

Lecture 9:

# Deep Learning for Medical Imaging

- AI revolution in radiology
- Breakthrough examples
- FDA approvals timeline

Introduction to Biomedical Data Science

# Lecture Contents

**Focus 1:** CNN architectures

**Focus 2:** Medical applications

**Focus 3:** Clinical deployment

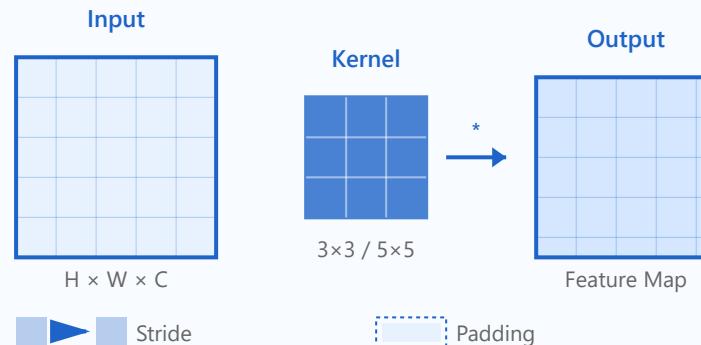
**Part 1/3:**

# **CNN Fundamentals**

- Convolutional operations
- Network architectures
- Training strategies

# Convolution Operation

## Convolution Process



### Kernel/Filter Concepts

Small learnable matrices that slide across input to extract features. Common sizes:  $3 \times 3$ ,  $5 \times 5$ ,  $7 \times 7$

### Stride and Padding

Stride: step size of kernel movement. Padding: adding borders to preserve spatial dimensions

### Feature Map Generation

Output of convolution operation. Each filter produces one feature map detecting specific patterns

### Receptive Fields

Region of input that affects a particular feature. Grows with network depth and kernel size

Special Case: **1×1 Convolutions** - Channel-wise operations for dimensionality reduction and cross-channel learning

# Pooling Layers

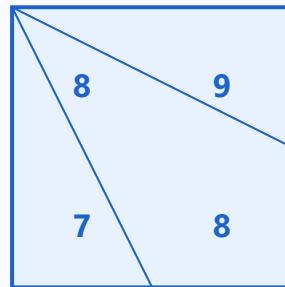
## Max vs Average Pooling

Input (4×4)

2	8	4	1
5	3	9	2
7	1	6	4
3	2	5	8

2×2 Pool

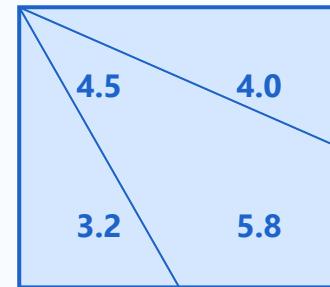
Max Pooling (2×2)



Same Input

4×4 matrix

Average Pooling (2×2)



### Max Pooling

Selects maximum value from each window. Preserves strongest activations and provides translation invariance

### Average Pooling

Computes average of values in each window. Smoother downsampling, often used before classification layers

### Global Pooling

Reduces entire feature map to single value per channel.  
Eliminates need for fixed input sizes

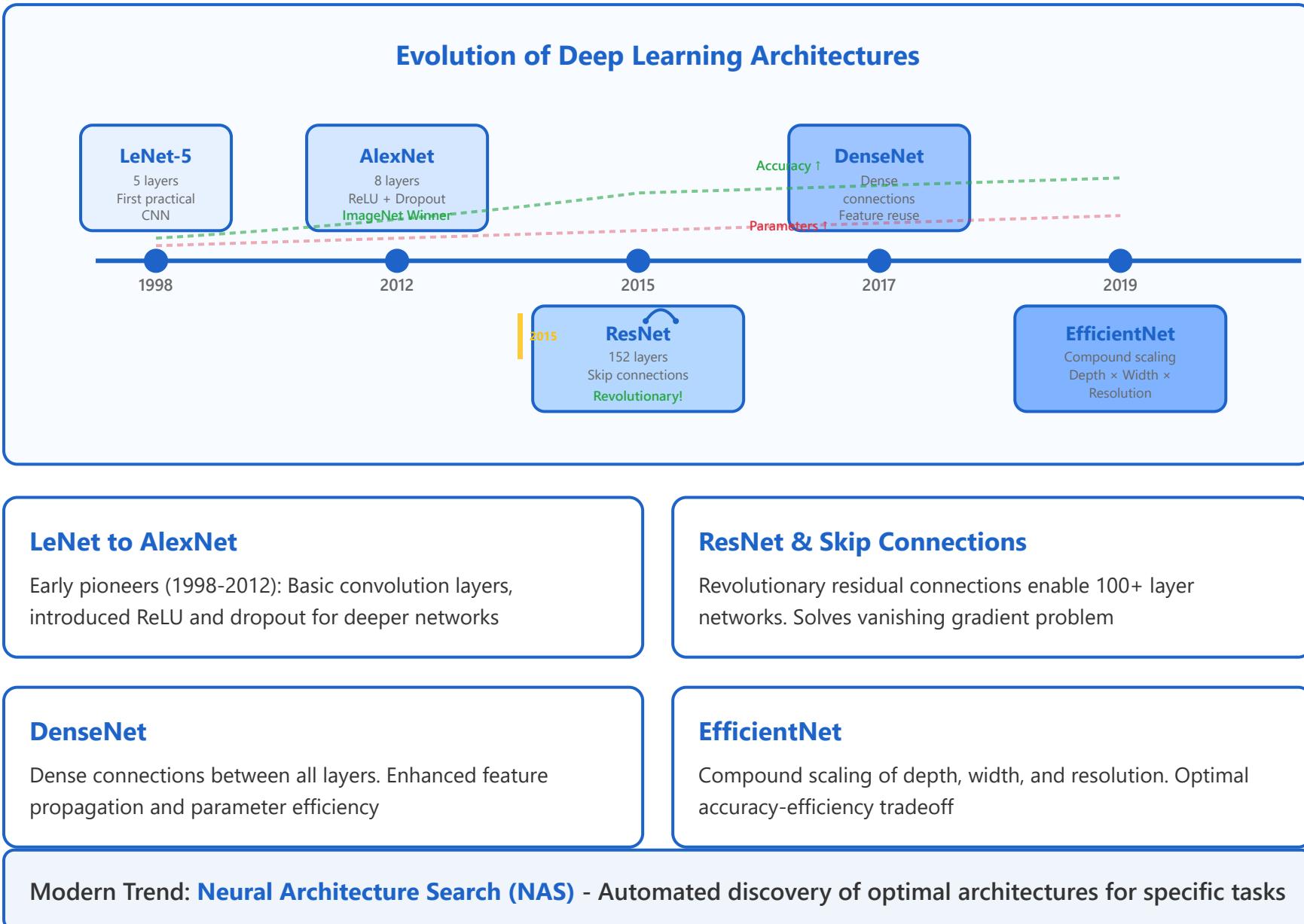
### Adaptive Pooling

Outputs fixed size regardless of input dimensions.  
Automatically adjusts pooling window and stride

### Modern Alternatives

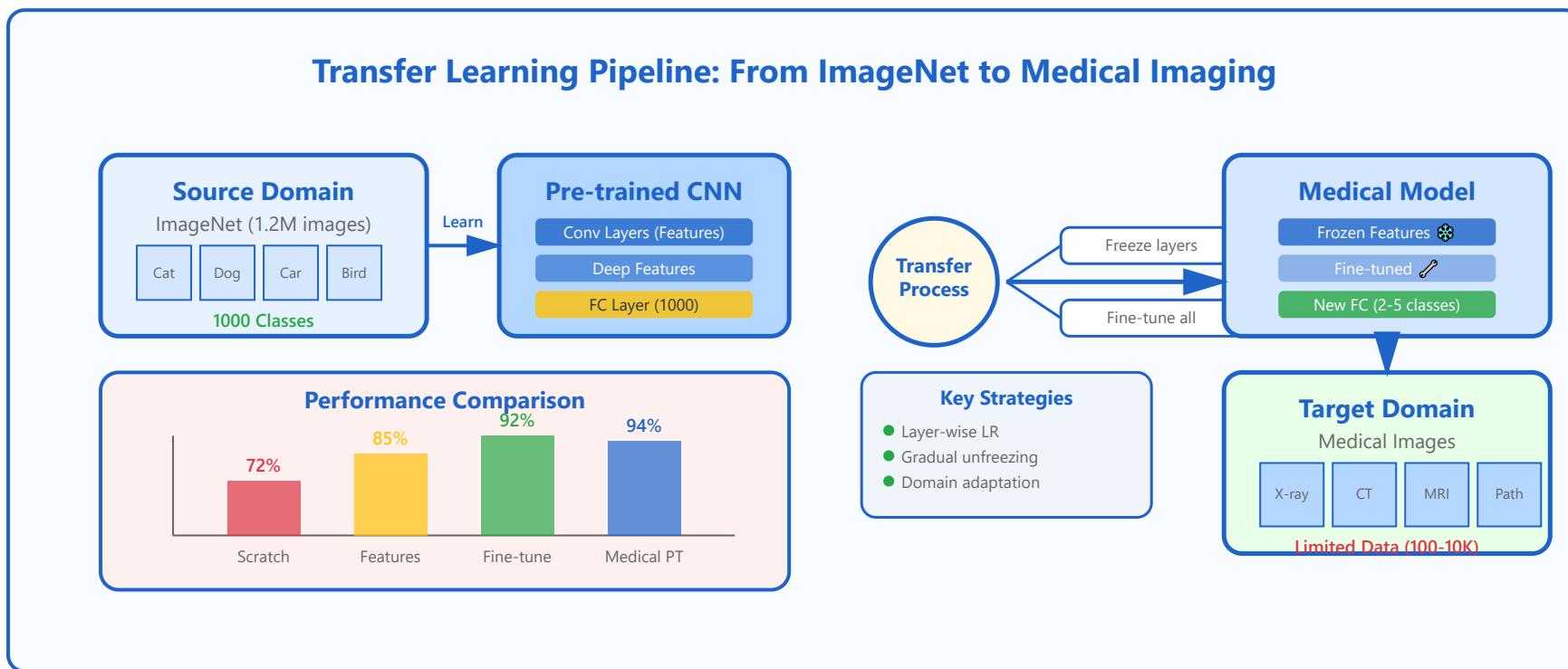
Strided convolutions can replace pooling while learning optimal downsampling patterns. Some architectures eliminate pooling entirely

# CNN Architectures Evolution





# Transfer Learning



## ImageNet Pretraining

Large-scale pretraining on natural images. Features transfer surprisingly well to medical domain

## Fine-tuning Strategies

Full fine-tuning vs. feature extraction. Layer-wise learning rate scheduling for optimal transfer

## Domain Adaptation

Techniques to bridge domain gap between natural and medical images. Adversarial and statistical methods

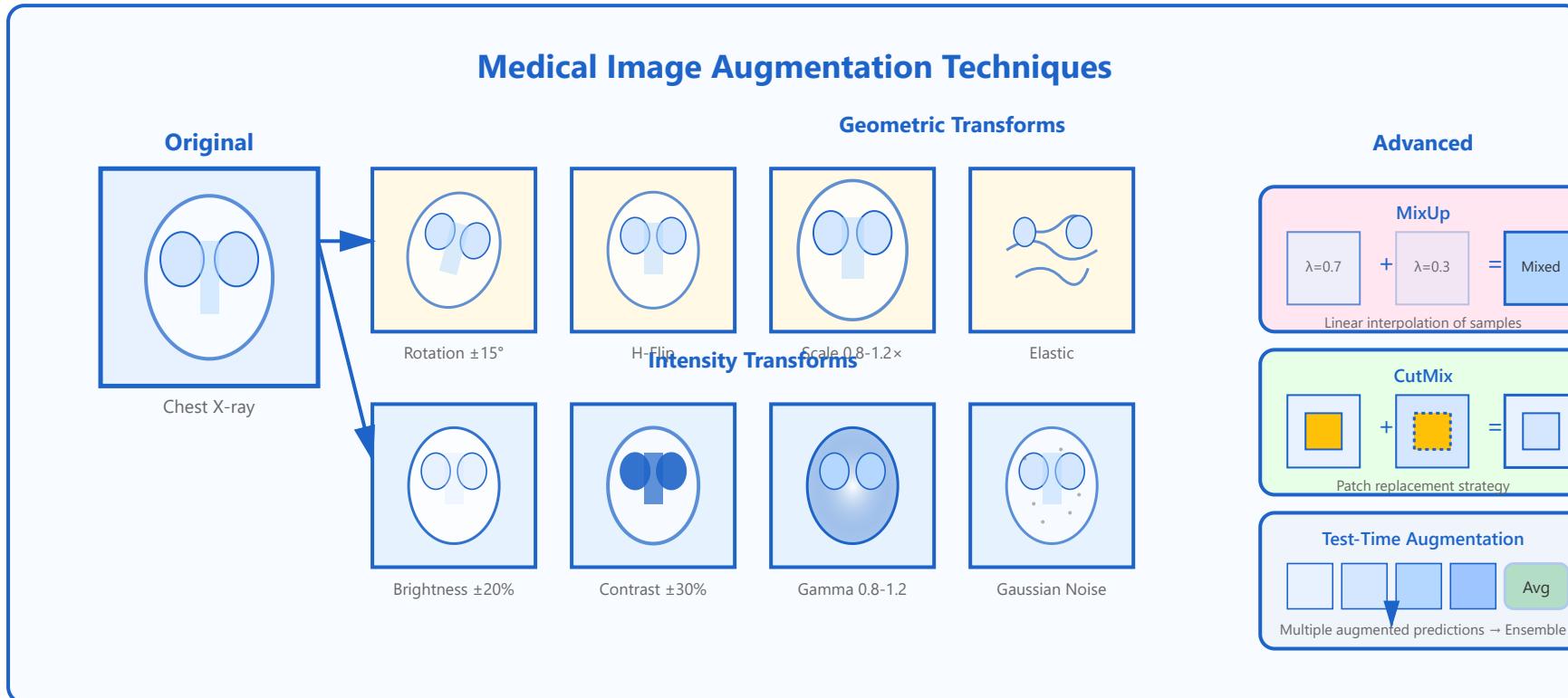
## Medical Pretraining

Self-supervised learning on medical data. Models like MedCLIP and BioViL trained on radiology reports

## **Few-shot Learning**

Learning from limited labeled data. Meta-learning and prototypical networks for rare diseases

# Data Augmentation



## Geometric Transforms

Rotation, flipping, scaling, elastic deformations. Must respect anatomical constraints

## Intensity Transforms

Contrast adjustment, brightness, gamma correction. Simulates different scanner protocols

## MixUp/CutMix

## Medical-Specific

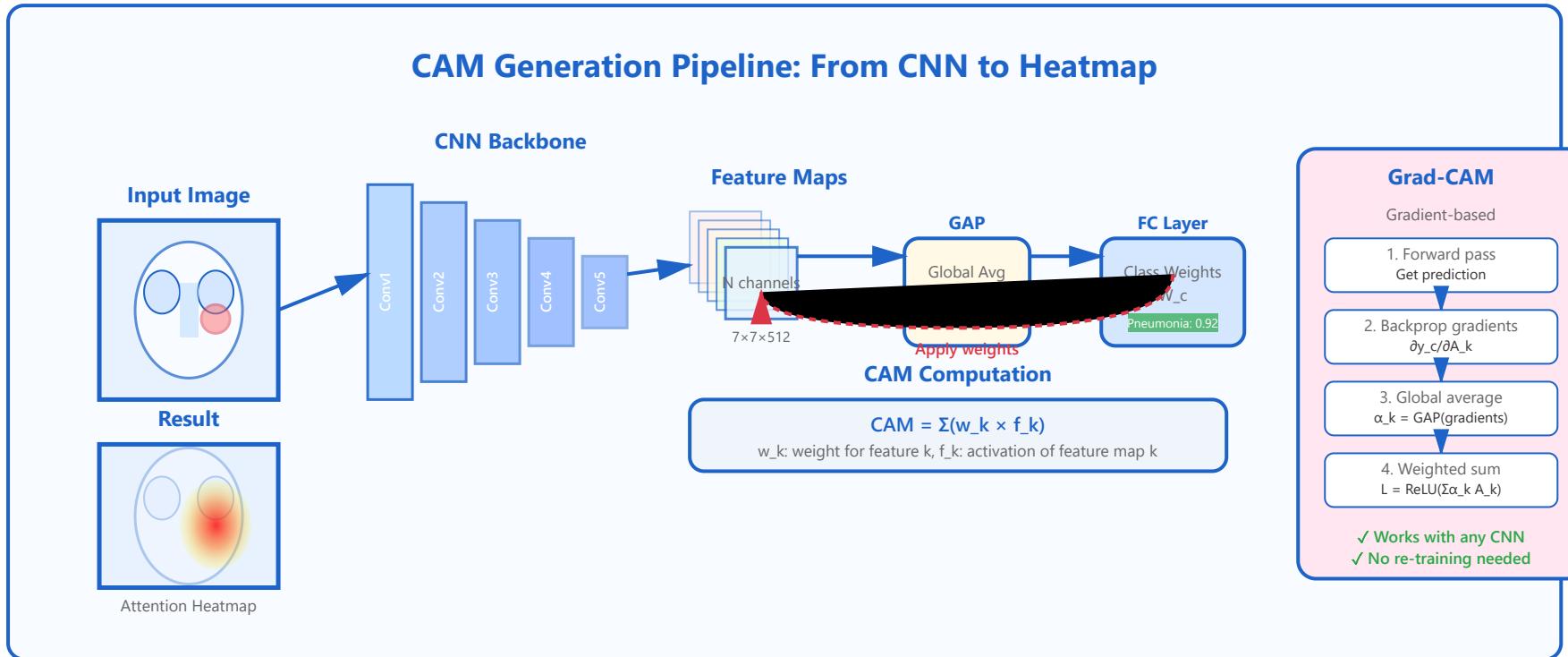
Mixing training examples. Creates synthetic samples for better generalization

Domain knowledge augmentation: simulating pathology, artifacts, different imaging protocols

### **Test-Time Augmentation**

Multiple predictions on augmented test images. Ensemble for improved robustness

# Class Activation Maps (CAM)



## CAM Principles

Visualize important regions for classification. Linear combination of feature maps weighted by class weights

## Grad-CAM

Gradient-based localization. Works with any CNN architecture without modification

## Grad-CAM++

Improved weighted combination. Better localization for multiple objects and weak activations

## Score-CAM

Gradient-free approach using forward passes. More stable and cleaner visualizations

## **Clinical Interpretation**

Essential for model validation and trust building. Helps radiologists understand AI decisions

**Part 2/3:**

# **Medical Applications**

- Task categories
- Architecture selection
- Performance benchmarks

# Classification Tasks

## Medical Image Classification Pipeline

### Classification Types

#### Binary Classification

Normal vs Abnormal

#### Multi-class Classification

Multiple exclusive classes

#### Multi-label Classification

Multiple co-occurring conditions

#### Ordinal Regression

Grade 0 → Grade 4

### Processing Pipeline

#### Input Processing

- Normalization
- Resize/Crop
- Augmentation

#### CNN Model

ResNet/Dense  
EfficientNet  
Vision Trans.

#### Predictions

Probabilities  
Class labels  
Confidence

### Uncertainty Estimation

Monte Carlo Dropout  
Multiple forward passes

Deep Ensembles  
Combine predictions

✓ Know when uncertain

### Real Performance

ChestX-ray14 Dataset:	90%
Diabetic Retinopathy:	95%
Skin Cancer Detection:	88%

## Disease Detection

Binary or multi-class classification. Pneumonia detection, cancer screening, retinopathy grading

## Multi-label Classification

Multiple diseases per image. Thoracic diseases (14 classes in ChestX-ray14 dataset)

## Ordinal Regression

Ordered categories (disease severity). Preserves ordering constraints in loss function

## Uncertainty Estimation

Confidence in predictions. Monte Carlo dropout, ensembles, or Bayesian approaches

## **Ensemble Methods**

Combining multiple models. Improves robustness and calibration of predictions

# Detection Tasks

## Object Detection Basics

Localizing and classifying objects. Bounding boxes around lesions, nodules, fractures

## YOLO for Medical

Real-time detection. Fast inference for large 3D volumes or video

## Faster R-CNN

Two-stage detector. Higher accuracy, commonly used in medical imaging

## Anchor-Free Methods

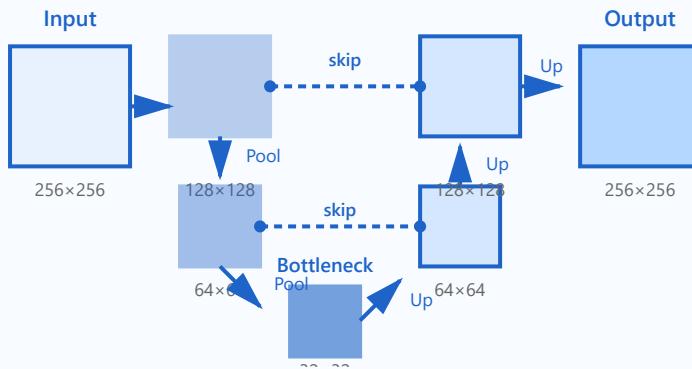
FCOS, CenterNet. Simpler pipelines without anchor design

## 3D Detection

Extending to volumetric data. 3D bounding boxes for CT/MRI lesions

# Segmentation with U-Net

## U-Net Architecture: Encoder-Decoder with Skip Connections



### Key Components:

- Encoder (Contracting path)  
Captures context, reduces spatial dim
- Decoder (Expanding path)  
Localizes, increases spatial dim
- Skip Connections  
Preserve spatial details
- Bottleneck  
Highest-level features

### Operations:

### U-Net Architecture

Encoder-decoder with skip connections. Standard for medical image segmentation

### Skip Connections

Combine low and high-level features. Preserve spatial details for precise boundaries

### Loss Functions

Dice loss, focal loss, boundary loss. Address class imbalance and boundary precision

### 3D U-Net

Extension to volumetric data. Processes entire 3D volumes for organ/tumor segmentation

## **nnU-Net Framework**

Self-configuring U-Net. Automatically adapts to dataset characteristics

# 3D Medical Imaging

## 2D vs 2.5D vs 3D Approaches

Memory Usage:  
2D: ~1GB | 2.5D: ~3-5GB | 3D: ~8-27GB



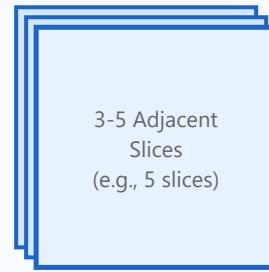
Single  
2D Slice



2D CNN  
Conv2D

✓ Fast. Low Memory

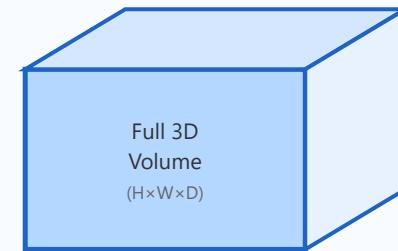
2.5D Multi-Slice | 3D: ~8-27GB



2D CNN  
Multi-channel input

✓ Limited 3D Context

3D Volumetric



Full 3D  
Volume  
( $H \times W \times D$ )

3D CNN  
Conv3D

✓ Full 3D Context

## 2.5D vs 3D Approaches

2.5D: Multi-slice input. 3D: Full volumetric processing.  
Tradeoffs in memory and context

## Memory Constraints

3D convolutions require 8-27x more memory. Careful batch size and patch size selection

## Patch-Based Methods

Process small overlapping 3D patches. Enables processing of large volumes

## Sliding Window

Inference strategy for large volumes. Overlapping predictions with smoothing

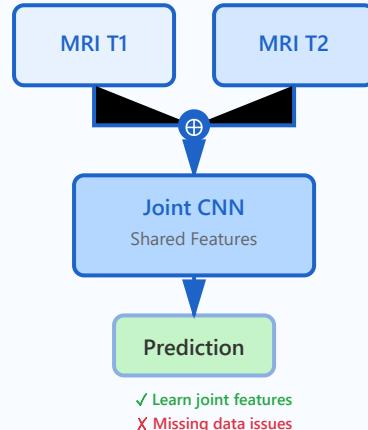
## Volumetric Networks

3D ResNet, V-Net, 3D U-Net. Leverage full 3D context for better accuracy

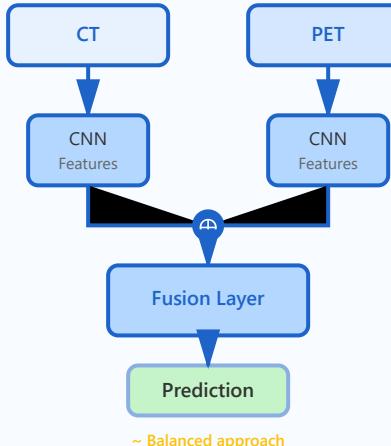
# Multi-modal Fusion

## Fusion Strategies Comparison

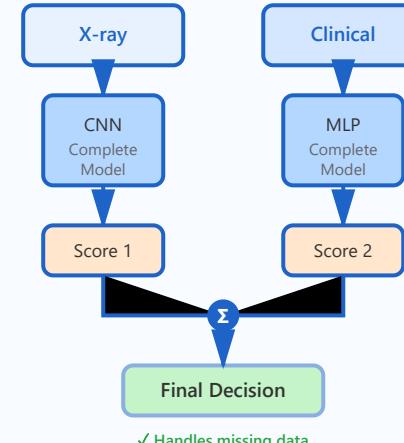
### Early Fusion



### Intermediate Fusion



### Late Fusion



### Early vs Late Fusion

Early: Combine at input/features. Late: Combine predictions.  
Depends on modality complementarity

### Attention Mechanisms

Learn importance of each modality. Dynamic weighting based on input

### Cross-Modal Learning

Transfer knowledge between modalities. Co-training and contrastive learning

### Missing Modalities

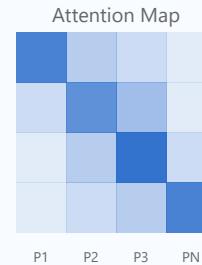
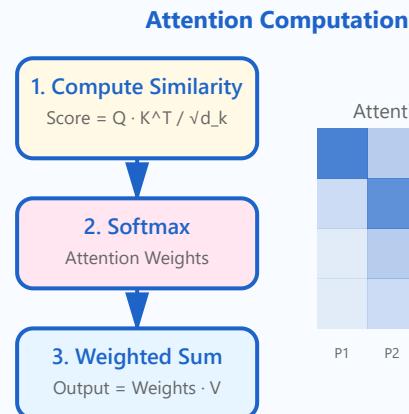
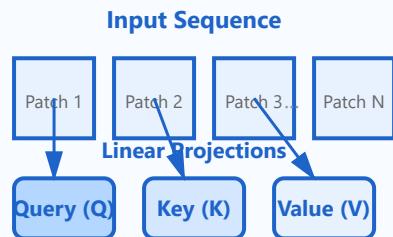
Handling incomplete data. Imputation or modality-specific pathways

## Clinical Protocols

MRI sequences (T1, T2, FLAIR), PET-CT fusion. Each modality provides unique information

# Attention Mechanisms

## Self-Attention Mechanism



### Context-Aware Output

Each position attends to all other positions  
Global receptive field

- ✓ Long-range dependencies
- ✓ Parallel computation
- ✓ Interpretable weights

### Self-Attention

Capture long-range dependencies. Every position attends to all others

### Cross-Attention

Attend between different modalities or sequences. Query from one, key/value from another

### Vision Transformers

Pure attention-based architecture. ViT, Swin Transformer for medical imaging

### Hybrid Architectures

CNN backbone + Transformer head. CoAtNet, TransUNet combine local and global context

### Interpretability Benefits

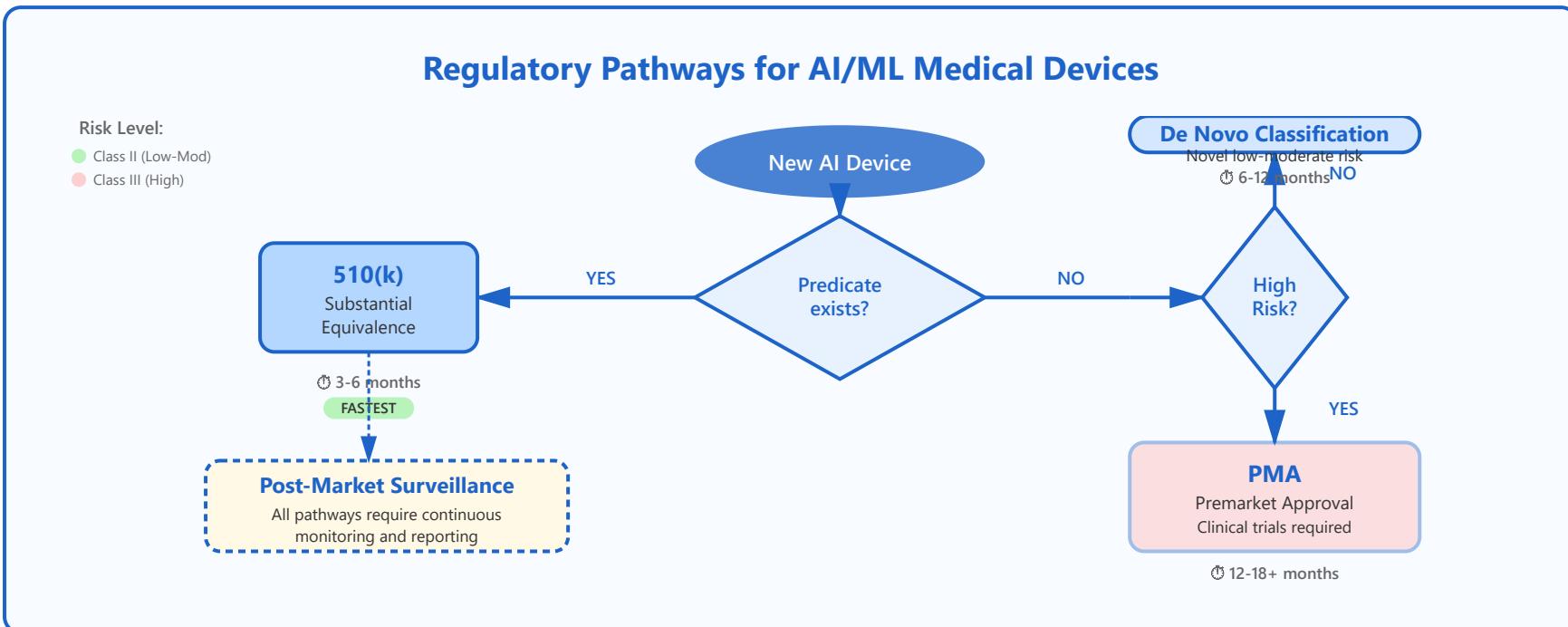
Attention maps show model focus. More intuitive than CNN activation maps

**Part 3/3:**

# **Clinical Implementation**

- Regulatory pathway
- Integration challenges
- Quality assurance

# FDA Approval Process



## 510(k) Pathway

Substantial equivalence to existing device. Fastest route, ~3-6 months if predicate exists

## De Novo Classification

Novel low-to-moderate risk devices. Creates new device category, ~6-12 months

## PMA Requirements

Premarket Approval for high-risk devices. Most rigorous, requires clinical trials

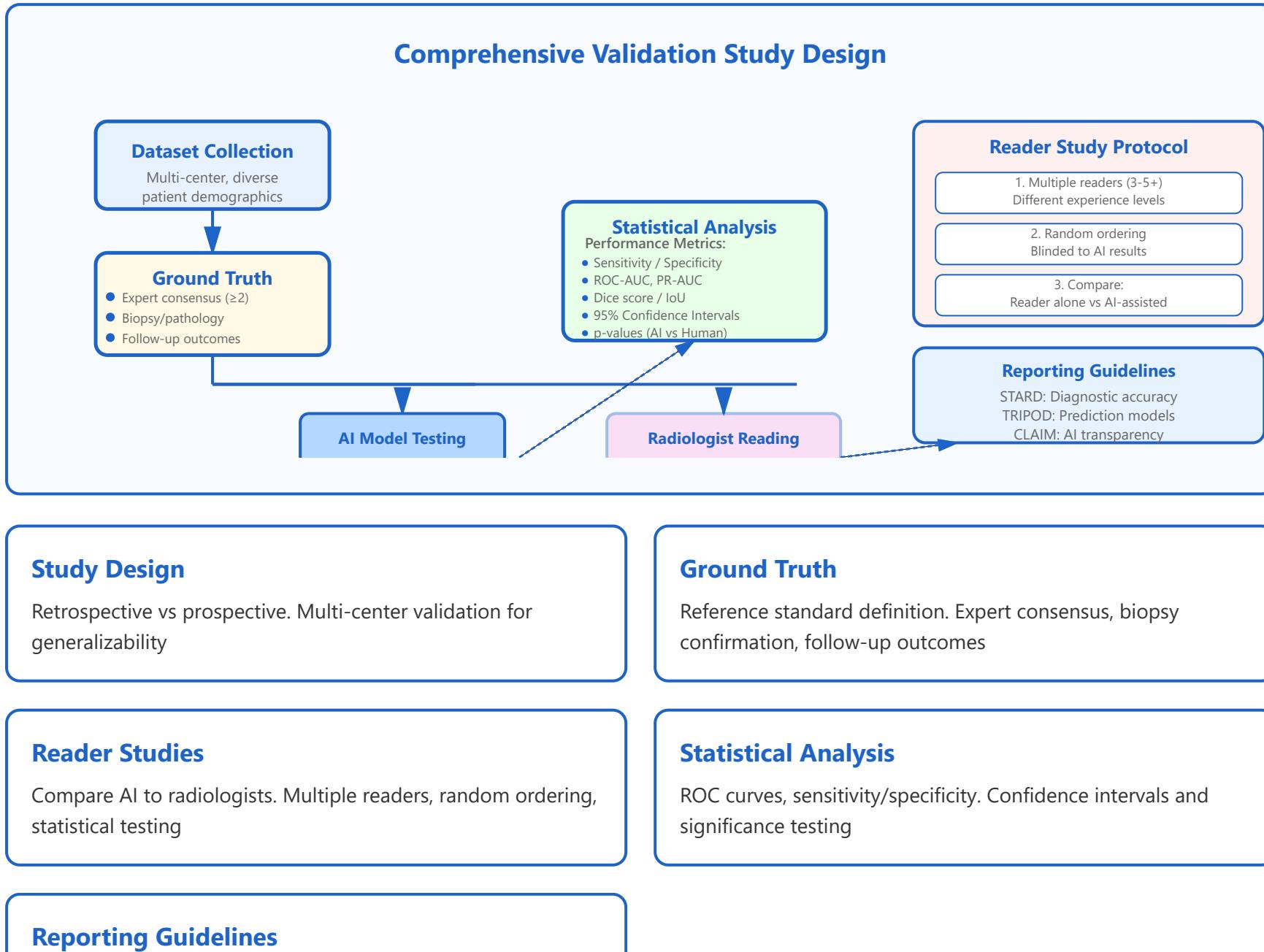
## Software Modifications

When algorithm changes require new submission. Predetermined change control plans

## **Real-World Surveillance**

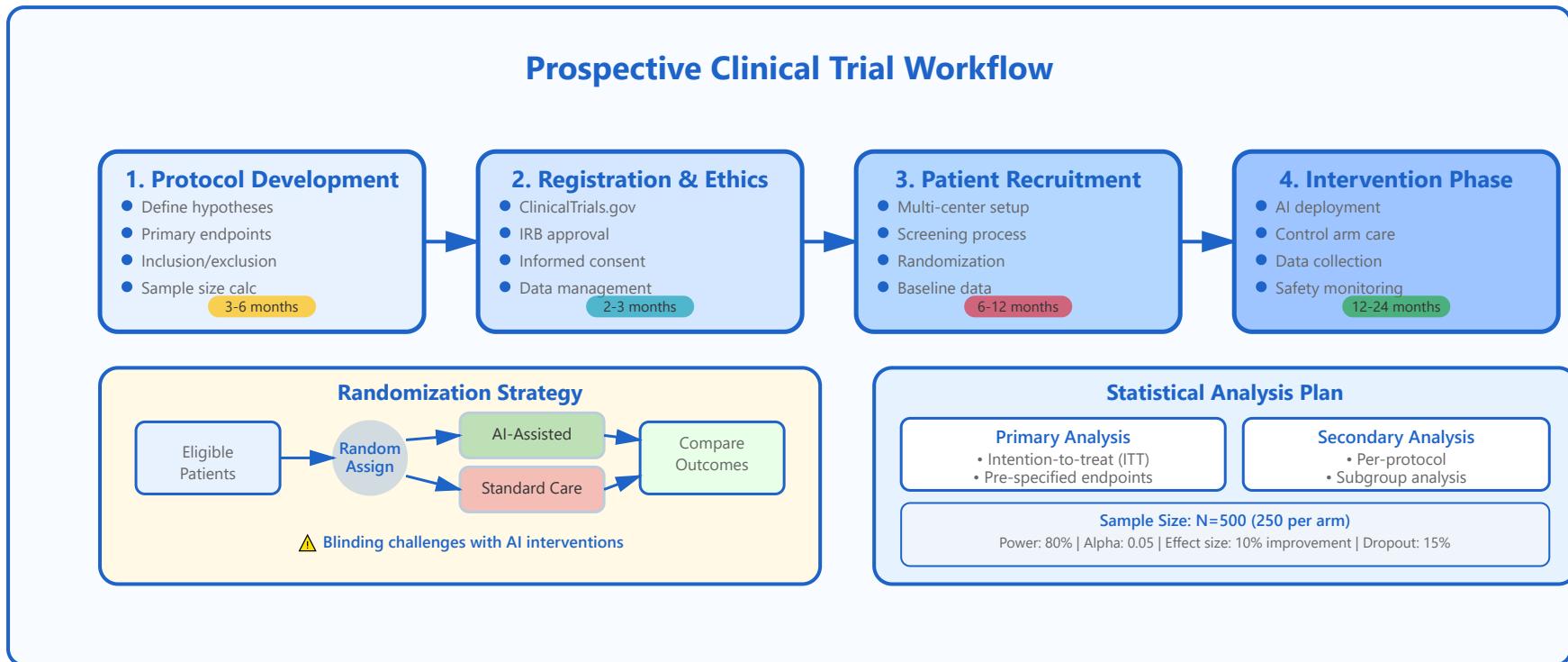
Post-market monitoring. Detect performance drift or adverse events

# Validation Studies



STARD, TRIPOD, CLAIM. Standardized reporting for  
reproducibility

# Prospective Trials



## Trial Protocols

Pre-specified hypotheses and endpoints. Registered in clinicaltrials.gov

## Endpoint Selection

Diagnostic accuracy vs clinical outcomes. Hard outcomes (mortality) vs surrogate markers

## Sample Size

Power analysis for adequate statistical power. Account for prevalence and effect size

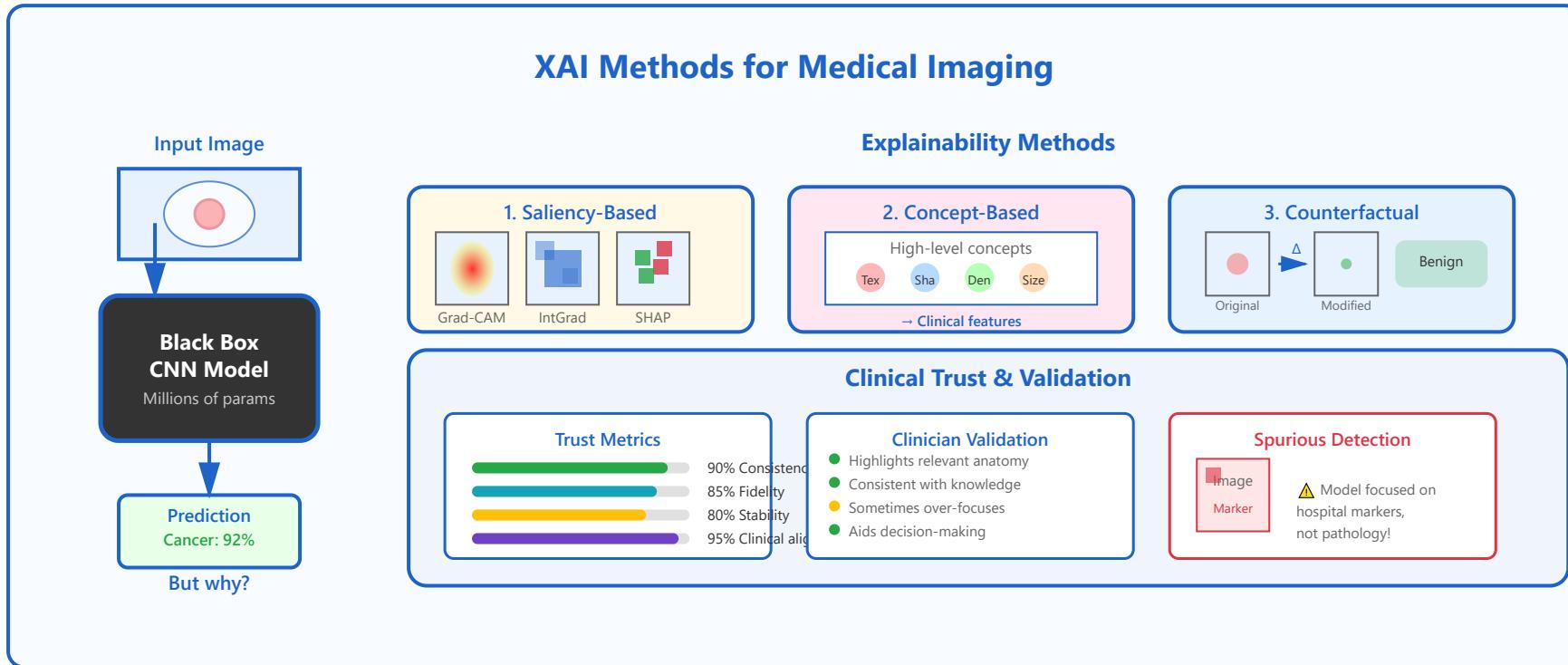
## Randomization

AI-assisted vs standard of care. Cluster randomization by site to avoid contamination

## **Analysis Plans**

Pre-specified statistical analysis. ITT vs per-protocol analysis

# Explainable AI (XAI)



## Interpretability Needs

Clinical trust and adoption. Regulatory requirements and liability concerns

## Saliency Maps

Grad-CAM, attention maps. Highlight important image regions

## Counterfactual Explanations

What changes would flip prediction. Minimal perturbations for opposite class

## Concept Attribution

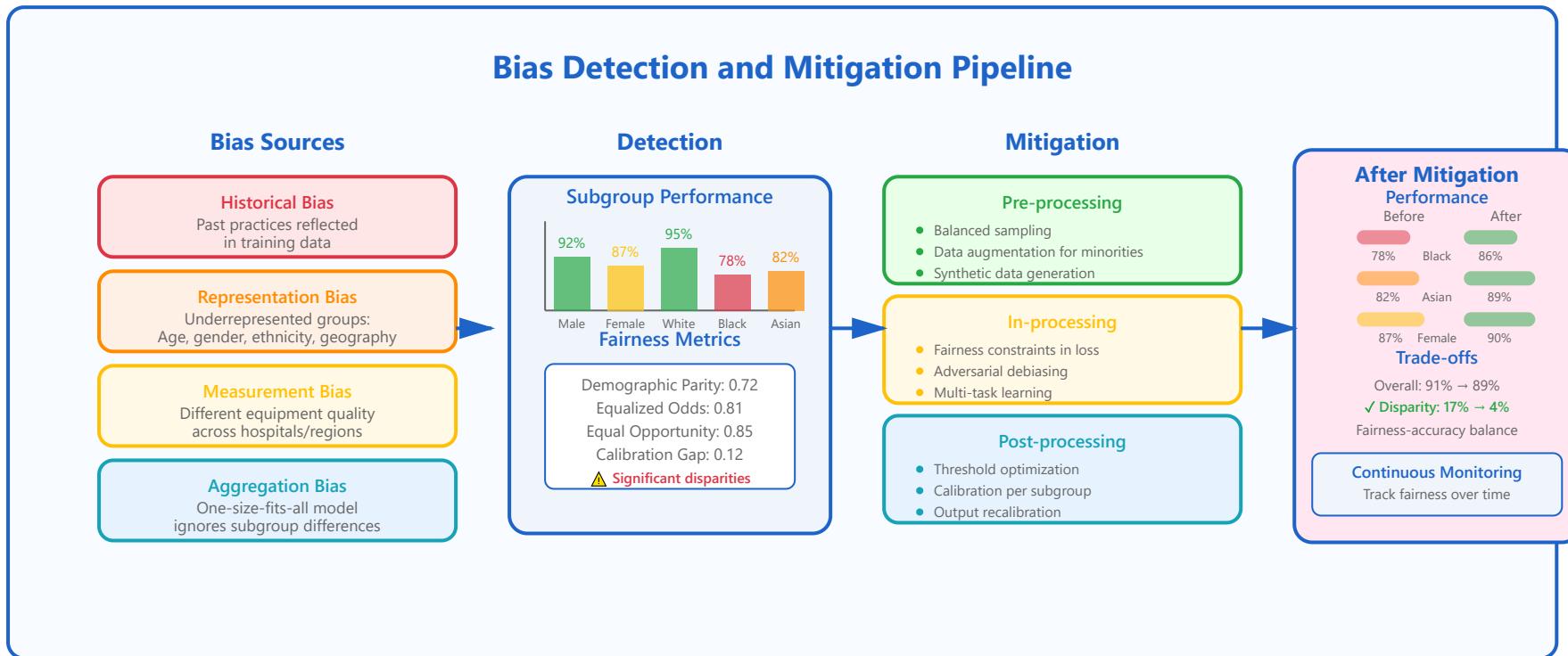
High-level concept importance. Relate to clinical features (texture, shape, density)

## **Trust Building**

Consistent explanations aligned with clinical knowledge.

Detect spurious correlations

# Bias and Fairness



## Dataset Bias

Selection bias, label bias. Underrepresentation of certain demographics

## Demographic Disparities

Performance gaps across age, sex, race. Different disease prevalence and presentation

## Fairness Metrics

Equalized odds, demographic parity. Group fairness vs individual fairness

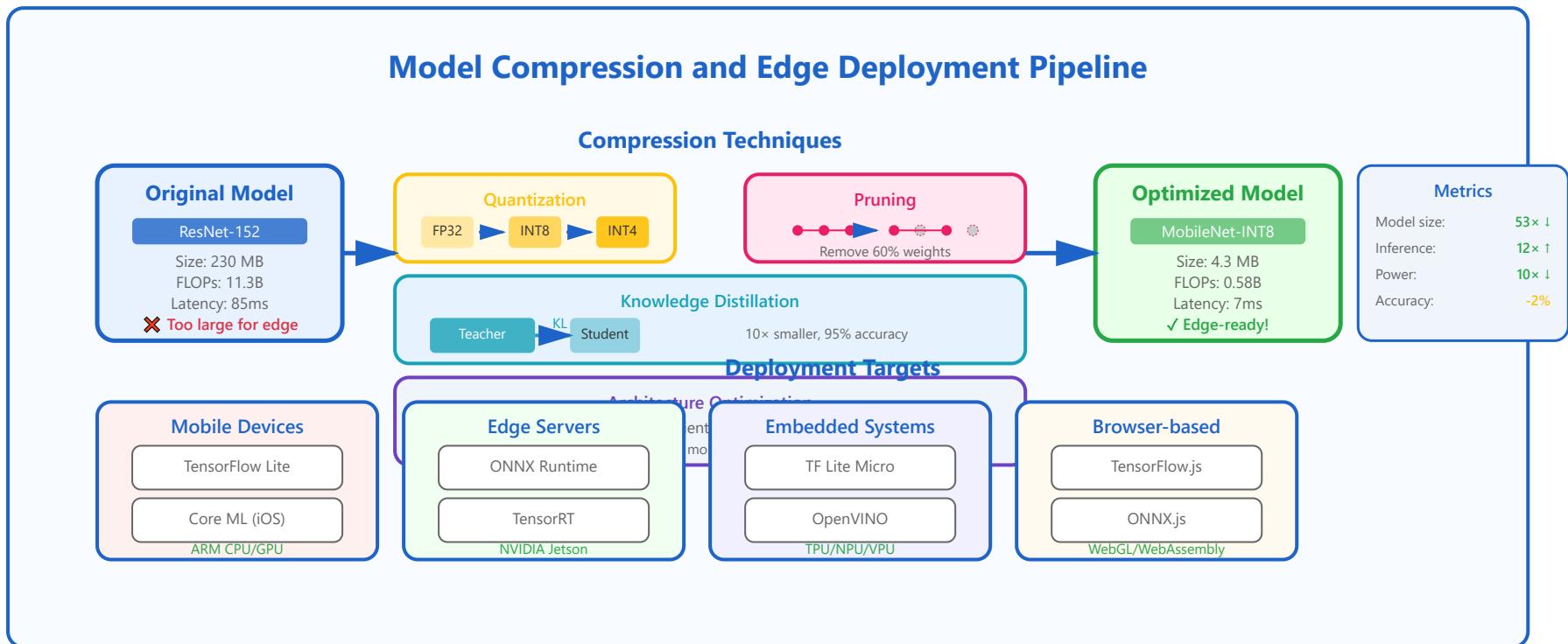
## Mitigation Strategies

Diverse training data, reweighting, adversarial debiasing. Fairness constraints

## **Continuous Monitoring**

Track performance by subgroup. Detect and address emerging disparities

# Edge Deployment



## Model Compression

Reduce model size and latency. Essential for edge devices and real-time applications

## Quantization

INT8 or INT4 precision. 4x smaller models with minimal accuracy loss

## Pruning

Remove redundant weights/neurons. Structured pruning for hardware efficiency

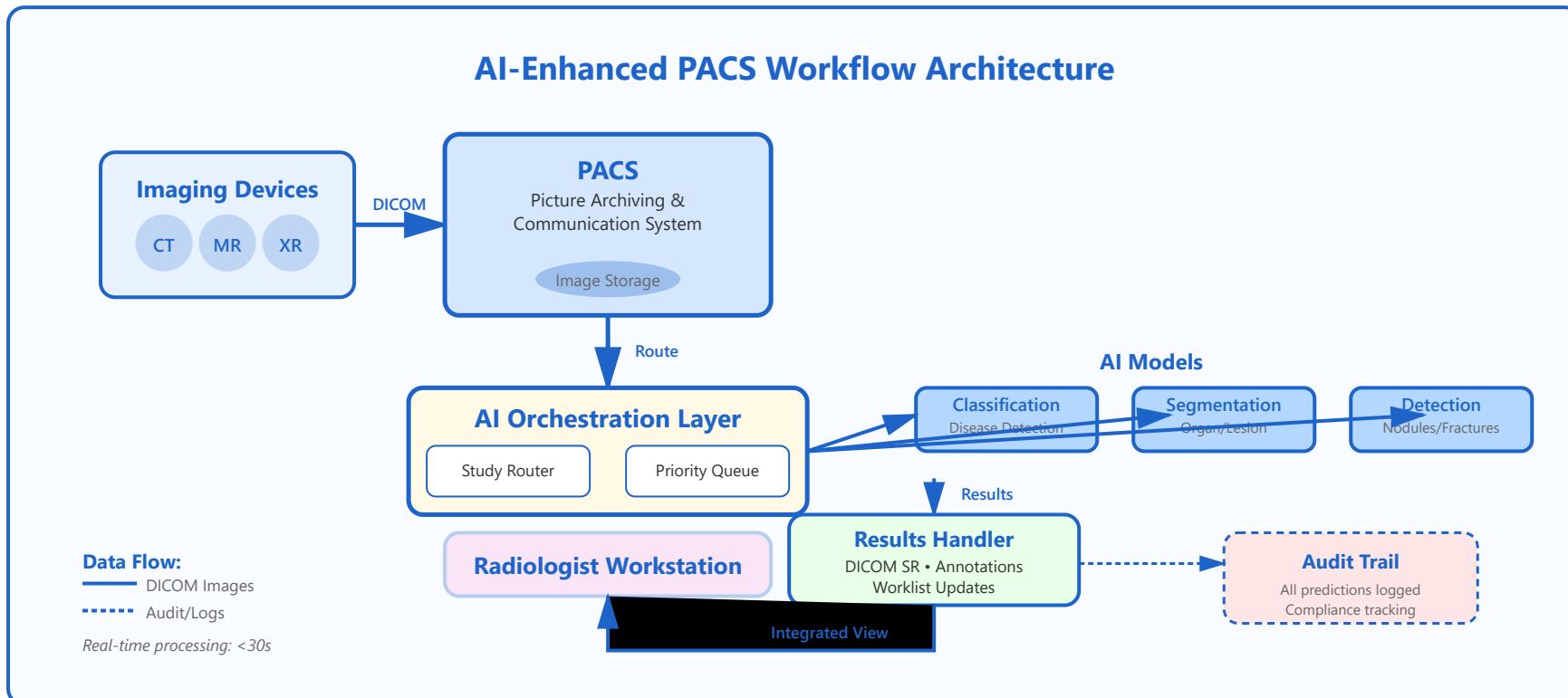
## Knowledge Distillation

Train small student from large teacher. Maintains performance with fewer parameters

## **Hardware Acceleration**

TensorRT, ONNX Runtime, GPU, TPU, or specialized medical imaging accelerators

# PACS Integration



## DICOM Workflows

Receive images, process, send results. Standard medical imaging communication

## AI Orchestration

Routing studies to appropriate AI models. Manage multiple algorithms and priorities

## Results Communication

DICOM SR, overlay annotations. Integration with radiology reporting systems

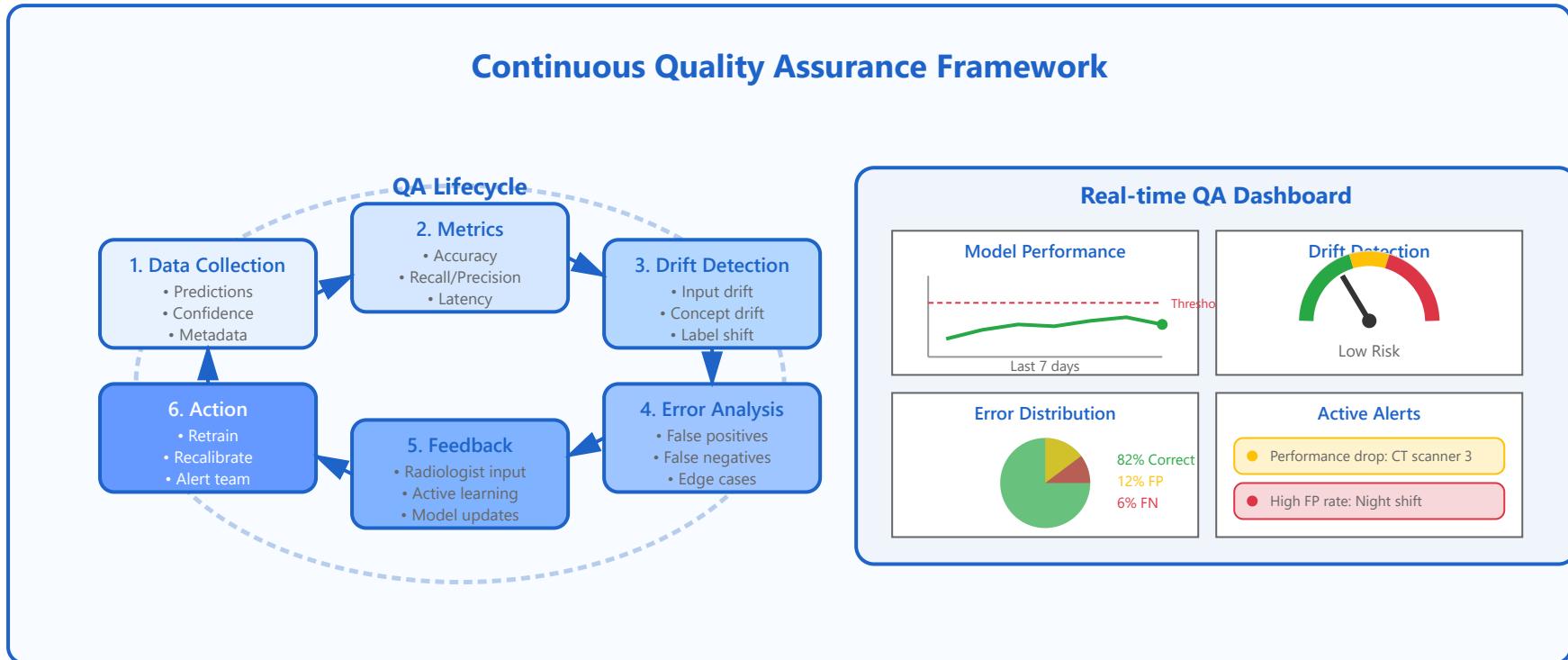
## Worklist Prioritization

AI-driven triaging. Urgent findings flagged for immediate review

## **Audit Trails**

Complete logging for compliance. Track every AI prediction and radiologist interaction

# Quality Assurance



## Performance Monitoring

Track accuracy, precision, recall over time. Automated dashboards

## Drift Detection

Identify distribution shifts. Input drift (scanner changes) vs concept drift (disease patterns)

## Error Analysis

Systematic review of failures. Identify error patterns and edge cases

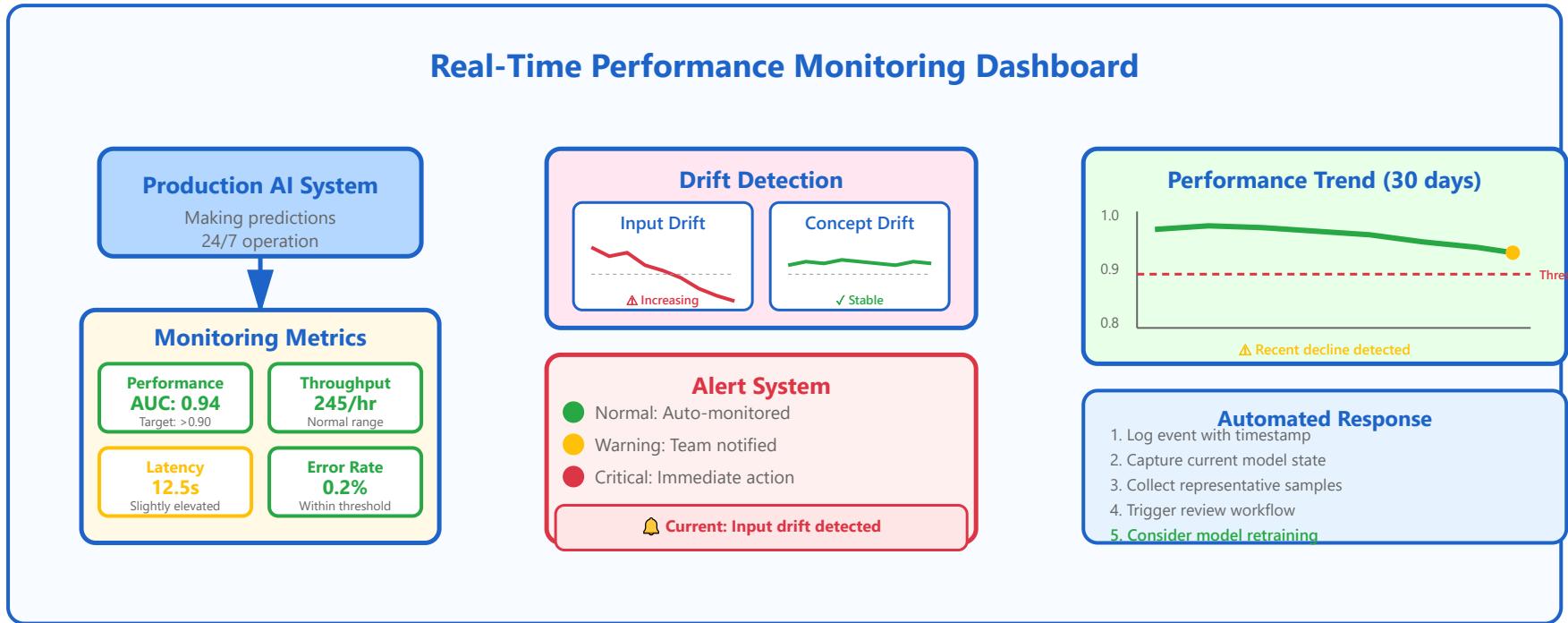
## Feedback Loops

Radiologist corrections. Active learning to improve model from production data

## **Continuous Improvement**

Iterative model updates. A/B testing of model versions

# Continuous Monitoring



## Real-World Metrics

Sensitivity, specificity in production. Compare to validation performance

## Alert Systems

Automated alerts for anomalies. Performance degradation, unusual predictions

## Performance Degradation

Detection of model staleness. Dataset shift from new equipment or protocols

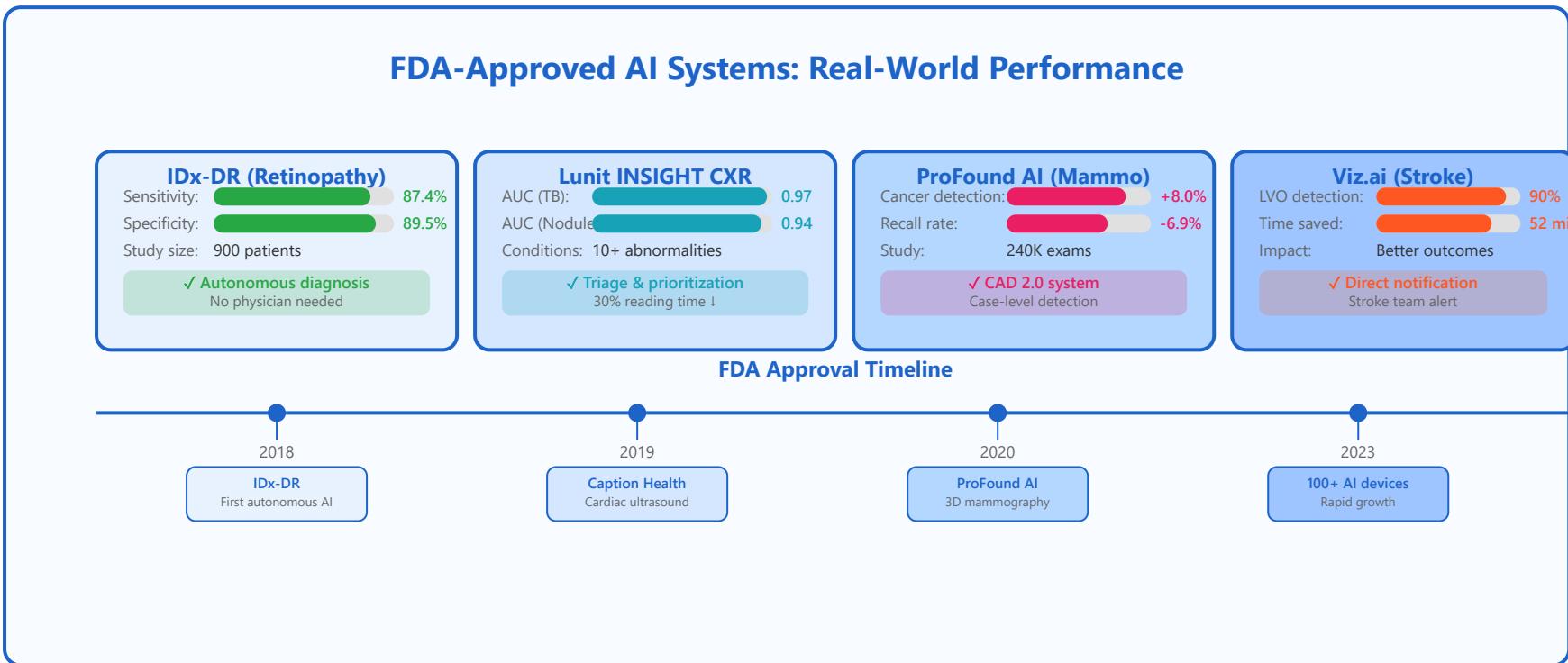
## Update Strategies

When and how to retrain. Regulatory considerations for algorithm changes

## **Regulatory Compliance**

Documentation for audits. Adverse event reporting to FDA

# Clinical Case Studies



### Diabetic Retinopathy

FDA-approved IDx-DR system. Autonomous diagnosis without physician review

### Chest X-ray Screening

Qure.ai qXR, Lunit INSIGHT CXR. Detection of 20+ thoracic abnormalities

### Mammography CAD

iCAD ProFound AI, Transpara. 5-8% increase in cancer detection rate

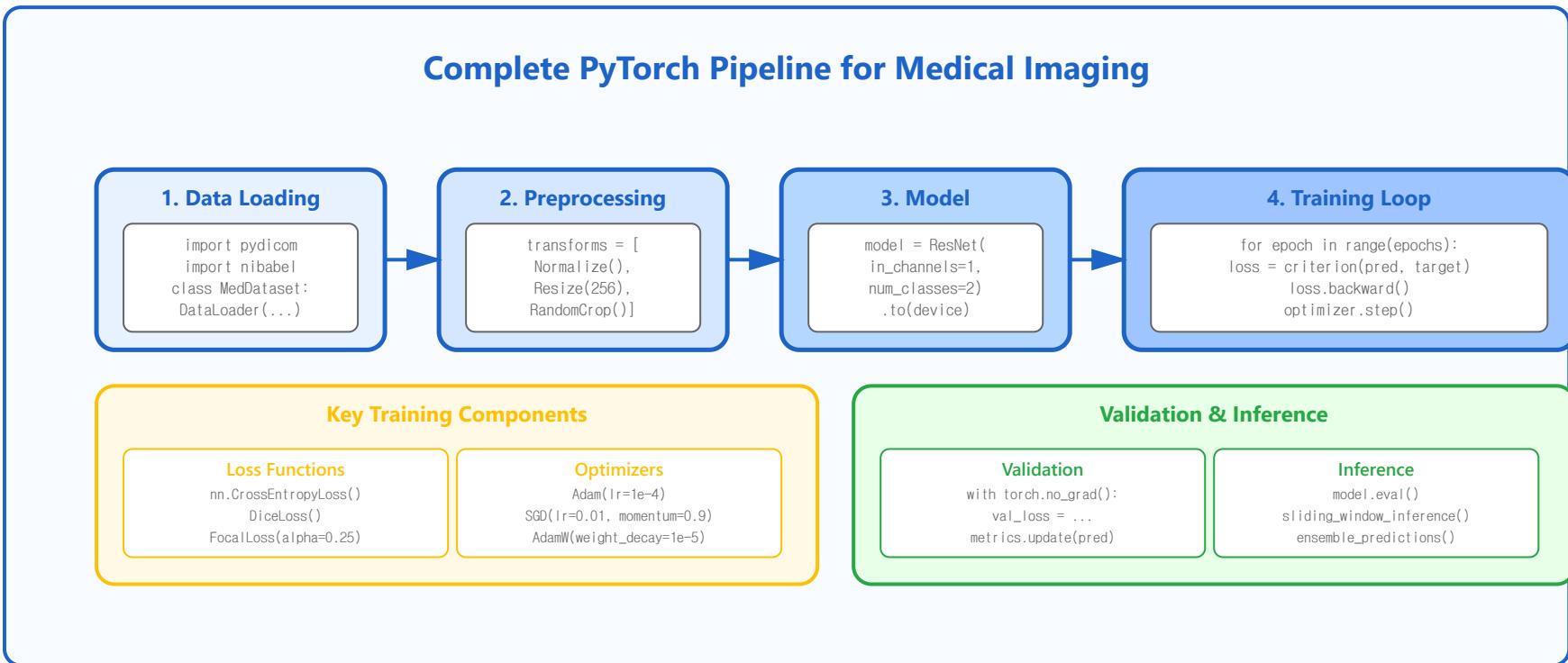
### Stroke Detection

Viz.ai, RapidAI. Automated LVO detection and care team notification

## **Pathology Applications**

Digital pathology with AI. Cancer detection in biopsies,  
PD-L1 scoring

# Hands-on: PyTorch Medical Imaging



## Data Loading

DICOM reading with pydicom, NIfTI with nibabel. Custom Dataset classes

## Model Implementation

ResNet, U-Net from scratch or torchvision. Custom layers for medical imaging

## Training Loops

Loss functions, optimizers, learning rate schedules. Mixed precision training

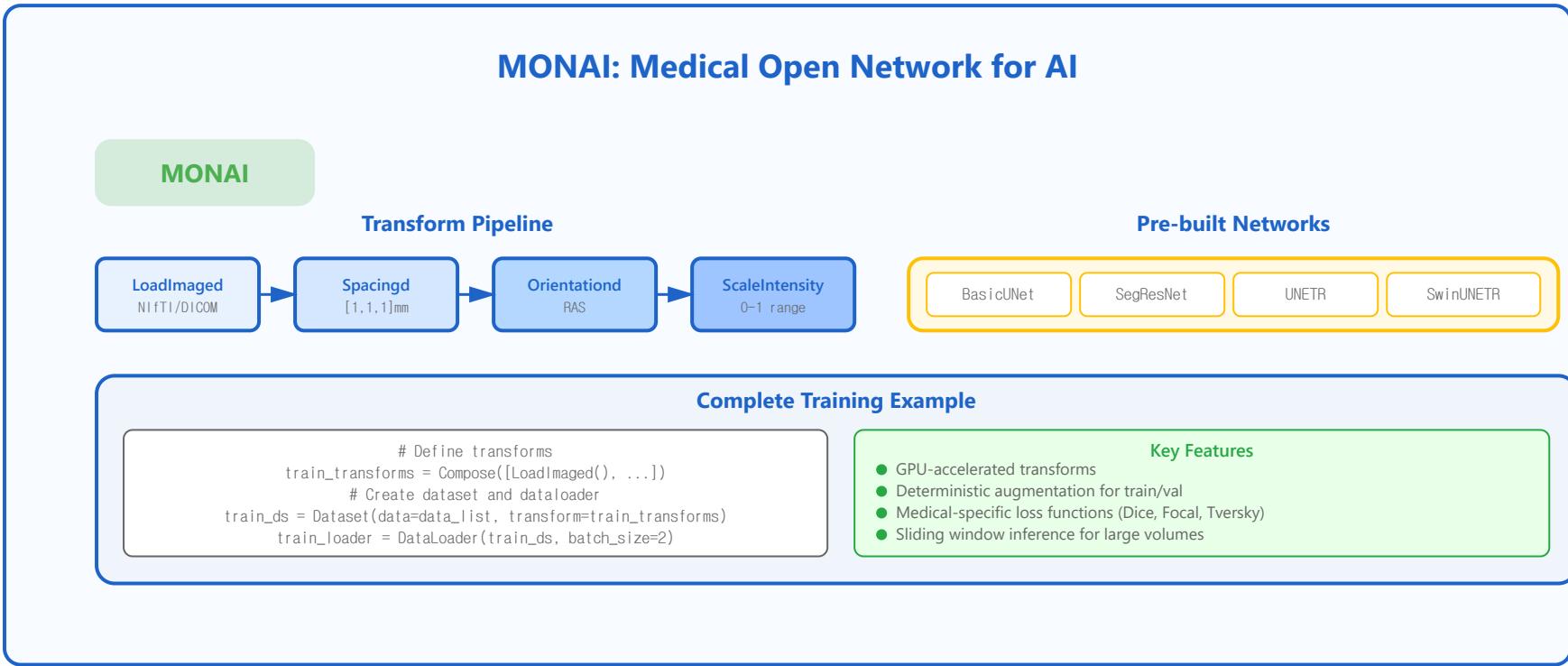
## Validation

Metrics computation, checkpointing. Early stopping and model selection

## **Inference**

Sliding window for large images. Batch processing and result aggregation

# Hands-on: MONAI Framework



## Medical Transforms

Specialized augmentation pipeline. Intensity normalization, resampling, cropping

## Pre-built Networks

DenseNet, SegResNet, UNETR. Optimized for medical imaging

## Loss Functions

DiceLoss, FocalLoss, TverskyLoss. Handle class imbalance

## Metrics

Mean Dice, Hausdorff distance. Standard medical imaging metrics

## **Deployment**

MONAI Deploy for production. Integration with PACS and inference servers

# Thank You & Future Directions

## Emerging Trends

Foundation models for medical imaging. Self-supervised learning at scale

## Generative Models

Synthesis for data augmentation and privacy. Conditional generation for rare cases

## Federated Learning

Collaborative learning without data sharing. Address data privacy and silos

## Career Paths

Clinical AI researcher, ML engineer in healthcare. Regulatory affairs specialist