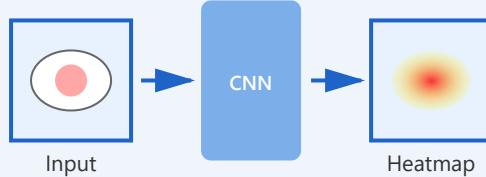


Explainable AI (XAI) - Visual Guide

1. Saliency-Based Methods

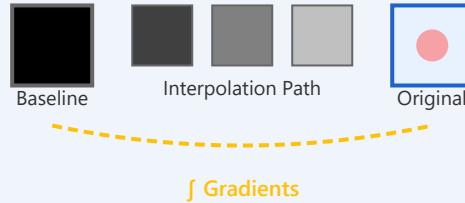
🔥 Grad-CAM



- ✓ Fast and class-discriminative
- ✓ Works with any CNN architecture
- ✗ Low spatial resolution

💡 Example: Highlights lung regions with pneumonia

📊 Integrated Gradients



- ✓ Theoretically grounded (completeness)
- ✓ Precise pixel-level attribution
- ✗ Computationally expensive

💡 Example: Identifies exact pixels contributing to tumor classification

infiltrates in chest X-rays

Oncology

Diagnosis

Radiology

Pathology

LIME



- ✓ Model-agnostic approach
- ✓ Interpretable local explanations
- ✗ Can be unstable

💡 Example: Explains which image regions support/oppose a diagnosis

Black-box

Any model

2. Concept Attribution Methods

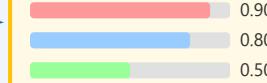


1. Define Concepts

Tex Sha Den

Learn CAVs
in activation
space

3. TCAV Scores



- ✓ Uses clinically meaningful concepts
- ✓ Quantifies concept importance
- ✗ Requires concept example datasets

Example: "Model is 90% sensitive to nodular texture in lung CT scans"

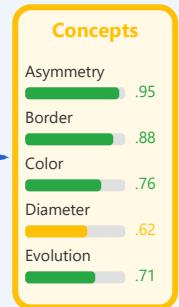
Clinical Concepts



Concept Bottleneck Models

Input

CNN



Pred
89%

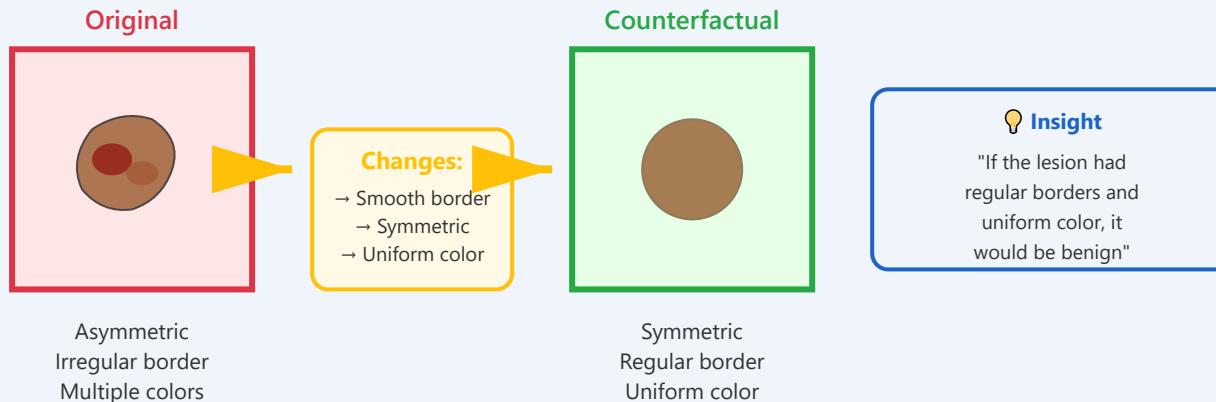
- ✓ Built-in interpretability
- ✓ Transparent decision pathway
- ✗ May sacrifice some accuracy

Example: Melanoma detection using ABCDE criteria (visible intermediate layer)

Dermatology ABCDE

3. Counterfactual Explanations

⌚ What-If Analysis



- ✓ Shows minimal changes needed to flip prediction
- ✓ Actionable insights for clinicians
- ✓ Helps understand decision boundaries
- ✗ May suggest unrealistic changes

💡 Example: "If border irregularity decreased from 0.85 to 0.45, prediction would flip to benign"

4. Trust Building & Validation

✓ Faithfulness Testing

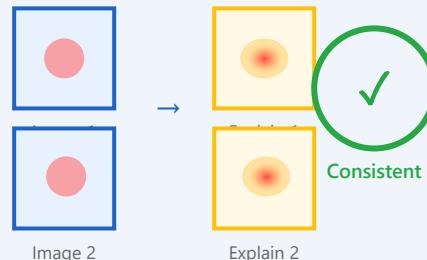


- ✓ Measures if explanations reflect actual model behavior
- ✓ Deletion/insertion tests
- X Masking artifacts can affect results

Validation

Metrics

🎯 Consistency Check



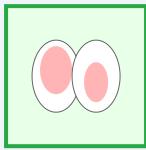
- ✓ Similar inputs → similar explanations
- ✓ Stable under small perturbations
- X Some methods inherently unstable (LIME)

Stability

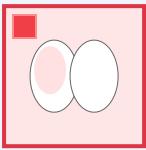
Trust

⚠ Spurious Detection

✓ Correct



✗ Spurious



Focuses on
Common issues:

- Hospital markers
- Medical devices
- Scanner artifacts

Focuses on
hospital marker!

- ✓ Identifies unreliable model reasoning
- ✓ Critical for safety
- ✗ Requires expert validation

💡 Real case: Pneumonia model achieved 95% but focused on portable X-ray markers!

Safety

Validation

5. Interpretability Needs by Stakeholder



Clinicians

Need:

- Case-specific explanations
- Clinical feature attribution
- Quick, actionable insights
- Uncertainty quantification

"Why is this lesion melanoma? Which features are most concerning?"



Patients

Need:

- Plain language
- What it means for health
- Treatment implications
- Confidence in AI use

"What does this result mean for me? Can I get a second opinion?"



Regulators

Need:

- Auditability
- Bias detection
- Compliance (FDA, GDPR)
- Accountability trails

"Can we audit this decision if legally challenged?"



AI Developers

Need:

- Model debugging
- Feature importance
- Failure mode detection
- Performance metrics

"Is the model using appropriate features? Where does it fail?"

Key Takeaways

Explainable AI: Essential for Medical AI Deployment

Saliency Methods

Visual attribution
Grad-CAM, LIME

Concept Attribution

Clinical concepts
TCAV, CBMs

Counterfactuals

What-if analysis
Actionable insights

Essential Requirements:

- ✓ Trust & Validation through faithfulness and consistency
- ✓ Stakeholder Alignment meeting diverse needs
- ✓ Safety through spurious correlation detection
- ✓ Regulatory Compliance (FDA, GDPR, EU AI Act)

"XAI enables clinicians to understand, validate, and appropriately rely on AI while maintaining safety, accountability, and trust"

