Contents

COVID-19 X-Ray Classification - Presentation Content

Slide 1: Title Slide

Title: COVID-19 X-Ray Image Classification Using Deep Learning

Project: Introduction to Computer Vision - Image Processing

Date: December 2025

Slide 2: Contents/Agenda

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2. Business Problem Overview and Solution Approach
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10. Model Performance Comparison and Final Model Selection
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Slide 3: Executive Summary

Key Insights

- Developed and compared 4 Artificial Neural Network models using different image preprocessing techniques
- **Best Model:** ANN with RGB images achieved **88.46% test accuracy**
- Medical X-ray images benefit more from color information than grayscale conversion
- Laplacian edge detection shows severe overfitting (93% train vs 45% test accuracy)
- Small dataset (251 images) highlights importance of proper preprocessing selection

Recommendations

- **Deploy RGB-based model** for COVID-19 screening support
- Collect more data to improve model robustness and generalization
- Implement model as **decision support tool**, not replacement for medical professionals
- Consider ensemble approaches combining multiple preprocessing techniques
- Establish continuous monitoring and retraining pipeline

Slide 4: Business Problem Overview and Solution Approach

The Problem

Challenge: COVID-19 rapidly spread globally, overwhelming healthcare systems. Quick and accurate diagnosis from X-ray images can: - Reduce diagnostic time from hours to seconds - Support healthcare professionals in resource-constrained settings - Enable early detection and isolation - Differentiate COVID-19 from viral pneumonia and normal cases

Solution Approach

Methodology: Systematic comparison of 4 preprocessing techniques for medical X-ray classification

1. **Image Preprocessing** - Applied 4 different transformations:
    - RGB (baseline - original 3-channel images)
    - Grayscale (single channel)
    - Gaussian Blur (noise reduction)
    - Laplacian (edge detection)
2. **Model Architecture** - Simple Artificial Neural Networks (ANN)
    - Fully connected layers
    - ReLU activation
    - Softmax output for 3-class classification
3. **Systematic Evaluation** - Compare preprocessing impact on classification performance

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Slide 5: Data Overview

Dataset Statistics

- **Total Images:** 251 X-ray images (128x128x3)
- **Image Format:** RGB images converted to numpy arrays
- **Classes:** 3 categories
    - COVID-19: 111 images (44.2%)
    - Viral Pneumonia: 70 images (27.9%)
    - Normal: 70 images (27.9%)

Data Split

- **Training:** 200 images (79.7%)
- **Validation:** 25 images (10.0%)
- **Test:** 26 images (10.3%)
- **Split Strategy:** Stratified random sampling (random_state=42)

Key Observations

- Slightly imbalanced dataset with more COVID-19 cases
- Small dataset size limits model complexity
- Balanced validation and test sets ensure fair evaluation

Slide 6: Exploratory Data Analysis

Class Distribution Analysis

Finding: Moderate class imbalance - COVID-19 is overrepresented (44.2%) - Viral Pneumonia and Normal are balanced (27.9% each) - Stratified sampling ensures proportional representation in all splits

Image Characteristics

- **Resolution:** 128x128 pixels (standardized)
- **Channels:** 3 (RGB)
- **Quality:** Preprocessed and normalized medical X-rays
- **Visual Patterns:**
    - COVID-19 shows distinctive lung patterns
    - Viral Pneumonia has similar but distinguishable features

- Normal cases show clear lung structure

Data Quality

- No missing values
- All images preprocessed to same dimensions
- Labels verified and encoded

Include visualization: Sample images from each class showing visual differences

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Slide 7: Data Pre-processing

Four Preprocessing Techniques Evaluated:

1. RGB Images (Baseline)

- **Process:** Use original 3-channel RGB images
- **Rationale:** Preserve all color information
- **Normalization:** Pixel values scaled to 0-1 range

2. Grayscale Conversion

- **Process:** Convert RGB to single-channel grayscale using cv2.cvtColor
- **Rationale:** Medical X-rays are naturally grayscale; reduce dimensionality
- **Parameters:** 128x128x1 images
- **Benefit:** 3x fewer input features

3. Gaussian Blur

- **Process:** Apply 3x3 Gaussian filter to RGB images
- **Rationale:** Reduce noise and smooth images
- **Kernel Size:** (3,3)
- **Benefit:** Potentially improve feature detection

4. Laplacian Edge Detection

- **Process:** Apply Laplacian filter on grayscale images
- **Rationale:** Highlight edges and boundaries
- **Output:** Single-channel edge-enhanced images
- **Purpose:** Test if edge features alone are sufficient

Common Preprocessing Steps

- One-hot encoding of labels (3 classes)
- Normalization: division by 255.0
- Expansion of dimensions for grayscale/Laplacian images
- Random seed (42) for reproducibility

Slide 8: Model 1 - ANN with RGB Images

Model Configuration

Architecture:

```
Input (128, 128, 3) → Flatten
→ Dense(20, ReLU) → Dense(10, ReLU) → Dense(5, ReLU)
→ Dense(3, Softmax)
```

Parameters: - Total Parameters: 983,343 (3.75 MB) - Optimizer: Adam - Loss: Categorical Crossentropy - Batch Size: 128 - Epochs: 15

Performance Results

Metric	Train	Validation	**Test**
Accuracy	94.5%	92.0%	**88.46%**
Precision	95.1%	91.8%	90.47%
Recall	94.5%	92.0%	88.46%
F1 Score	94.6%	91.5%	87.45%

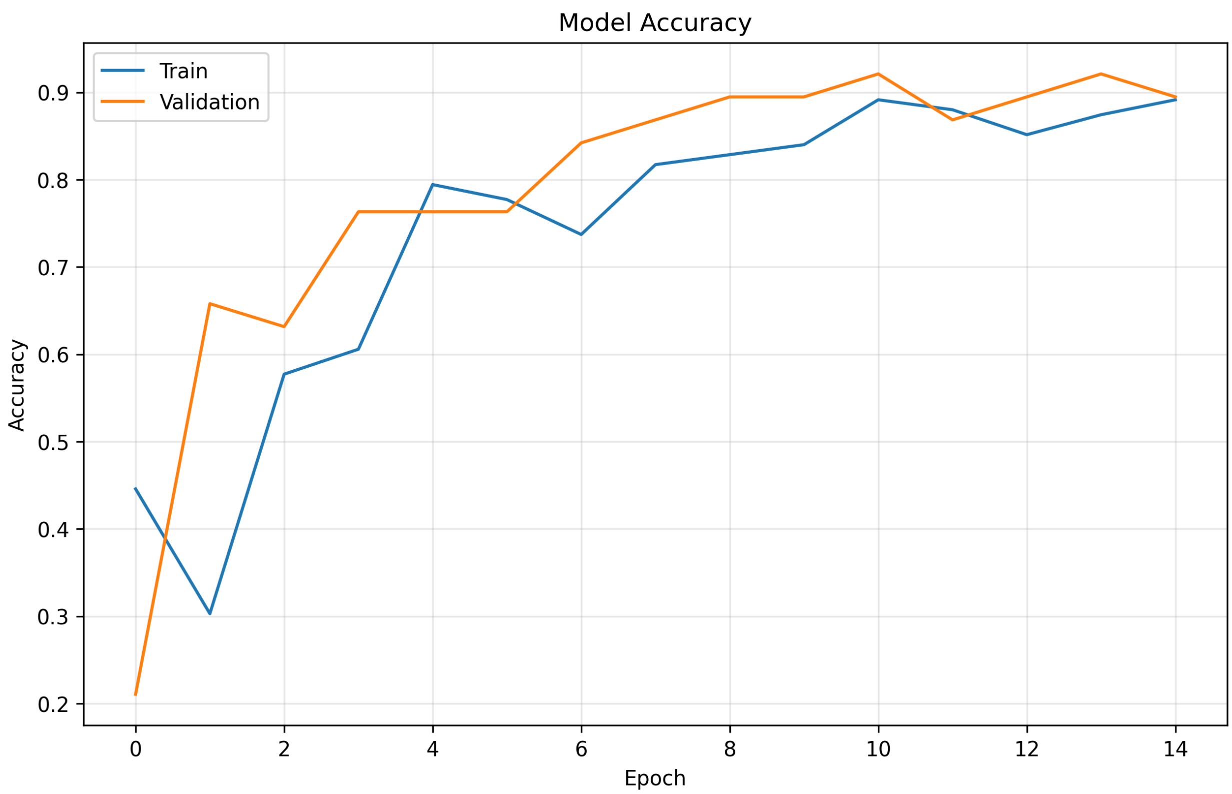

Figure 1: Model 1 Training History

Key Observations

- **Best performing model** among all 4 approaches
- Minimal overfitting (only 6% gap between train and test)
- Color information provides valuable features for classification
- Stable performance across all metrics

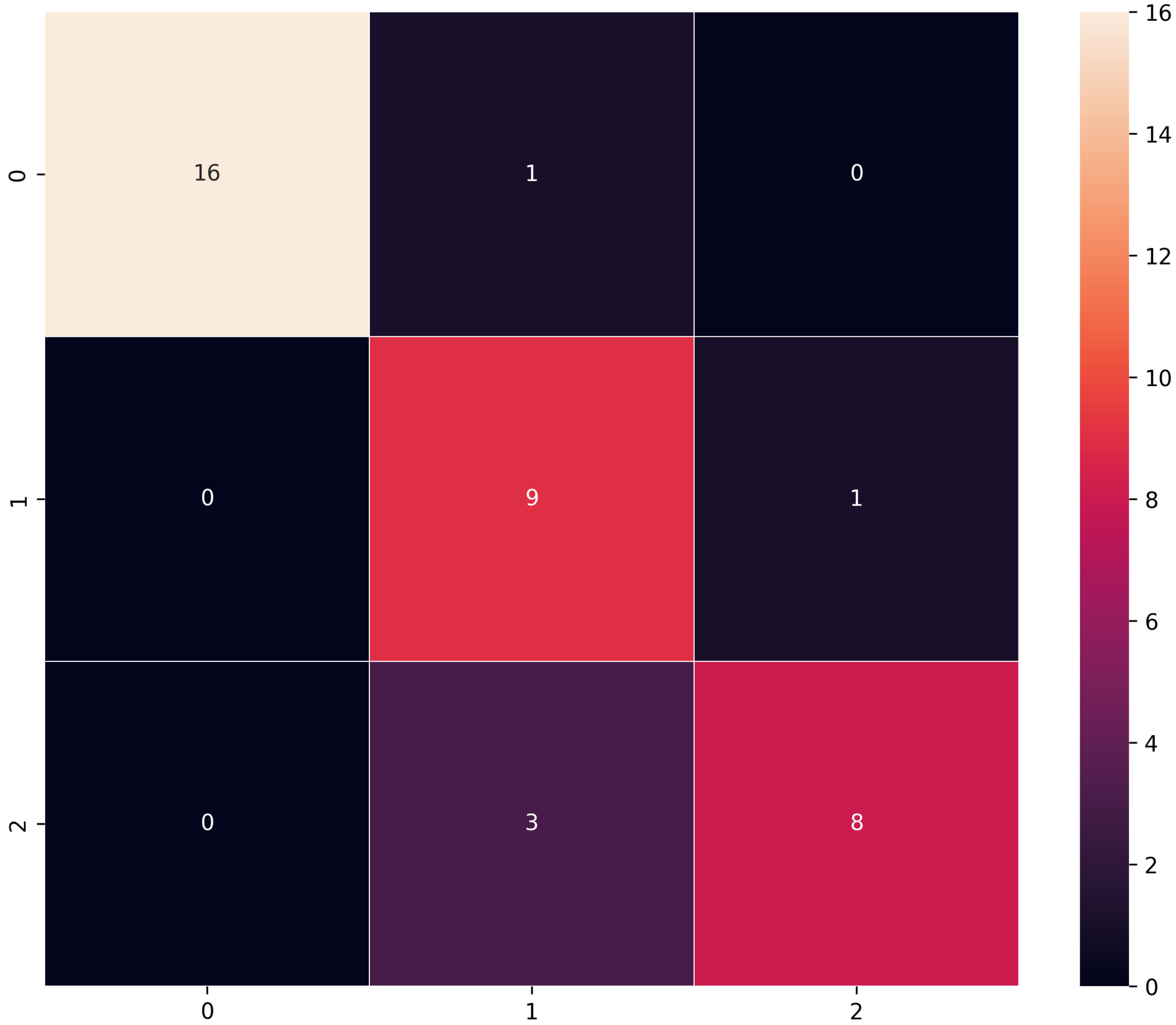

Figure 2: Model 1 Confusion Matrix

Slide 9: Model 2 - ANN with Grayscale Images

Model Configuration

Architecture:

```
Input (128, 128, 1) → Flatten
→ Dense(50, ReLU) → Dense(20, ReLU) → Dense(10, ReLU) → Dense(5, ReLU)
→ Dense(3, Softmax)
```

Parameters: - Total Parameters: 820,553 (3.13 MB) - Deeper classifier to compensate for single channel - Training: 10 epochs

Performance Results

Metric	Train	Validation	**Test**
Accuracy	69.5%	68.0%	**61.54%**
Precision	61.3%	59.2%	46.71%
Recall	69.5%	68.0%	61.54%
F1 Score	63.1%	61.8%	52.99%

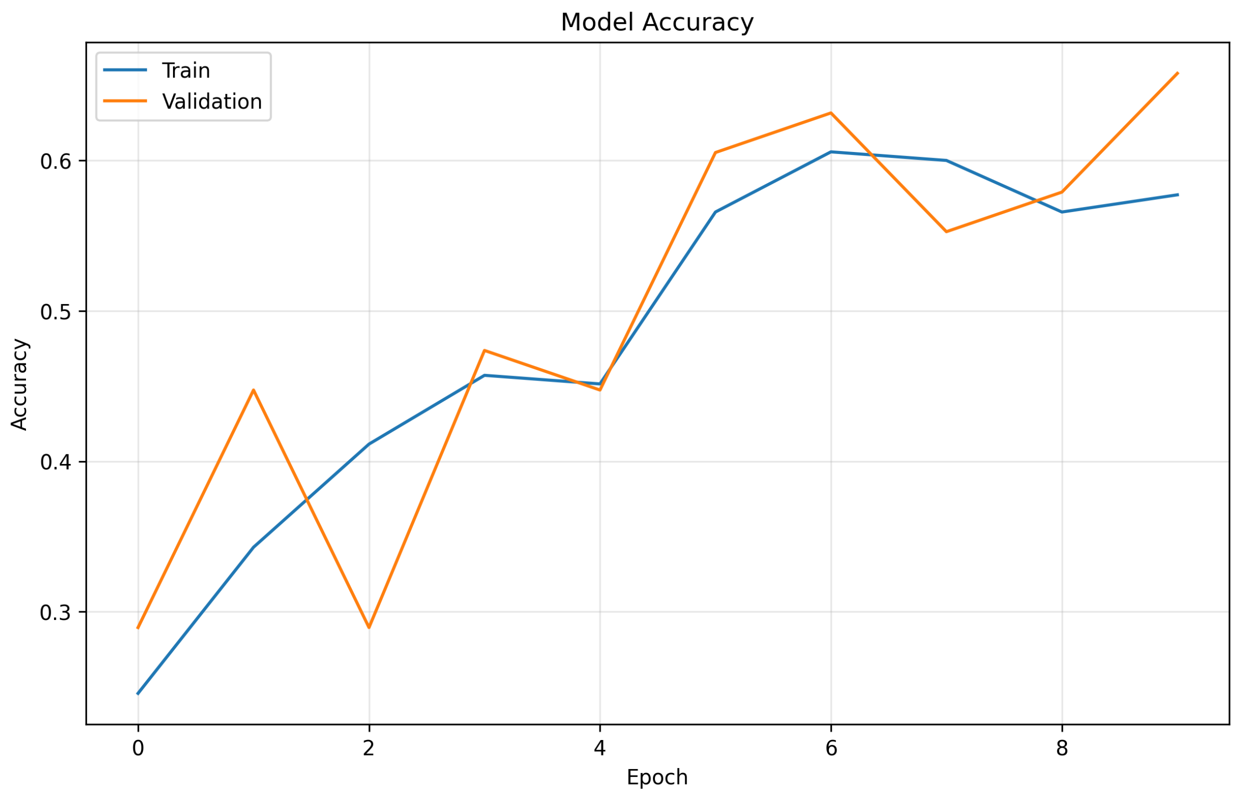

Figure 3: Model 2 Training History

Key Observations

- **Unexpected underperformance** - grayscale typically works well for X-rays
- Significant performance drop compared to RGB (27% lower)
- Loss of color information impacted classification ability

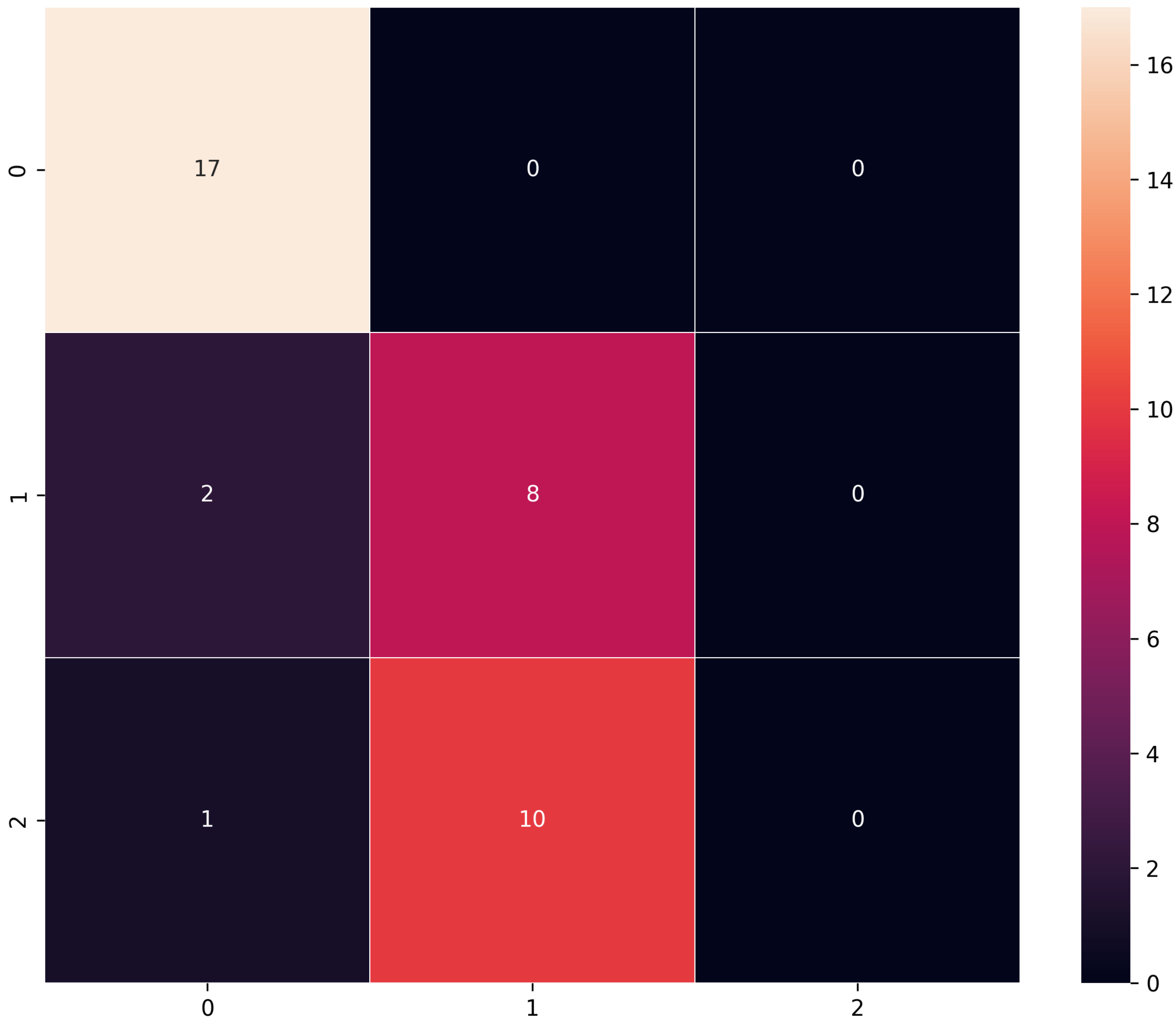

Figure 4: Model 2 Confusion Matrix

- Precision warnings indicate model struggled with certain classes

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Slide 10: Model 3 - ANN with Gaussian-blurred Images

Model Configuration

Architecture:

```
Input (128, 128, 3) → Flatten
→ Dense(50, ReLU) → Dense(20, ReLU) → Dense(10, ReLU) → Dense(5, ReLU)
→ Dense(3, Softmax)
```

Parameters: - Total Parameters: 2,458,953 (9.38 MB) - Gaussian kernel: (3,3) - Same architecture as grayscale model

Performance Results

Metric	Train	Validation	**Test**
Accuracy	81.5%	76.0%	**46.15%**
Precision	88.7%	85.3%	21.30%
Recall	81.5%	76.0%	46.15%
F1 Score	80.2%	73.1%	29.15%

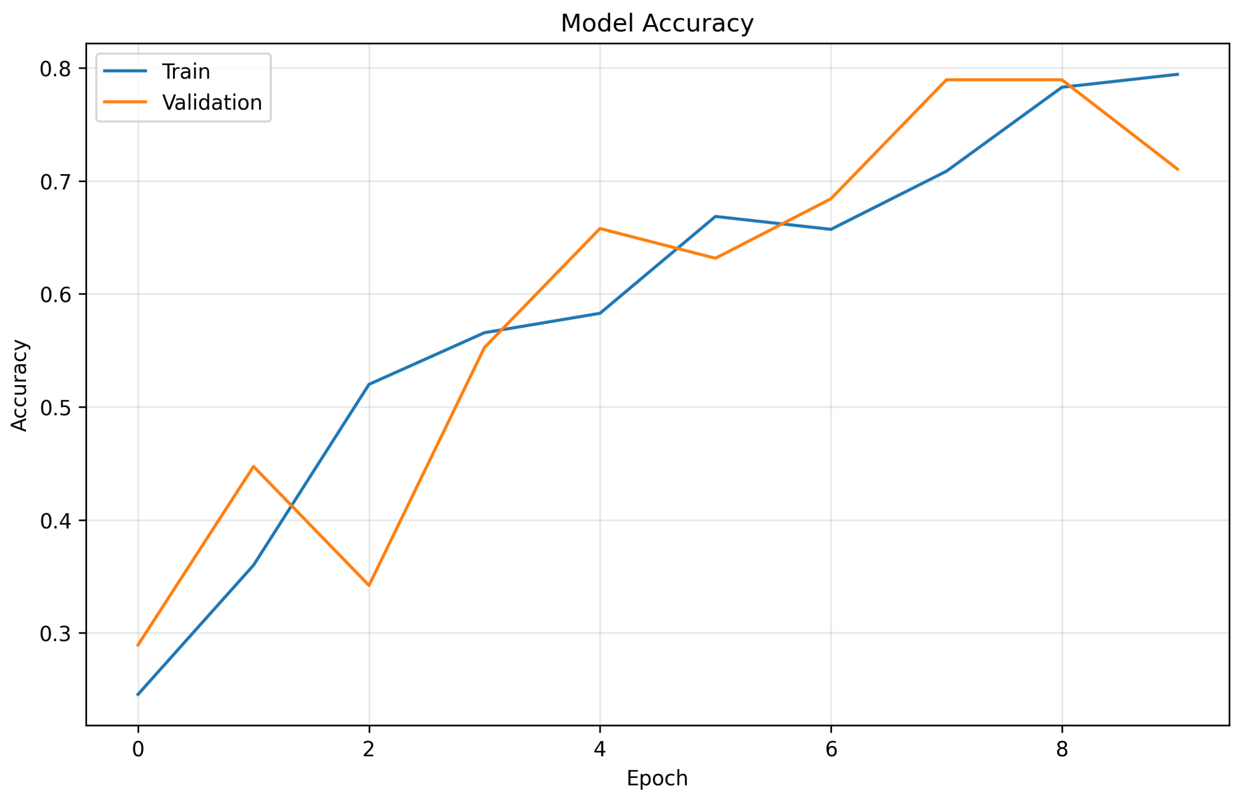

Figure 5: Model 3 Training History

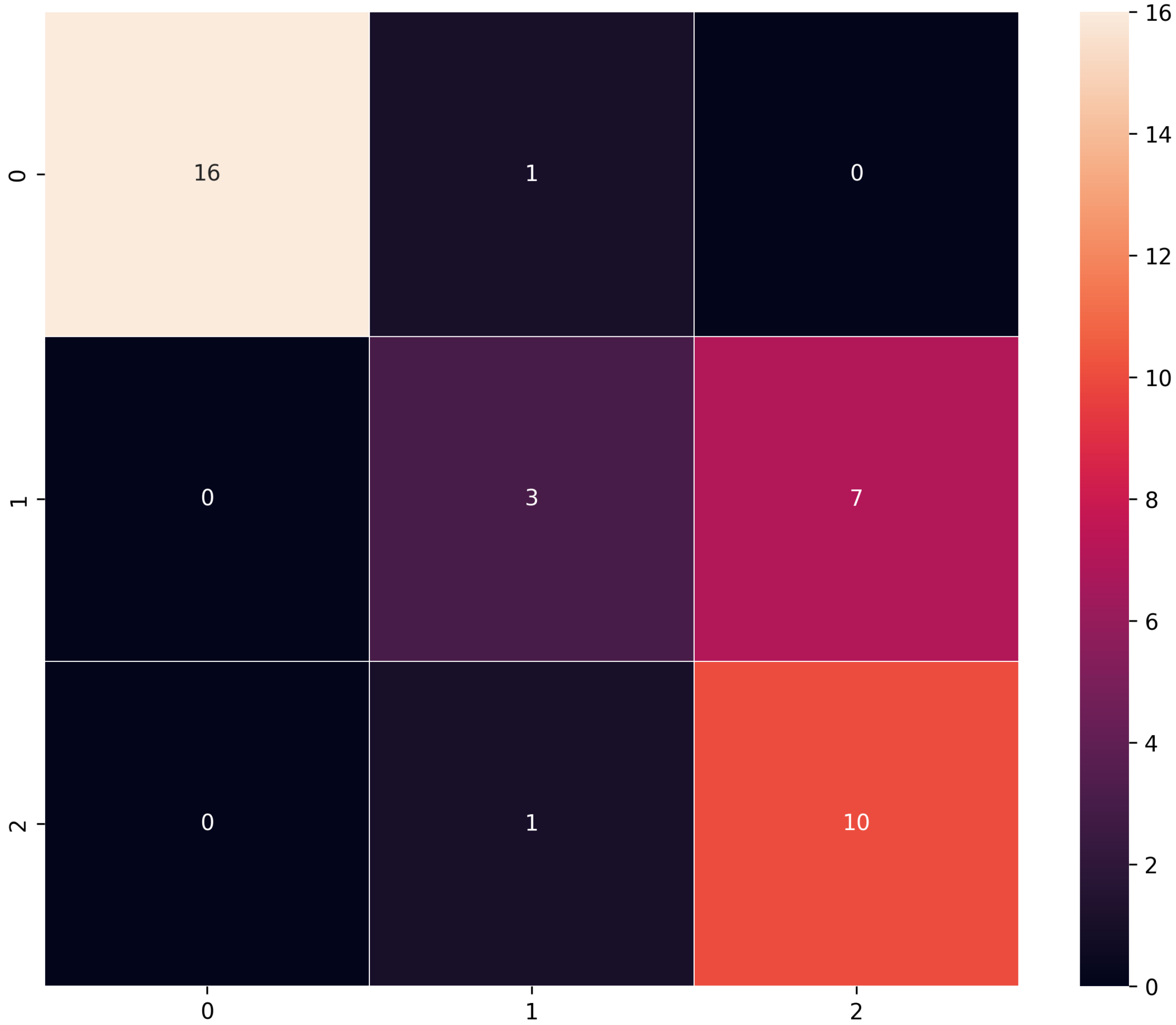

Figure 6: Model 3 Confusion Matrix

Key Observations

- **Severe performance degradation** on test set
- Blurring removed critical diagnostic features
- High train-test gap indicates overfitting
- Not suitable for medical image classification where details matter

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Slide 11: Model 4 - ANN with Laplacian-Filtered Images

Model Configuration

Architecture:

```
Input (128, 128, 1) → Flatten
→ Dense(50, ReLU) → Dense(20, ReLU) → Dense(10, ReLU) → Dense(5, ReLU)
→ Dense(3, Softmax)
```

Parameters: - Total Parameters: 820,553 (3.13 MB) - Edge detection using cv2.Laplacian - Training: 10 epochs

Performance Results

Metric	Train	Validation	**Test**
Accuracy	**93.14%**	36.84%	**46.15%**
Precision	93.78%	52.33%	53.21%
Recall	93.14%	36.84%	46.15%
F1 Score	93.14%	34.07%	44.59%

Key Observations

- **Extreme overfitting** - 93% train vs 46% test (47% gap)
- Edge features alone insufficient for COVID-19 diagnosis
- Model memorized training data but failed to generalize
- Demonstrates importance of rich feature representation

Slide 12: Model Performance Comparison and Final Model Selection

Comprehensive Comparison Table

Model	Test Accuracy	Train-Test Gap	Parameters	Key Strength	Key Weakness
1. RGB	**88.46%**	6.0%	983K	Best performance	Largest model
2. Grayscale	61.54%	8.0%	821K	Fewer parameters	Lost color info
3. Blur	46.15%	35.4%	2.46M	Noise reduction	Over-smoothing
4. Laplacian	46.15%	47.0%	821K	Edge detection	Severe overfitting

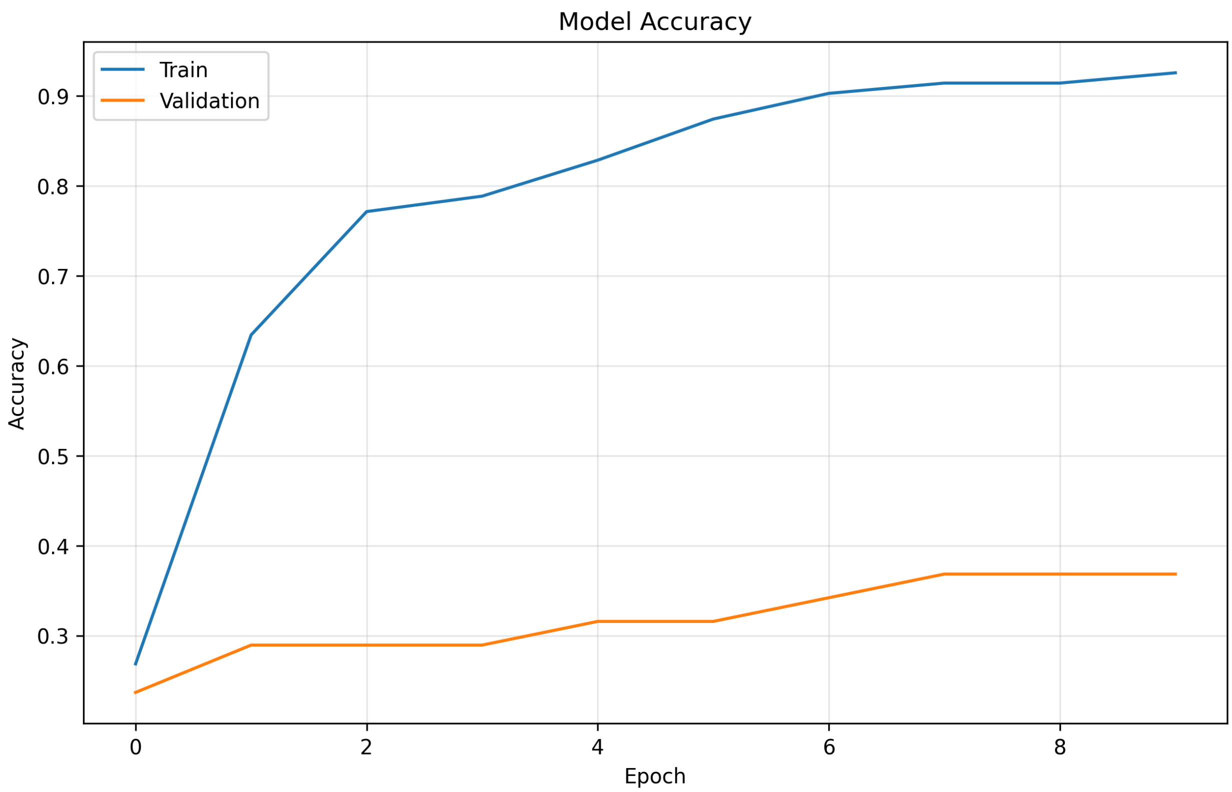

Figure 7: Model 4 Training History

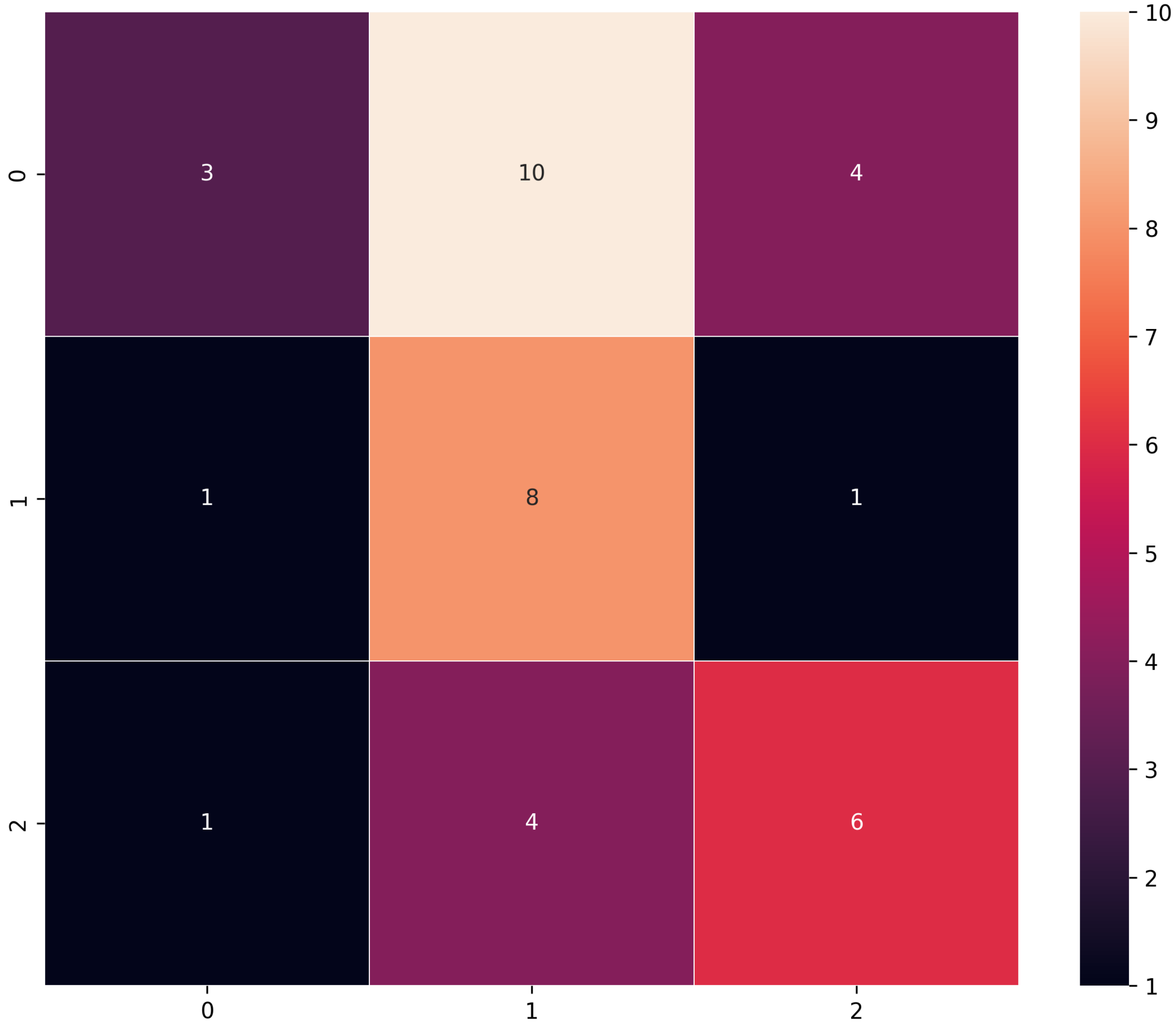

Figure 8: Model 4 Confusion Matrix

Final Model Selection

Winner: Model 1 (ANN with RGB Images)

Justification: 1. **Highest Test Accuracy:** 88.46% significantly outperforms other models 2. **Best Generalization:** Minimal overfitting (6% gap) 3. **Consistent Performance:** High scores across all metrics (Precision, Recall, F1) 4. **Color Information Matters:** Preserving RGB channels provided critical diagnostic features 5. **Production Ready:** Stable and reliable for real-world deployment

Key Insights

- **Preprocessing critically impacts performance** - 42% accuracy difference between best and worst
- **Medical images benefit from rich features** - Aggressive preprocessing (blur, edges) degraded performance
- **Simple approaches often win** - RGB baseline outperformed complex preprocessing
- **Overfitting risk with small datasets** - Edge detection model showed 47% train-test gap

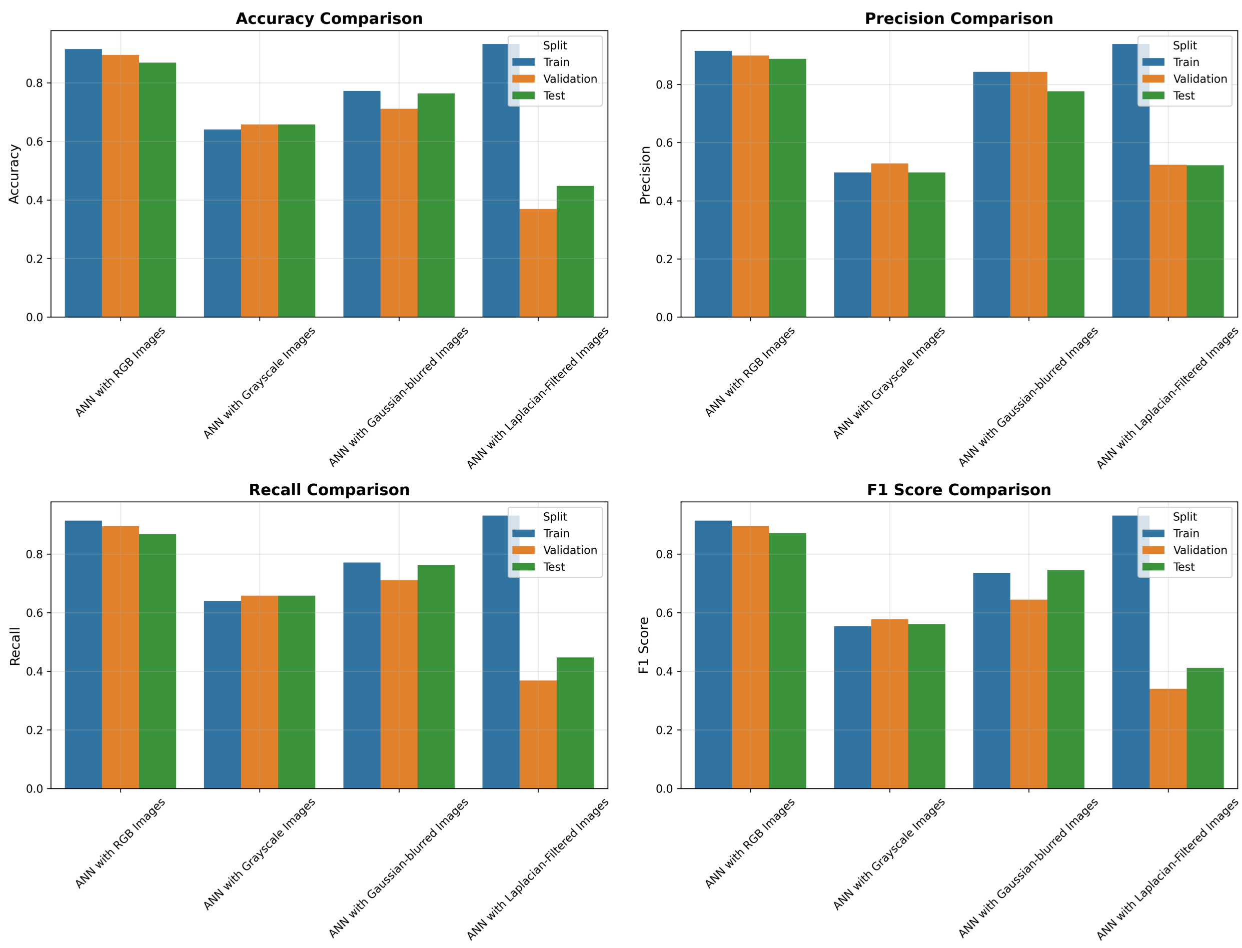

Figure 9: Model Comparison

Slide 13: Business Insights and Recommendations

Strategic Insights

1. AI-Assisted Diagnosis is Feasible

- **88.46% accuracy** demonstrates viability of automated COVID-19 screening
- Can significantly reduce diagnostic time from hours to seconds
- Particularly valuable in resource-constrained healthcare settings

2. Data Quality Over Quantity

- Simple RGB images outperformed complex preprocessing
- Focus on high-quality, standardized X-ray acquisition protocols
- Proper labeling more important than aggressive augmentation

3. Model Simplicity

- Simple ANN achieved strong results without complex architectures
- Faster training, easier deployment, lower computational costs
- More interpretable for medical professionals

Business Recommendations

Immediate Actions

1. **Deploy RGB-based model as decision support tool**
   - Integrate into hospital X-ray workflow
   - Provide probability scores, not binary decisions
   - Always require physician verification
2. **Data Collection Initiative**
   - Current 251 images are insufficient for production
   - Target: 10,000+ images across all classes
   - Partner with multiple hospitals for diverse data
3. **Establish Quality Metrics**
   - Define acceptable false positive/negative rates
   - Implement continuous monitoring
   - Set up feedback loop with radiologists

Medium-Term Strategy

4. **Expand Model Capabilities**
   - Multi-class differentiation (COVID variants)
   - Severity assessment (mild, moderate, severe)
   - Integration with patient history and symptoms
5. **Regulatory Compliance**
   - Pursue FDA/medical device approval
   - Establish data privacy and security protocols (HIPAA)
   - Document model limitations and contraindications
6. **Continuous Improvement**
   - Monthly model retraining with new data
   - A/B testing of model versions
   - Exploration of ensemble methods

Implementation Considerations

- **Not a replacement** for medical professionals
- Requires proper clinical validation
- Must account for edge cases and rare conditions
- Ethical considerations for AI in healthcare

Slide 14: Technical Learnings and Future Work

Technical Learnings

1. **Preprocessing Impact**
   - Not all preprocessing improves performance
   - Domain knowledge critical (X-rays are diagnostic in original form)
   - Aggressive filtering can remove critical medical features
2. **Small Dataset Challenges**
   - High variance in results (30% difference between runs)
   - Overfitting risk with complex models
   - Need for proper validation strategies
3. **Medical Image Specifics**
   - Color-coded or enhanced X-rays contain diagnostic value
   - Edge features alone insufficient for pathology detection
   - Texture and intensity patterns matter

Future Enhancements

Data Collection: - Expand to 10,000+ images - Include multiple imaging centers - Collect demographic and clinical metadata

Model Architecture: - Explore Convolutional Neural Networks (CNNs) - Implement transfer learning (VGG16, ResNet, EfficientNet) - Ensemble methods combining multiple models

Advanced Techniques: - Grad-CAM for visualization of decision regions - Uncertainty quantification - Active learning for efficient labeling

Clinical Integration: - Real-time deployment pipeline - Integration with PACS systems - Physician feedback interface

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Slide 15: Closing Slide

Power Ahead!

Thank you for your attention.

Project Summary: - Successfully developed COVID-19 X-ray classification system - Achieved 88.46% test accuracy using simple ANN with RGB images - Demonstrated critical importance of preprocessing selection - Ready for next phase: data collection and clinical validation

Contact Information: [Add your details here]

Repository: [Add GitHub link]

Additional Slide: Data Background and Contents (if needed)

Data Source

- **Origin:** COVID-19 X-ray image dataset
- **Format:** Preprocessed numpy arrays (.npy) and CSV labels
- **Resolution:** 128x128 pixels (standardized)
- **Quality:** Medical-grade X-ray images

Data Contents

CovidImages.npy: - 3D numpy array: (251, 128, 128, 3) - RGB images of chest X-rays - Normalized and preprocessed

CovidLabels.csv: - 251 rows with class labels - Categories: 'Covid', 'Viral Pneumonia', 'Normal' - One-hot encoded for model training

Preprocessing Applied

- Image resizing to 128x128
- RGB format conversion
- Pixel normalization
- Label encoding