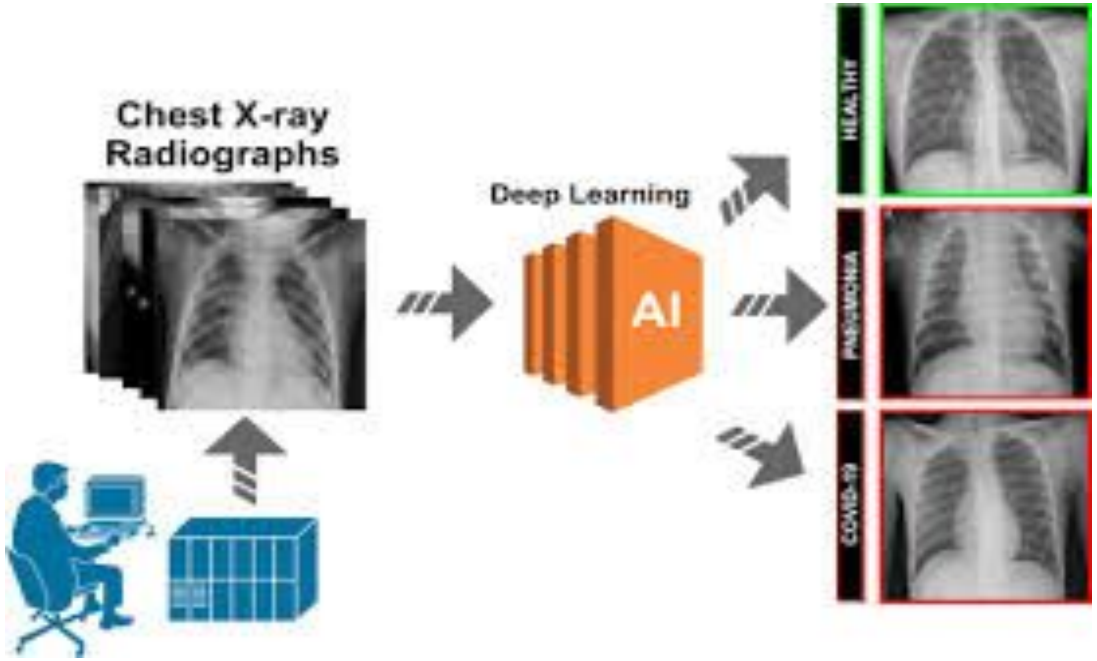
AI Driven Chest X-ray classification for COVID-19 and Pneumonia detection using deep learning



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Introduction

- Our project focuses on automating the classification of chest X-ray images into three diagnostic categories: COVID-19, Pneumonia, and Normal.
- By leveraging deep learning, our goal is to provide a clinically useful, accurate, and explainable AI tool that supports radiologists in making faster and more consistent decisions.

Why Chest X-ray Classification?

- Chest X-rays are fast, accessible, and widely used in clinical settings, especially during pandemics.
- Early and accurate identification of COVID-19, pneumonia, and normal cases is crucial for treatment decisions.

Problem Statement & Objectives

The Challenge:
Diagnosing COVID-19 and pneumonia via chest X-rays is challenging due to overlapping symptoms and imaging features. Manual interpretation is time-intensive, prone to variability, and difficult in low-resource settings.

Our Objectives:

- Develop CNN-based models for accurate classification of chest X-rays.
- Evaluate model performance on both internal and external datasets to ensure generalizability.
- Improve interpretability through Grad-CAM visualizations to support clinical decision-making.

Literature Review

- **COVID-Net (Wang et al., 2020):** A CNN tailored for COVID-19 diagnosis; high accuracy but limited generalizability.
- **ResNet (He et al., 2016):** Deep residual networks known for strong performance in medical imaging.
- **Grad-CAM (Selvaraju et al., 2017):** Enabled visual interpretability in CNNs, essential for clinical trust.
- **Albahli et al. (2021):** Demonstrated that noise augmentation improves model robustness.
- **Zhou et al. (2016):** Highlighted importance of aligning AI attention with human clinical reasoning.

Our approach integrates key innovations from these works to enhance both performance and interpretability.

Dataset & Population Justification

Datasets Used:

- Internal Dataset: [COVID19+PNEUMONIA+NORMAL Chest X-Ray Image Dataset]
    - 5,228 images | Classes: COVID-19, Pneumonia, Normal
- External Dataset:[Chest X-ray (Covid-19 & Pneumonia)]
    - 6,432 images split into Train/Test (20% test)
    - Organized into 3 folders: COVID-19, Pneumonia, Normal

Population Justification:

- Multi-source, expert-labeled images ensure clinical relevance and diversity in patient demographics and imaging conditions.
- Cross-dataset validation allows us to test generalizability and avoid overfitting.
- Chest X-rays are fast, accessible tools for diagnosis—ideal for AI-based COVID-19 and pneumonia screening, especially where RT-PCR is limited.

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Code Workflow

Models Implemented:

- SimpleCNN**:** Custom 3-layer CNN with ReLU and Dropout (0.4); used as a baseline model.
- ResNet-50: Pretrained model adapted for grayscale input and fine-tuned for classification.

Why ResNet-50?

- Outperformed SimpleCNN on both internal and external datasets.
- Superior feature extraction using depth and residual connections.

Implementation Steps:

- Load and preprocess internal and external datasets.
- Apply noise-based data augmentation to improve robustness.
- Train both models on augmented datasets.
- Evaluate using accuracy, precision, recall, and F1-score.
- Visualize prediction regions using Grad-CAM for model interpretability.

Noise

We implemented noise-based augmentation techniques to simulate real-world clinical imaging:

- AddGaussianNoise: Introduces subtle pixel noise to mimic scanner distortions
- AddSpeckleNoise: Simulates grainy/low-quality images from portable X-ray machines
- RandomContrast: Adjusts brightness/contrast to reflect variable imaging conditions

```python
# Custom Noise Transforms
import torchvision.transforms.functional as TF

class AddGaussianNoise:
    def __init__(self, mean=0., std=0.05):
        self.mean = mean
        self.std = std

    def __call__(self, tensor):
        return torch.clamp(tensor + torch.randn_like(tensor) * self.std + self.mean, 0., 1.)

class AddSpeckleNoise:
    def __init__(self, std=0.1):
        self.std = std

    def __call__(self, tensor):
        noise = tensor + tensor * torch.randn_like(tensor) * self.std
        return torch.clamp(noise, 0., 1.)

class RandomContrast:
    def __init__(self, lower=0.75, upper=1.25):
        self.lower = lower
        self.upper = upper

    def __call__(self, img):
        factor = random.uniform(self.lower, self.upper)
        return TF.adjust_contrast(img, factor)
```

Data Augmentation with Noise

Grad-CAM Model explainability

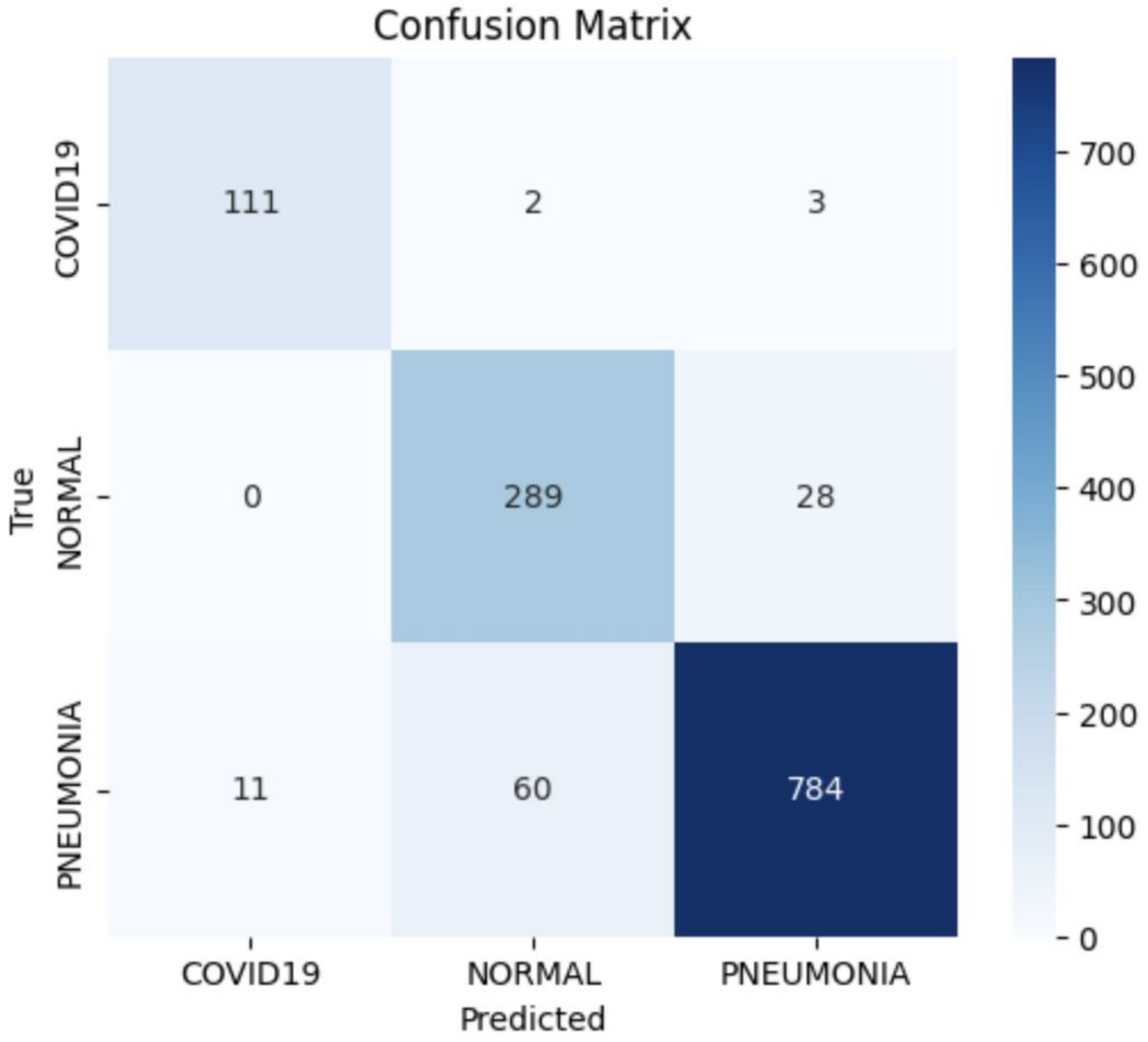
- Used forward and backward hooks to capture internal layer activations and gradients
- Applied to ResNet-50’s final convolutional layer for interpretability
- Enables visualization of important image regions influencing classification
- Critical for ensuring clinical trust and identifying model blind spots

```python
def apply_gradcam_resnet(model, image_tensor, target_class, layer_name='layer4'):
    model.eval()

    image_tensor = image_tensor.unsqueeze(0).to(device)
    gradients = []
    activations = []

    # Get the target layer
    target_layer = dict([*model.named_modules()])[layer_name]

    # Forward hook
    def forward_hook(module, input, output):
        activations.append(output)

    # Backward hook
    def backward_hook(module, grad_input, grad_output):
        gradients.append(grad_output[0])

    # Register hooks
    forward_handle = target_layer.register_forward_hook(forward_hook)
    backward_handle = target_layer.register_full_backward_hook(backward_hook)

    try:
        # Forward pass
        output = model(image_tensor)
        class_score = output[0, target_class]

        # Backward pass
        model.zero_grad()
        class_score.backward()
```

Results & Evaluation

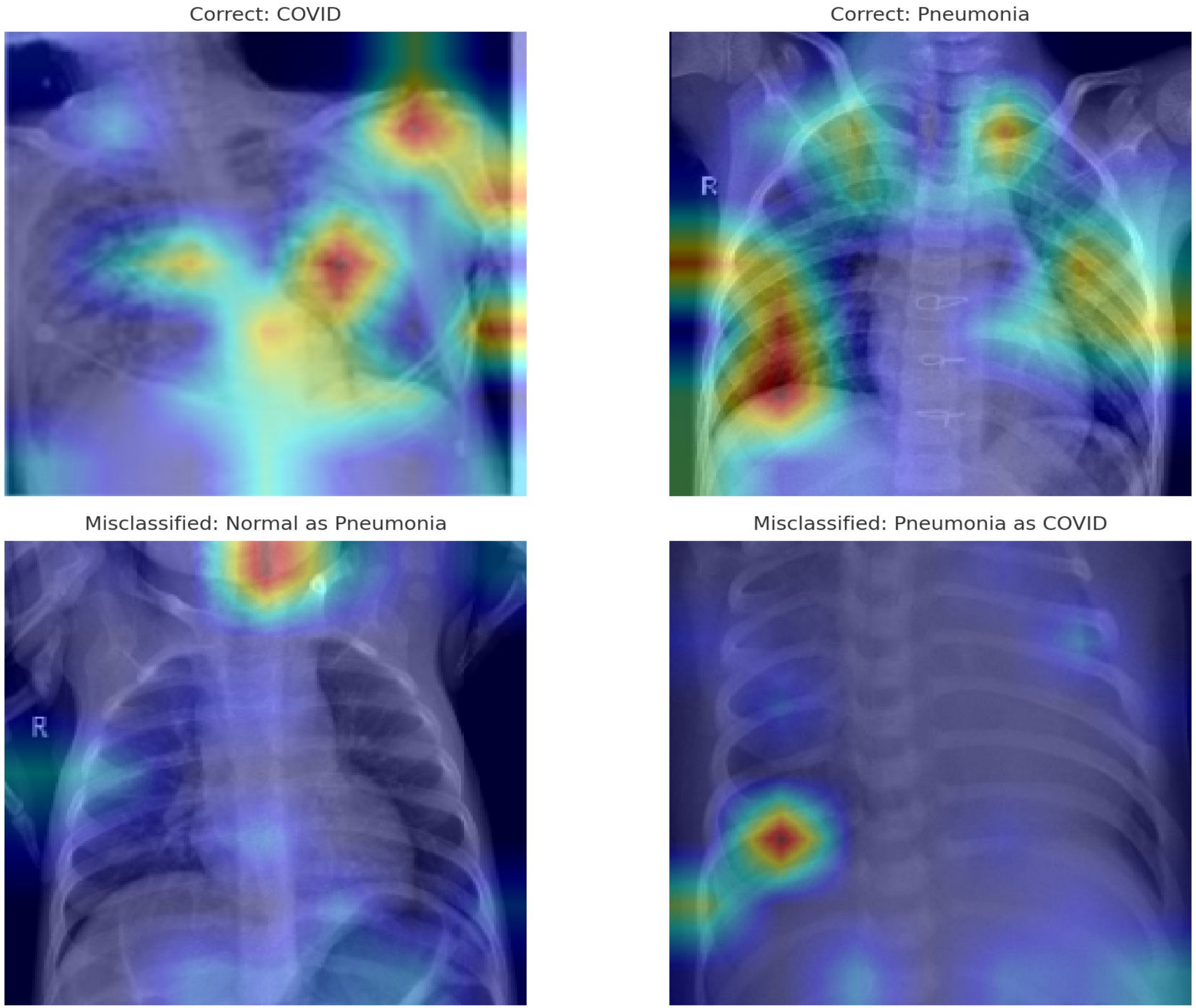
External Dataset

- Evaluated ResNet-50 on external dataset
- Maintained strong COVID-19 recall (96%)
- Most NORMAL misclassifications were as PNEUMONIA
- Confirms generalization ability but reveals overlap in features between classes



Grad-CAM

- Grad-CAM highlights areas influencing the model's prediction
- Correct predictions show focus on infected regions (e.g., lungs)
- Misclassifications reveal distractions or feature overlaps
- Helps validate model behavior and explain clinical relevance



Conclusion

Achievements:

- Successfully trained and compared two models (SimpleCNN and ResNet50) for classifying chest X-rays into COVID-19, pneumonia, and normal
- Integrated Grad-CAM visualizations to improve model transparency and support clinical trust
- Our SimpleCNN model outperformed ResNet-50 on internal evaluation, achieving higher accuracy and recall across all classes. While ResNet showed slightly better generalization on the external dataset, the CNN demonstrated more consistent results and better interpretability overall
- Performance dropped on the external dataset, highlighting the challenge of real-world generalization

Future Enhancements:

- Improve Grad-CAM alignment using expert-annotated datasets.
- Extend to include CT scan analysis or multi-modal imaging.
- Implement Explainable AI (XAI) Frameworks for more comprehensive model explanations.

References

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Thank you