



Missouri University of Science and Technology

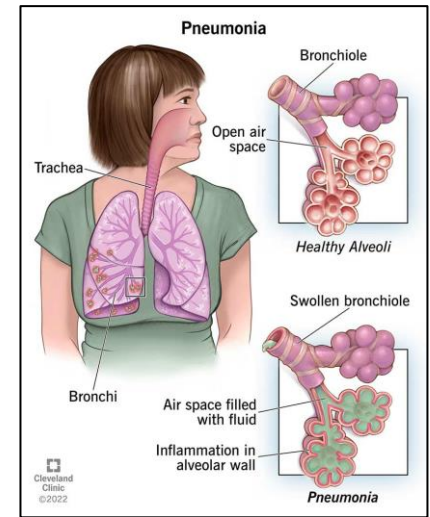
# PneumoCatcher: Automated Pneumonia Detection from Chest X-Rays Using Deep Learning

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# Introduction

- ▶ What is pneumonia?
- ▶ Pneumonia is a global health concern, especially in children and the elderly.
  - ~55,000 people die each year of pneumonia in U.S. [1]
  - Most common cause of death in developing countries. [1]
- ▶ Early detection improves outcomes, but skilled radiologists are often unavailable in low-resource settings.
- ▶ Deep learning offers a potential solution for rapid and reliable diagnosis.



[1] Cleveland Clinic (<https://my.clevelandclinic.org/health/diseases/4471-pneumonia>)

# Study Goals

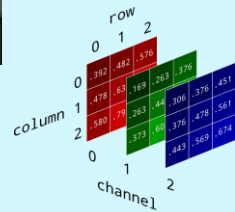
## Objective Statements:

- Build and evaluate deep learning models for pneumonia detection.
- Compare a custom CNN model with fine-tuned ResNet-50 models.
- Use Grad-CAM for model interpretability.

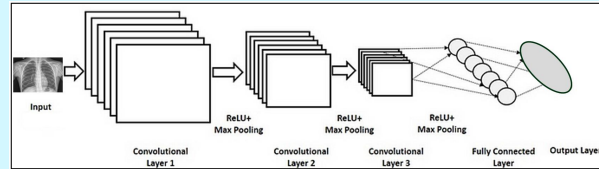
## Desired Effects:

- Accurate model predictions for pneumonia detection.
- High precision and recall.
- Grad-CAM visualizations to highlight clinically significant areas of the X-rays.

JPEG files



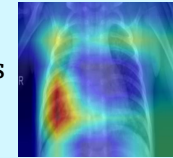
Preprocessing



Trained Model

Model Prediction

Post Processing:  
Grad-CAM heatmaps



Normal

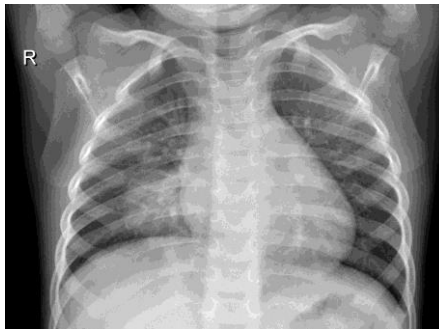
**Pneumonia**

# Dataset Selection

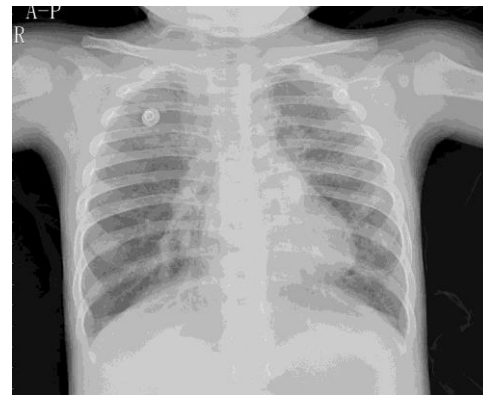
- ▶ Kaggle Chest X-ray (Pneumonia) Dataset:
  - 5,856 JPEG images.
  - Pediatric X-rays collected in Children's Medical Center (China).
- ▶ Binary classification: Normal vs. Pneumonia.
- ▶ Dataset quality ensured by expert validation.



Normal



Bacterial Pneumonia



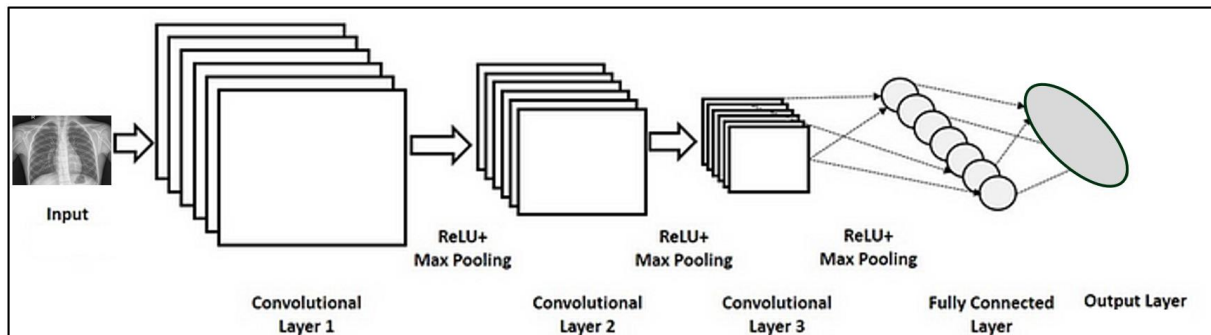
Viral Pneumonia

# Preprocessing

- ▶ Color Channels: RGB → Gray scale (decrease latency)
- ▶ Resize: Varying resolution → Uniform size (180x180 pixels)
- ▶ Reformat: JPEG → NumPy
- ▶ Normalization: [0 – 255] → [0 – 1]
- ▶ Data Split: Training/test sets (80/20 ratio)

# Model Development

- Custom CNN: Lightweight, efficient, tailored for X-rays.
  - Model 1: [convolution + ReLU + pooling layers] x 3 + [dense] x 2.

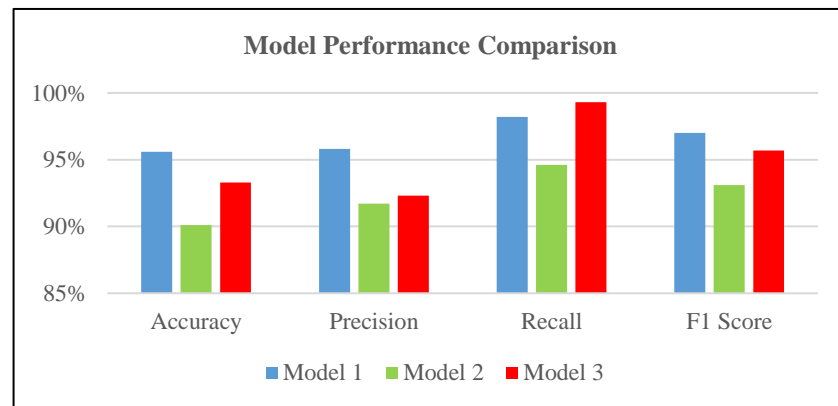


- Fine-Tuned ResNet-50:
  - Model 2: Moderate retraining.
  - Model 3: Extended retraining of deeper layers.

# Results

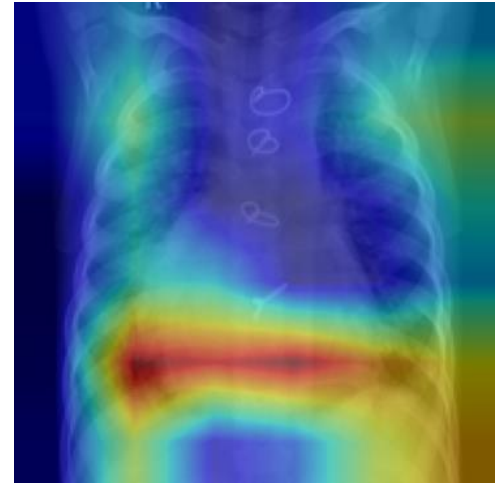
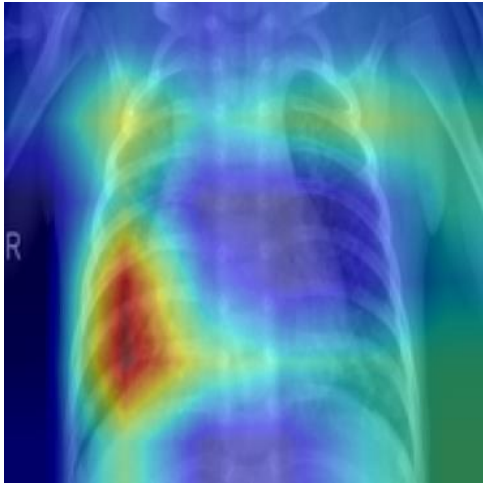
- Performance Metrics: Accuracy, Precision, Recall, F1 Score.
- Custom CNN outperformed both ResNet-50 models.
- Model 3 outperformed Model 2.

Model	Accuracy	Precision	Recall	F1 Score
Model 1	95.6%	95.8%	98.2%	97.0%
Model 2	90.1%	91.7%	94.6%	93.1%
Model 3	93.3%	92.3%	99.3%	95.7%



# Grad-CAM Visualizations

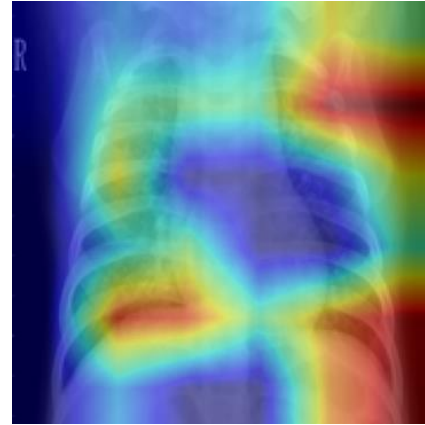
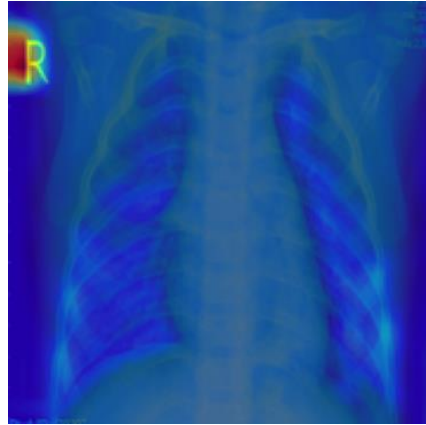
- ▶ Highlighted regions of the X-rays which were most impactful in the model's predictions.





# Challenges and Limitations

- ▶ Grad-CAM visualizations often highlighted non-relevant regions outside the chest area, especially artifacts.
- ▶ Diminishes trustworthiness of the models for clinical use without further refinement.



- ▶ Limited dataset scope (pediatric X-rays only).
- ▶ Need for broader testing and real-world validation.

# Key Insights and Discussion

- ▶ Best performance: Custom CNN Model.
  - Lightweight, suitable for resource-limited settings.
- ▶ ResNet-50 Models:
  - Strong performance with transfer learning.
  - Model 3 improved with deeper fine-tuning.
- ▶ Grad-CAM misidentifies incorrect regions as relevant.
- ▶ Potential overfitting that must be addressed to gain clinical trust.

# Future Work

- ▶ Improve Grad-CAM visualization reliability.
  - Enhance preprocessing methods (e.g. removing artifacts).
  - Data augmentation (e.g. cropping, zooming).
- ▶ Expand datasets (adult X-rays, diverse cases).
- ▶ Explore other architectures (e.g., VGG-16).
- ▶ Implement multi-class classification (bacterial vs. viral pneumonia).
- ▶ Deploy on lightweight devices for real-time diagnostics.

# Conclusion

- ▶ Custom CNN and fine-tuned ResNet-50 models show promise for pneumonia detection.
- ▶ Deep learning can enhance diagnostic capacity in under-resourced settings.
- ▶ Custom CNN demonstrated high performance; however, Grad-CAM visualizations exposed critical weaknesses in interpretability.
- ▶ Explainability and interpretability are crucial for clinical trust and deployment, therefore the Grad-CAM visualizations must be improved.



**Thank you!**

**Questions?**