

# BRIDGING ACCURACY AND TRUST: EXPLAINABLE DEEP LEARNING VS. CLASSICAL COMPUTER VISION FOR MALARIA DIAGNOSIS

A COMPARATIVE ANALYSIS OF MOBILENETV2  
AND HOG-RANDOM FOREST

Presented by

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# THE DUAL CRISIS

## The Global Health Challenge

- **282 million cases of Malaria, 610,000 deaths (2024) [1]**
- Gold Standard (Microscopy) is slow, error-prone, and dependent on human expertise. [1]



## The AI Dilemma:

- **High accuracy** is not enough
- The "Black Box" Paradox
  - Doctors cannot trust a model they cannot understand. [2]
- Safety Risk:
  - A False Negative can be fatal.



[1] World Health Organization, World malaria report 2025: Addressing the threat of antimalarial drug resistance, Geneva: WHO, 2025.

[2] F. Pesapane, M. Codari, and F. Sardanelli, "Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine," European Radiology Experimental, vol. 2, no. 1, p. 35, 2018.

# METHODOLOGICAL DUEL

## SYMBOLIC VS. CONNECTIONIST

### Method A: Symbolic AI (The Baseline)

- Pipeline: HOG (Histogram of Oriented Gradients) + Random Forest.
- The Math: We explicitly calculate gradient magnitude (M) and orientation ( $\theta$ ) for every pixel (x,y) to detect edges:

$$M(x, y) = \sqrt{g_x^2 + g_y^2}$$

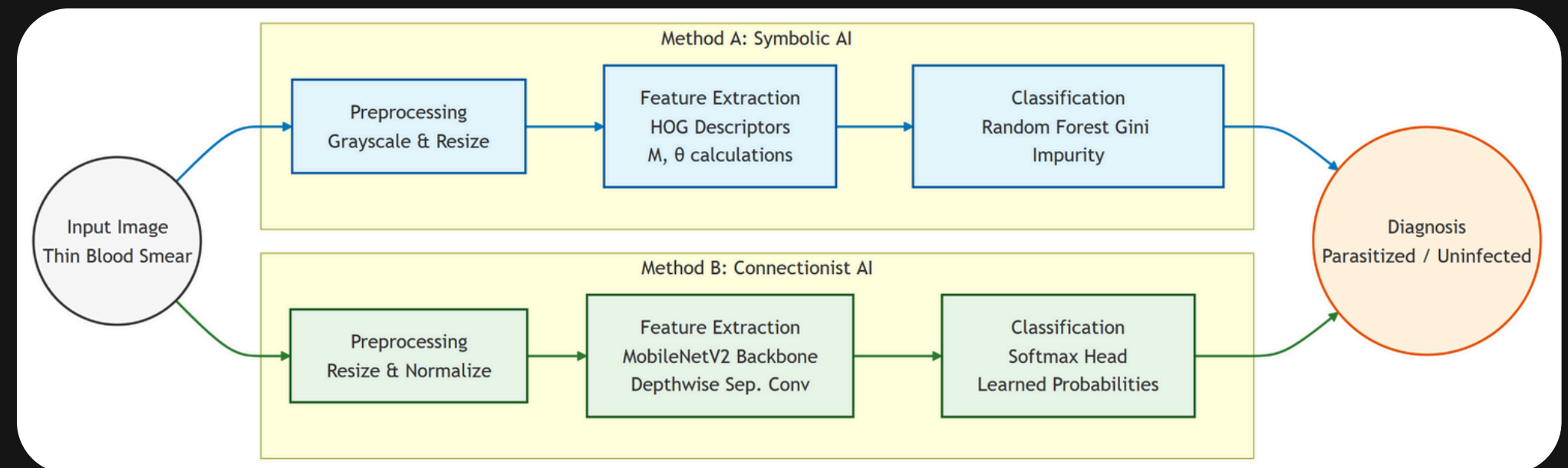
$$\theta(x, y) = \arctan \frac{g_y}{g_x}$$

- Classification: Random Forest splits trees by minimizing Gini Impurity:

$$I_G(t) = 1 - \sum_{i=1}^C p(i|t)^2$$

### Method B: Connectionist AI (The Challenger)

- Pipeline: Transfer Learning with MobileNetV2.
- Philosophy: Features are learned implicitly via backpropagation.



# DEEP LEARNING ARCHITECTURE

## The Constraint

Deployment on edge devices requires low computational cost.

## The Efficiency Formula

The computational cost reduction factor compared to standard convolution is :

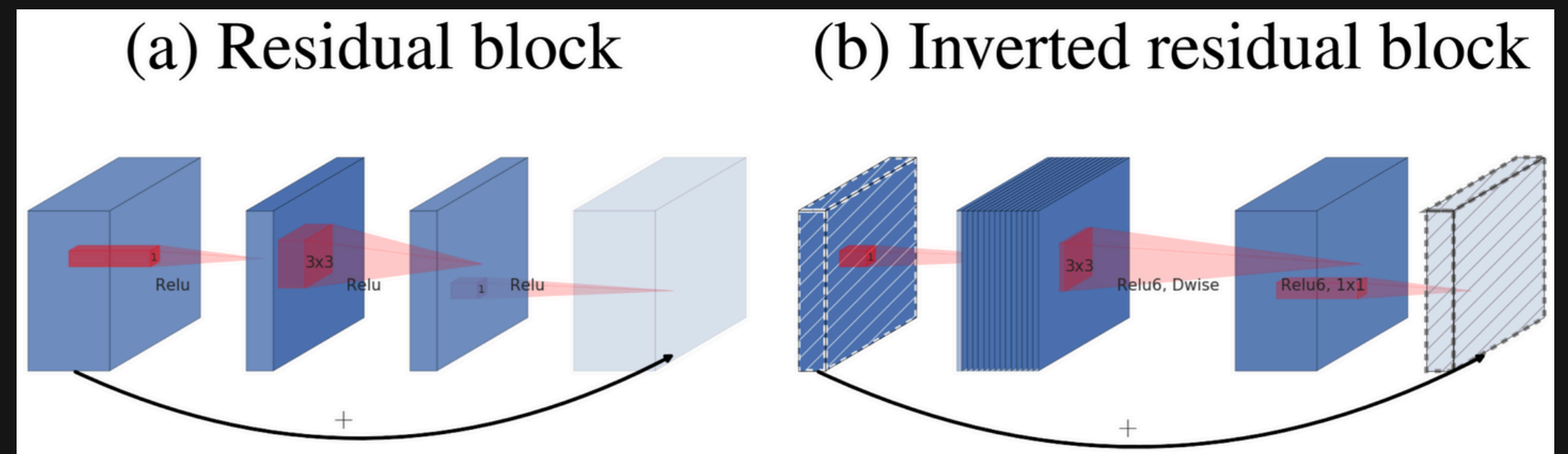
$$\text{Reduction} \approx \frac{1}{N} + \frac{1}{D_K^2}$$

Where N is output channels and DK is kernel size.

Result: With a 3×3 kernel, this yields ≈8–9x less computation.

## The Solution: MobileNetV2 & Depthwise Separable Convolutions.

Splits standard convolution into Depthwise and Pointwise layers.



# THE "EFFICIENCY PARADOX"

## (RESULTS)

### Accuracy

Method B (93%) > Method A (83%).

### Inference Speed

- Method A: ~6.6 ms/image (Bottleneck: CPU Feature Extraction).
- Method B: 1.06 ms/image (GPU Accelerated)

### Key Finding

Deep Learning is 6x Faster and 10% More Accurate.

Metric	Classical (HOG + RF)	Deep Learning (MobileNetV2)
Accuracy	83.07%	93.00%
False Negatives	379	166
Total Training Time	570s	255s
Inference Speed	6.6 ms/image	1.06 ms/image

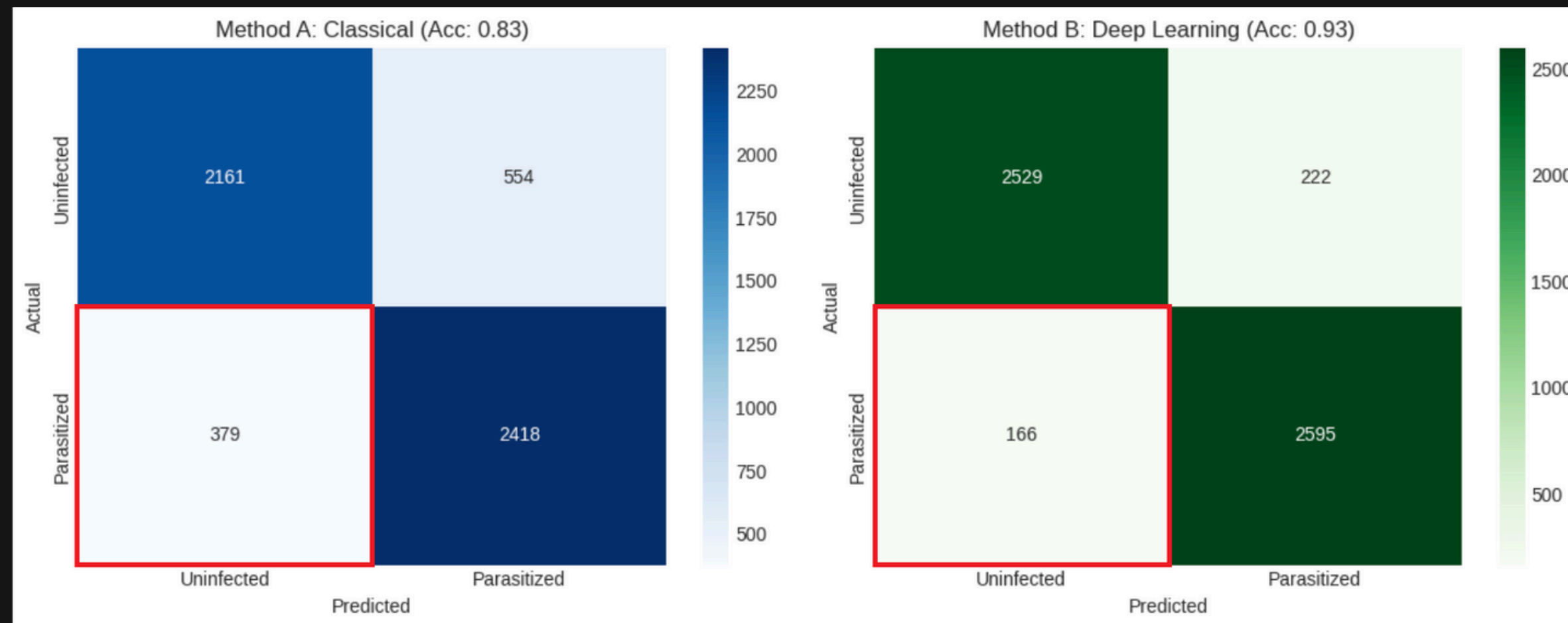
# CLINICAL SAFETY

Ethical Question: Is 93% accuracy sufficient when 166 cases are still missed?

The Critical Metric: **False Negatives** (Missed Infections).

## Method A

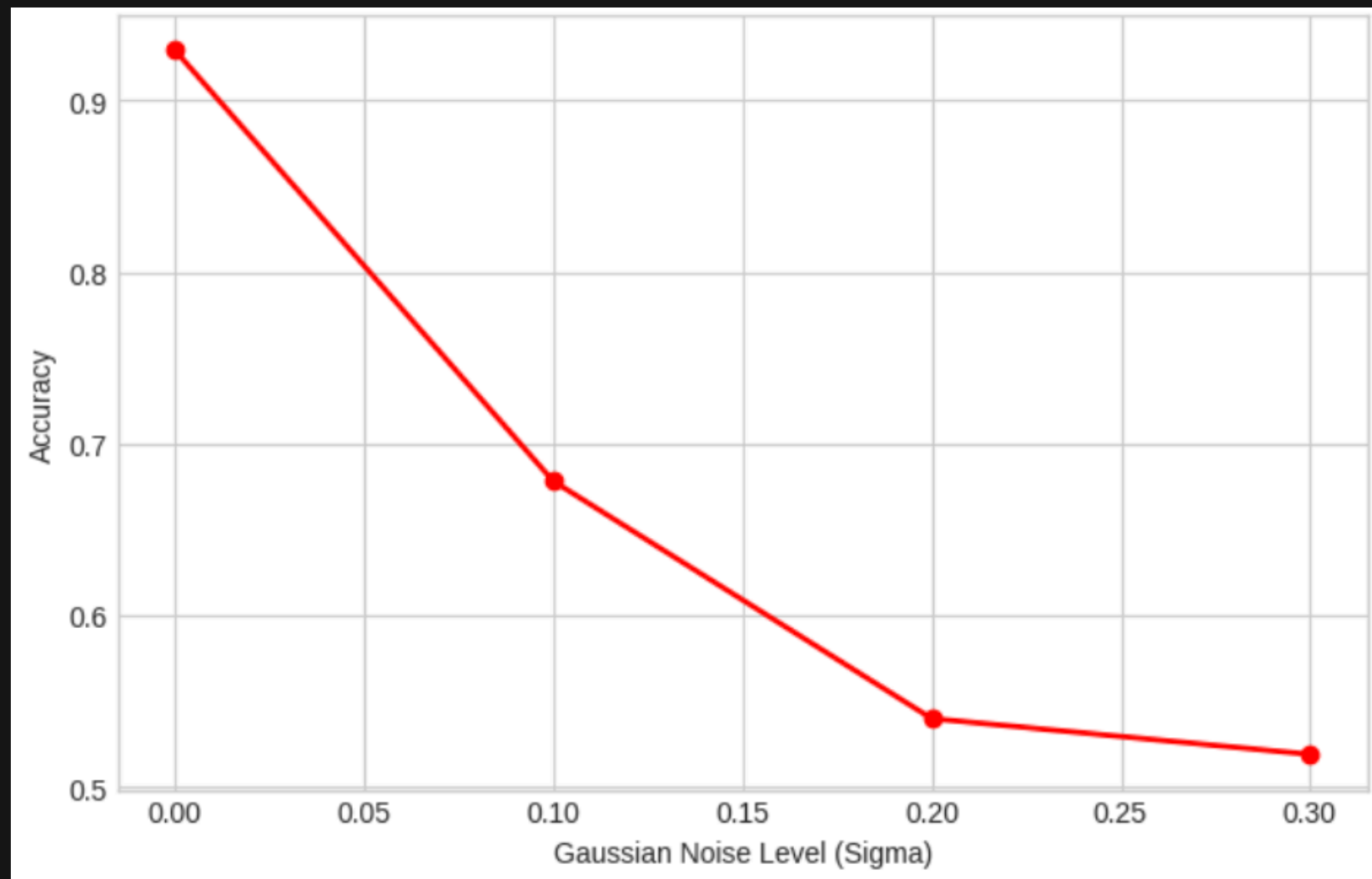
379 Missed Cases





# CRITICAL ANALYSIS

## THE ROBUSTNESS BARRIER



### The Test

Gaussian Noise  
Injection ( $\sigma=0.0 \rightarrow 0.3$ ).

### The Reality Check

- Clean Data: 93% Accuracy.
- Noisy Data ( $\sigma=0.3$ ):  
~52% Accuracy  
(Random Guessing).

**Implication:** The model lacks "Input Invariance." It is brittle to sensor dust or poor focus.

# AUDITING TRUST

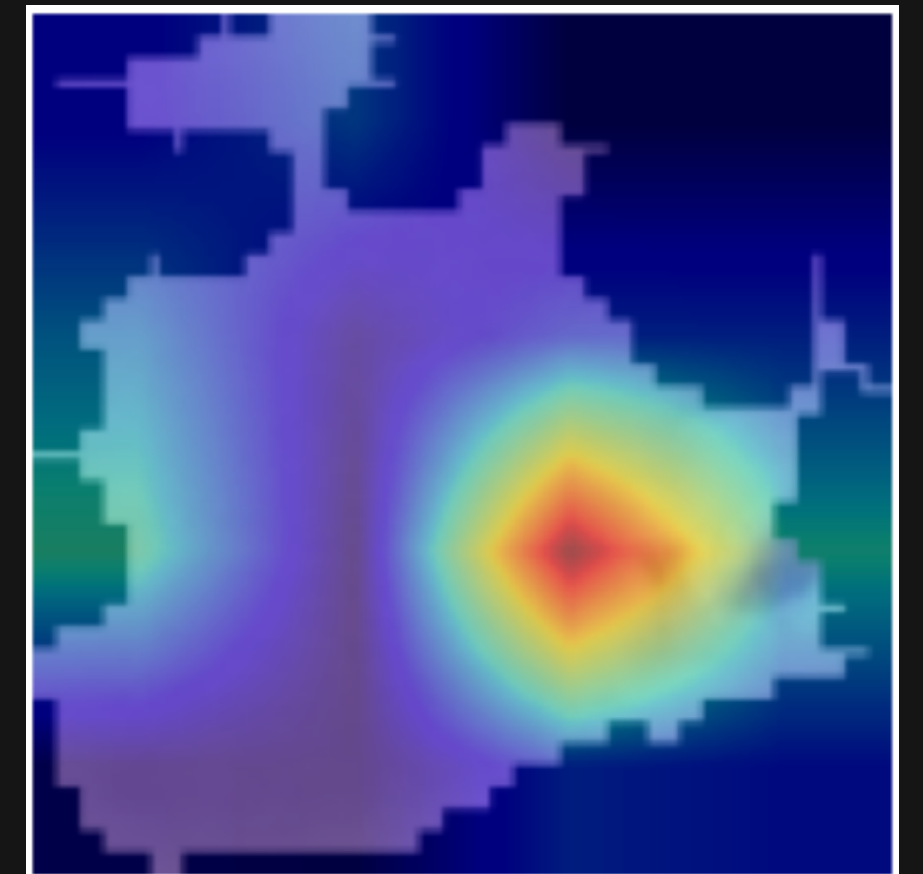
**Technique:** Grad-CAM (Gradient-weighted Class Activation Mapping)

## The Mechanism

1. Compute gradients of the target class score with respect to feature maps.
2. Calculate neuron importance weights.
3. The Localization Map Equation:

$$L_{Grad-CAM}^c = ReLU(\sum_k \alpha_k^c A^k)$$

Interpretation: The ReLU ensures we only visualize pixels that have a positive influence on the "Parasitized" prediction.





# CONCLUSIONS & FUTURE WORK

- Verdict: MobileNetV2 is the superior candidate (Faster, Safer, More Accurate).
- Limitations:
  - Brittleness: Sensitive to image noise.
  - Domain Bias: Results valid for NIH dataset; risk of Domain Shift in new labs.
- Future Roadmap:
  - Multi-Center Validation: Test on data from different countries to ensure equity.
  - Generative Restoration Pipeline: Implement Diffusion Models (e.g., VADiffusion) to denoise and restore low-quality microscopy images prior to classification, ensuring the model always receives 'clean' inputs regardless of hardware quality.

**THANK YOU**