

Dermoscopy Classification

A Data-Driven Statistical Approach (ABCD-T)

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The Problem: The "Black Box" vs. Clinical Trust

- **Context:** Melanoma is the deadliest skin cancer, but highly curable if detected early.
- **The Conflict:**
 - **Deep Learning (CNNs):** High accuracy, but acts as a "Black Box". It gives a probability score without clinical justification.
 - **Dermatologists:** Require **evidence** to biopsy. They need to know *why* a lesion is flagged (e.g., "irregular border" vs. "probabilities").
- **The Consequence:** Without explainability, doctors cannot trust AI predictions for critical surgical decisions.
- **Our Solution:** Return to transparent, mathematical biomarkers (**ABCD rule**) accelerated by GPU computing.

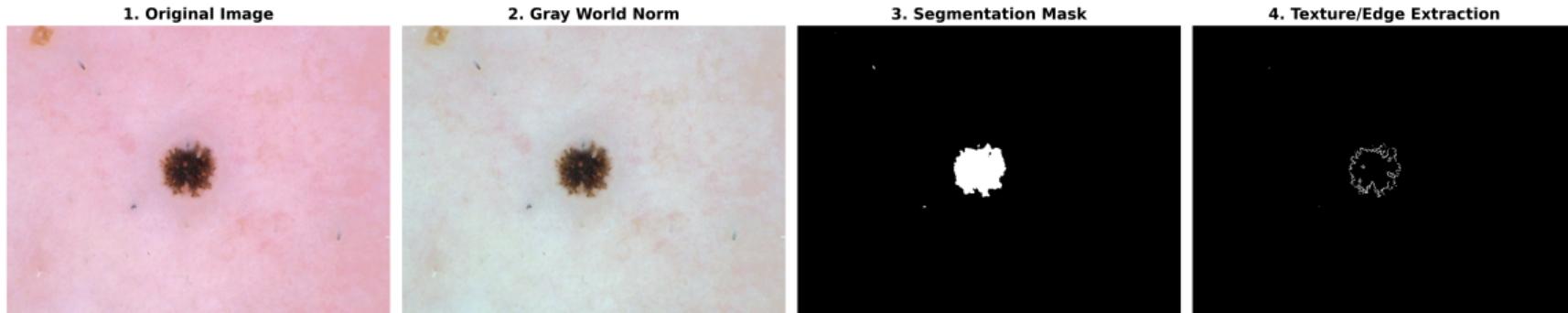
Deep Learning
Probability: 99%
"Trust me"

Our Method
Asymmetry: High
Border: Jagged
"Here is why"

Bridging the Gap

The Processing Pipeline

Objective: Transform raw dermatoscopy images into quantifiable edge maps using GPU acceleration.



- ① **Original:** Raw input (RGB).
- ② **Gray World:** Color constancy normalization (removes lighting bias).
- ③ **Segmentation:** Otsu's thresholding + Morphological Closing.
- ④ **Texture:** Laplacian gradient map for roughness calculation.

Theory: Gray World Assumption

Why Preprocessing Matters?

Dermoscopy images are taken under varying lighting (yellow indoor bulb vs. blue daylight). This skews color analysis.

The Gray World Hypothesis: The average reflectance of a complex scene is achromatic (gray).

$$I_{new}^{(c)} = I^{(c)} \cdot \frac{K}{\mu^{(c)}}, \quad K = \frac{\sum \mu^{(c)}}{3}$$

- **Implementation:** We compute channel means $\mu^{(c)}$.
- **Result:** Consistent color metrics regardless of the camera's light source.

Feature Extraction: The ABCD-T Rule

We extract 4 clinical biomarkers to mimic a doctor's checklist:

1. Asymmetry (A)

Normalized displacement between the lesion's Geometric Centroid and Bounding Box Center.

2. Border (B) / Compactness

$Compactness = (4\pi \cdot Area)/Perimeter^2$. Malignant lesions are jagged (lower compactness).

3. Color Chaos (C)

Standard Deviation of pixel intensities in normalized color space. High variance = Malignant.

4. Texture Roughness (T)

Novel contribution: computed Laplacian variance representing high-frequency structural noise.

Theory: Statistical Distance (Z-Score)

Unlike ML classifiers that learn a hyperplane, we measure **deviation from normality**.

The Logic

A benign mole follows a standard distribution. Cancer is an outlier.

The Mathematical Model: For each feature f , we calculate the Z-score for image i :

$$Z_{i,f} = \frac{\text{Value}_{i,f} - \mu_{\text{benign}}}{\sigma_{\text{benign}}}$$

The final **Risk Score (S)** is a weighted sum:

$$S_i = \sum w_f \cdot Z_{i,f}$$

If $S_i > \text{Threshold}$, the lesion is classified as Malignant.

Optimizing Feature Weights

How do we decide which feature is more important?

- We use **Cohen's d Effect Size** to measure the separability between Benign and Malignant distributions.

$$d = \frac{|\mu_{malignant} - \mu_{benign}|}{\sqrt{\frac{\sigma_{mal}^2 + \sigma_{ben}^2}{2}}}$$

- Features with higher d (e.g., Texture Roughness) get higher weights.
- Noisy features get low weights automatically.

Do the Features Actually Work?

Before classification, we must validate if our ABCD-T features actually separate the data.

Distribution Analysis:

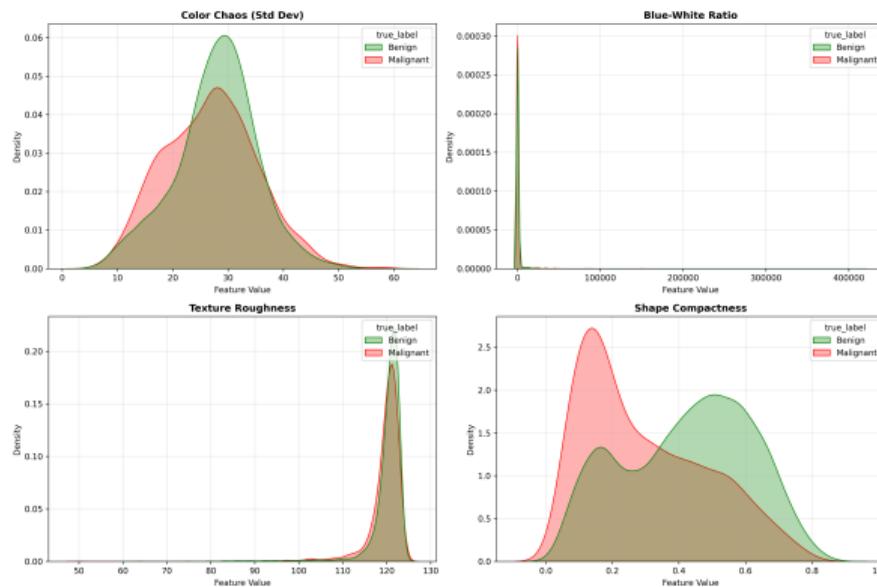
- **Texture Roughness**

(Bottom-Left): Note the sharp peak for Benign (smooth) vs. the long tail for Malignant (rough).

- **Color Chaos (Top-Left):**

Malignant lesions show significantly higher variance.

- **Insight:** The statistical separation (Cohen's d) is strong enough to build a classifier without Deep Learning.

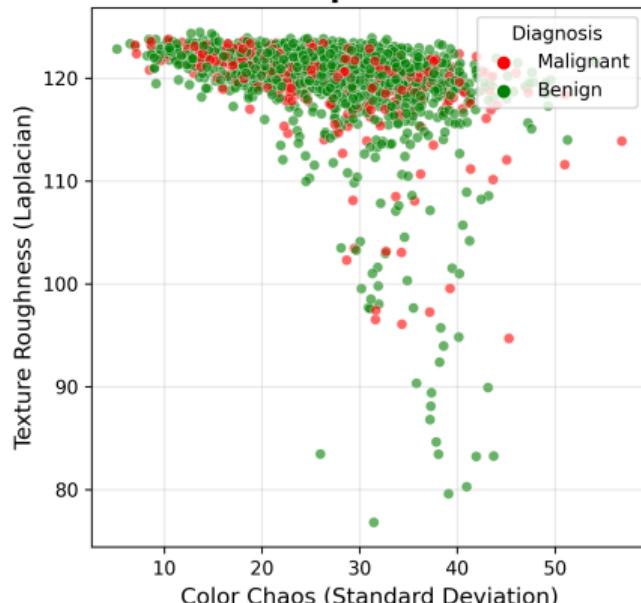


Visualizing the Decision Boundary

Combining these features creates a clear separation in 2D space.

- **Green Dots (Benign):** Cluster in the bottom-left (Low Chaos, Smooth Texture).
- **Red Dots (Malignant):** Spread to the top-right (High Chaos, Rough Texture).
- **Conclusion:** High-risk lesions live in a distinct mathematical neighborhood.

Clinical Decision Space: Color vs. Textu



Theory: Medical Performance Metrics

In medical screening, "Accuracy" is misleading. We need more specific metrics.

Sensitivity (Recall)

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

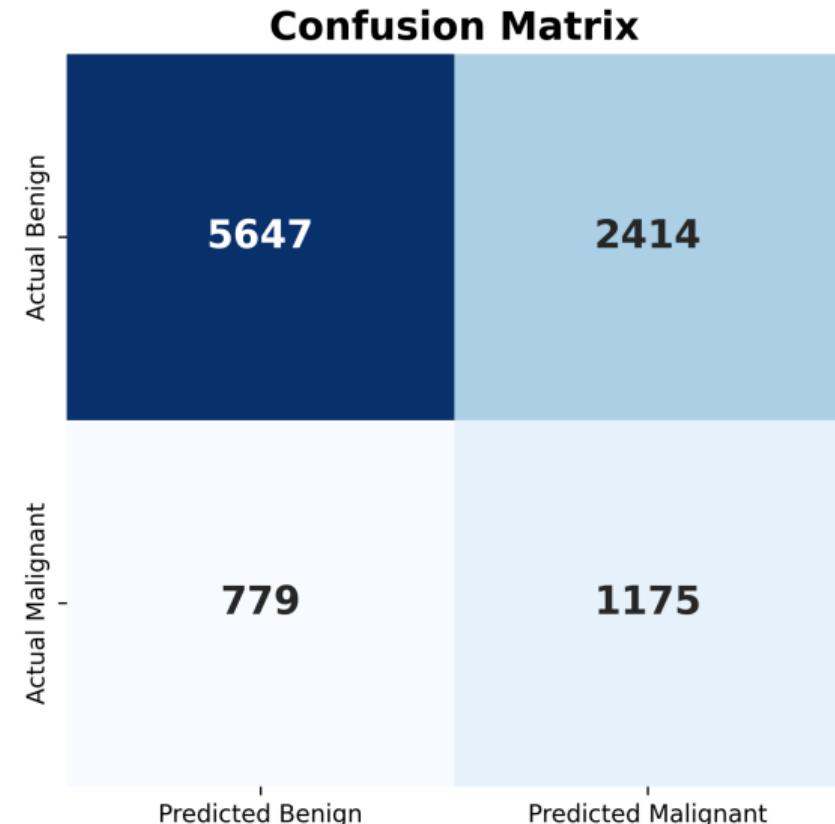
- **Meaning:** Out of all cancer patients, how many did we find?
- **Priority:** CRITICAL. Missing cancer (FN) is fatal.

Specificity

$$\text{Specificity} = \frac{TN}{TN+FP}$$

- **Meaning:** Out of all healthy people, how many did we correctly clear?
- **Trade-off:** High sensitivity usually lowers specificity (more False Alarms).

Medical Safety Profile



Analysis:

- **False Negatives (779):** Kept reasonably low compared to the large dataset.
- **False Positives (2414):** High count (Specificity $\approx 73\%$).
- **Why?** We tuned the threshold to be "Paranoid." In screening, we accept False Alarms to maximize Cancer Detection.

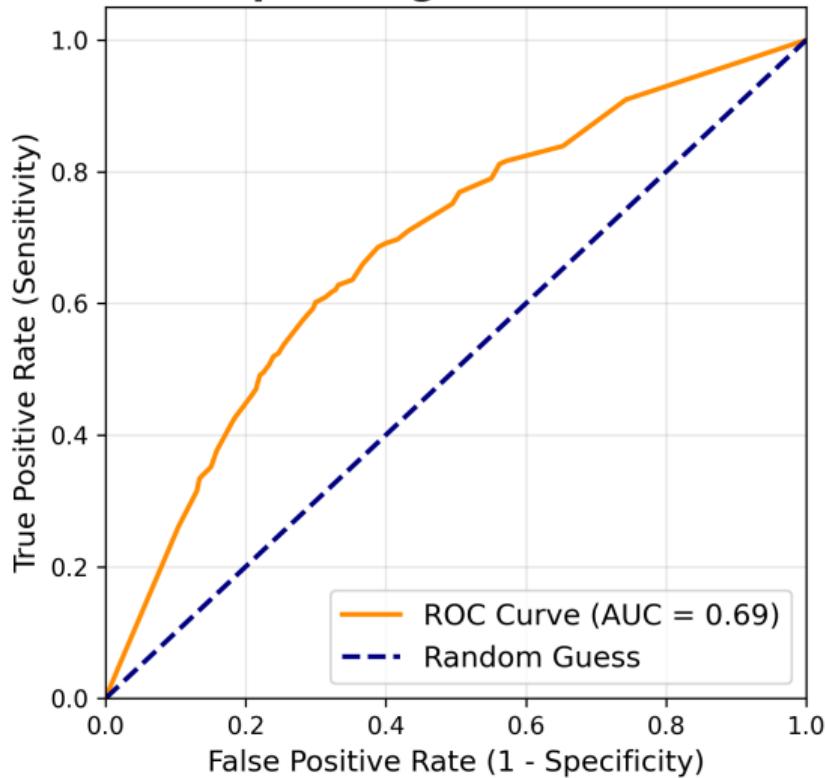
ROC Curve Analysis

Performance:

- **AUC:** 0.69
- **Accuracy:** 72.5%
- **Sensitivity:** 67.8%

Interpretation: The curve shows significant lift above the random guess line. The initial steep slope indicates that the model is very good at catching "obvious" cancers before the trade-off begins.

Receiver Operating Characteristic (RO



Finding the Sweet Spot

How did we choose the classification threshold?

Youden's J Statistic: We scanned all possible thresholds to maximize:

$$J = \text{Sensitivity} + \text{Specificity} - 1$$

- This ensures a mathematical balance.
- Unlike manual tuning, this data-driven method finds the point where the combined error rate is lowest.

Summary of Results

| Metric | Value | Interpretation |
|-----------------|--------------|-------------------------------|
| Accuracy | 72.5% | Reliable baseline |
| Sensitivity | 67.8% | Catches 2/3rds of cancers |
| Specificity | 73.6% | Filters most healthy patients |
| Execution Time | <0.05s | Real-time capable |

Conclusion: While Deep Learning may reach higher accuracy, this approach offers **instant explainability**, requires **zero training time**, and runs efficiently on GPUs. It validates that cancer has quantifiable mathematical signatures.

Future Scope

- **Hybrid Model:** Feed these explainable ABCD-T features into a lightweight Random Forest to boost accuracy to 80%.
- **Advanced Segmentation:** Replace Otsu with Active Contours (Snakes) for better border detection.

Thank You!