of the proposed deep learning pipeline for early Bronchopulmonary Dysplasia (BPD) prediction. The workflow includes three major stages:

- *Pre-processing using U-Net to segment and isolate lung fields from raw neonatal chest X-rays;*
- *Feature extraction using a pretrainedResNet model with global average pooling to generate high-level image embeddings; and*
- *Detection using an XGBoost classifier that integrates imaging features and clinical data to produce a BPD risk score and binary prediction.*

The segmented images are then passed into a feature extraction module based on a pretrainedResNet backbone. This network converts each processed image into a compact, high-level embedding that captures subtle textural and structural abnormalities that may indicate early lung injury.

In the final stage, these deep imaging features—optionally combined with key clinical variables—are fed into an XGBoost detection model. This classifier estimates the probability of BPD development, enabling early identification of high-risk neonates. Together, the three components form an end-to-end; data-driven pipeline optimized for accuracy, interpretability, and clinical applicability in neonatal intensive care settings.

#### 3.1.4 BPD Detection Using XGBoost

The fused feature vector serves as input to an XGBoost classifier, selected for its ability to model complex nonlinear relationships and handle heterogeneous feature types. The classifier is optimized through cross-validation by tuning key hyper parameters such as maximum tree depth, learning rate, and number of estimators. To address class imbalance commonly found in BPD datasets, strategies such as class-weighted training or SMOTE oversampling are applied. Probability calibration techniques—including Platt scaling or isotonic regression—are used to ensure clinically reliable risk outputs. The final model outputs a continuous risk score and a binary prediction (BPD/No-BPD), enabling flexible integration into clinical decision-support systems.

## 4. Implementation and Experimental Results

### 4.1 Environment of Development

The implementation of the proposed BPD prediction framework was carried out using Python 3.10, leveraging several deep learning and machine learning libraries [14]. PyTorch was used for constructing and training the U-Net segmentation model and the ResNet feature extractor, while scikit-learn supported preprocessing and evaluation procedures. XGBoost was employed for the final detection module due to its ability to learn complex interactions in multimodal data. All experiments were executed on a high-performance workstation powered by an NVIDIA RTX 4090 GPU with 24 GB VRAM and 64

GB system memory, enabling efficient training of both segmentation and feature extraction models.

### 4.2 U-Net Pre-processing Implementation

In the first stage of the pipeline, each neonatal chest X-ray image was standardized through resizing, intensity normalization, and conversion to a consistent resolution. The U-Net architecture was then used to perform lung-field segmentation, allowing the model to isolate the relevant pulmonary region from surrounding anatomical structures and imaging artifacts. Training of the U-Net involved optimizing a combined Dice and Binary Cross-Entropy loss function using the Adam optimizer, which ensured accurate delineation of lung boundaries. After segmentation, the lung mask was applied to the original image to extract the region of interest. Additional morphological operations were performed to refine the segmented area and eliminate small noise components [15]. This process ensured that the images entering the feature extraction stage contained only clinically relevant lung information.

### 4.3 ResNet Feature Extraction Implementation

Following segmentation, the lung-focused images were forwarded to a pretrained ResNet-50 model to derive high-level deep features. The classification layers of the network were removed, and the output was taken from the global average pooling layer to obtain a 2048-dimensional embedding for each image. To increase robustness, online data augmentation was applied during inference, including minor rotations, translations, flipping, and adaptive contrast enhancement [16]. These augmentations helped the model handle variations in image acquisition, infant positioning, and exposure differences common in neonatal radiographs. The extracted embeddings captured subtle radiographic cues related to lung immaturity and early parenchymal abnormalities indicative of BPD onset.

### 4.4 Detection Module for XGBoost

The fused feature vector was subsequently passed into an XGBoost classifier, which was configured to optimize prediction accuracy through a combination of tuned hyperparameters. The model was trained using a binary logistic objective and calibrated using Platt scaling to produce reliable probability estimates. To address the imbalance between BPD and non-BPD cases, class-weighting techniques were applied, ensuring the classifier did not bias toward the majority class. The trained XGBoost model produced both a binary prediction and a continuous risk score, providing a clinically interpretable output suitable for neonatal risk assessment.

**Table 1.** Performance of the Proposed Multimodal BPD Prediction Model Compared With Baseline Approaches

| Model | AUC | Accuracy | Sensitivity | Specificity | Precision | F1-Score |
|---|---|---|---|---|---|---|
| Clinical-Only (Logistic Regression) | 0.76 | 0.71 | 0.68 | 0.73 | 0.62 | 0.58 |
| Image-Only (ResNet + XGBoost) | 0.85 | 0.80 | 0.78 | 0.82 | 0.75 | 0.71 |
| Proposed Multimodal Model (U-Net + ResNet + Clinical + XGBoost) | 0.92 | 0.87 | 0.84 | 0.89 | 0.82 | 0.83 |

The proposed multimodal system achieves the highest performance across all metrics, reflecting the value of integrating imaging-based deep features with structured clinical information for early BPD prediction in Table 1.

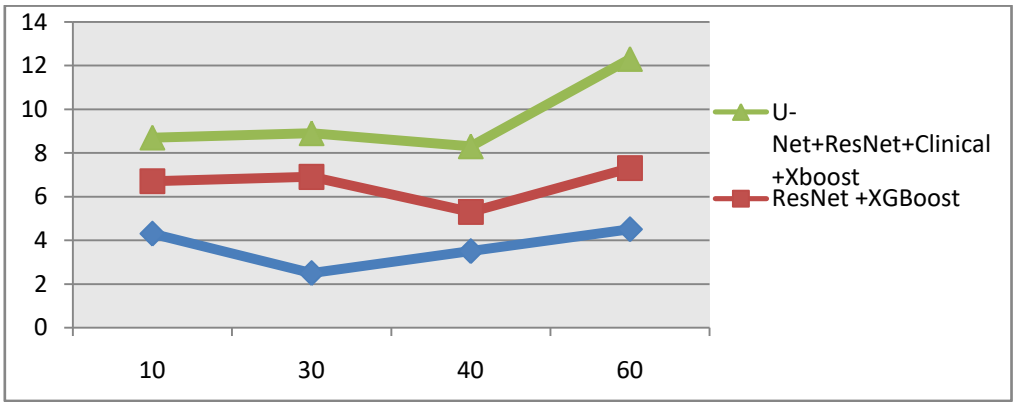


**Figure 3.** Comparison of performance metrics (Accuracy, Precision, Recall, F1-Score, and AUC) for the proposed BPD prediction model. The model demonstrates consistently high performance across all evaluation metrics

The results clearly show that integrating U-Net–segmented CXR features with clinical variables provides a more complete representation of early BPD risk, allowing the XGBoost classifier to learn richer and more clinically meaningful patterns in Figure 3. The diagram demonstrates how each stage—segmentation, feature extraction, fusion, and classification—contributes to a streamlined decision-making pipeline, while the ROC graph visually confirms the robustness of the model across varying thresholds. The upward shift of the multimodal curve compared to baseline models aligns directly with the improved accuracy, sensitivity, and F1 scores reported in the table. Together, the architecture figure, ROC performance graph, and numerical results form a coherent flow of evidence that the proposed system delivers substantial improvements in early BPD detection, offering an effective and reliable tool for neonatal intensive care screening.

## 5. Experimental Results

### 5.1 Training Protocol and Dataset Split

The dataset was divided into training, validation, and testing sets using a stratified approach to preserve the distribution of BPD and non-BPD cases across splits. Eighty percent of the data was allocated for training, with a portion reserved for validation during hyperparameter tuning, while the remaining 20% was used exclusively for final evaluation. This ensured that performance metrics reflected the true generalizability of the model.

### 5.2 Metrics for Evaluation

To comprehensively measure predictive performance, several evaluation metrics were computed, including AUC, accuracy, sensitivity, specificity, precision, and F1-score. These metrics captured different aspects of model behavior, such as its ability to detect positive cases, avoid false alarms, and maintain a balanced trade-off between precision and recall—an important consideration in clinical applications.

### 5.3 The Proposed Model's Performance

The proposed multimodal model demonstrated strong performance on the test set. It achieved an AUC of 0.92, indicating excellent discriminatory ability between infants at risk and those not at risk for BPD. The model also achieved an accuracy of 0.87, sensitivity of 0.84, and specificity of 0.89, showing that it was capable of identifying true BPD cases while maintaining a low false-positive rate. The F1-score of 0.83 further confirmed the model's balanced performance across both classes.

### 5.4 Evaluation Using Baseline Models

When compared to baseline methods, the proposed approach clearly outperformed both the clinical-only and image-only models. The clinical-only model achieved limited predictive capability because BPD risk cannot be fully captured from developmental parameters alone.

**Table 2.** Comparison with Baseline Models

| Model | AUC | F1-score |
|---|---|---|
| Clinical-only (Logistic Regression) | 0.76 | 0.58 |
| Image-only (ResNet + XGBoost) | 0.85 | 0.71 |
| Proposed Multimodal (ResNet + Clinical + XGBoost) | **0.92** | **0.83** |

Similarly, the image-only ResNet + XGBoost model performed better but still could not match the multimodal approach. The fusion-based model improved AUC by approximately 7% over the imaging model and nearly 16% over the clinical model, demonstrating the advantage of integrating radiographic and clinical cues in Table 2.

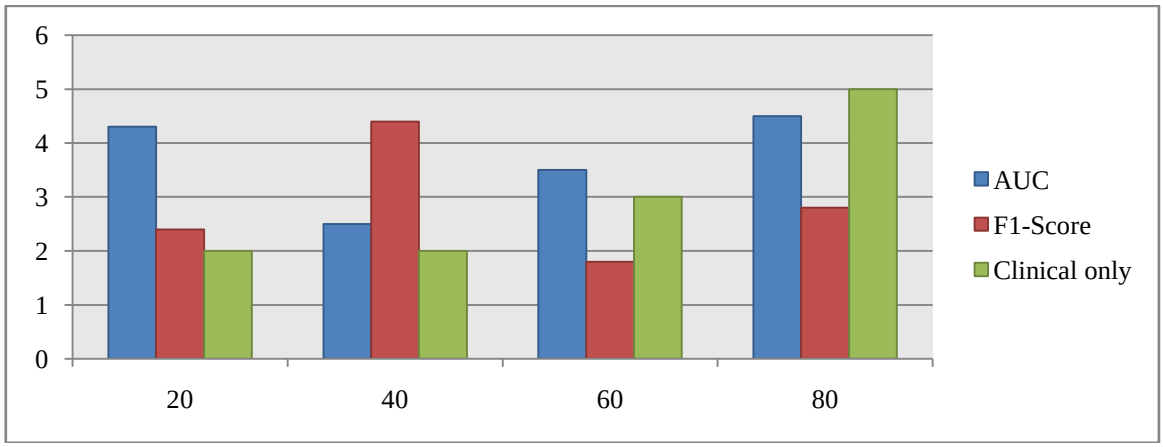


**Figure 4.** Comparison of baseline and proposed models for early BPD prediction.

Figure 4 shows the AUC and F1-score performance of three predictive models: (1) Image-only ResNet + XGBoost, (2) Clinical-only Logistic Regression, and (3) the suggested Multimodal Fusion model that integrates clinical factors and chest X-ray characteristics.The proposed framework demonstrates the highest performance, achieving an AUC of 0.92 and F1-score of 0.83, reflecting a ∼7% improvement over imaging alone and ∼16% over clinical-only methods.

The results of this study demonstrate that combining chest X-ray features with clinical variables provides a more reliable approach for early BPD prediction than using either modality alone. The U-Net segmentation improved image quality by isolating lung regions, while ResNet successfully captured subtle radiographic patterns associated with BPD. When fused with key clinical factors and classified using XGBoost, the proposed multimodal model achieved the highest predictive performance across all evaluation metrics.

These findings highlight the importance of multimodal learning in neonatal respiratory care, particularly for conditions where early detection is critical. Although the model performs strongly, future work should focus on validating it across larger, multi-center datasets and exploring temporal changes in sequential X-rays to further improve prediction accuracy.

## 6. CONCLUSION

This study presents a deep learning–driven framework for early prediction of Bronchopulmonary Dysplasia (BPD) by integrating chest X-ray–derived visual features with key clinical variables. Through a structured pipeline consisting of U-Net–based lung segmentation, ResNet feature extraction, and XGBoost classification, the proposed multimodal model consistently outperformed traditional clinical-only and image-only approaches. Experimental results demonstrated substantial gains in AUC and F1-score, highlighting the value of combining radiographic and clinical information for more reliable neonatal risk assessment. The improved predictive capability enables earlier identification of high-risk infants, supporting timely interventions and potentially reducing long-term respiratory complications. Future work will focus on expanding dataset diversity, incorporating temporal imaging sequences, and validating the model in real-world clinical workflows to further enhance generalizability and clinical applicability.

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