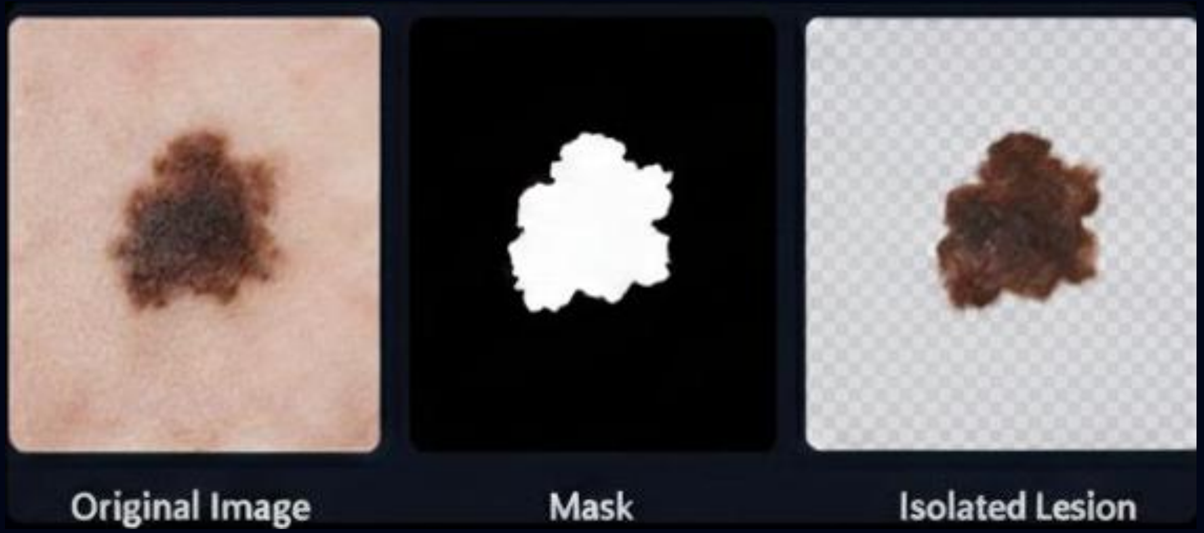

DermaSense
AI-Powered Skin Lesion Analysis
& Bias Mitigation
AI
Presented By:
Romi Yosef
Shir Molakandove
Afik Haviv

Phase 1: Automated Lesion Isolation

Extracting Diagnostic Artifacts

The first stage of our pipeline focuses on isolating the biological lesion from its original light-skin context. This is critical to ensure that no "light-skin" features pollute the subsequent augmentation.

- Library: Leveraging the RemBG library for AI-powered background removal.
- Masking: Creating binary masks using *cv2.threshold* and *cv2.findNonZero* to locate precise coordinates.
- Feature Preservation: By isolating the mole, we preserve the original texture, asymmetry, and color distribution required for ResNet analysis.



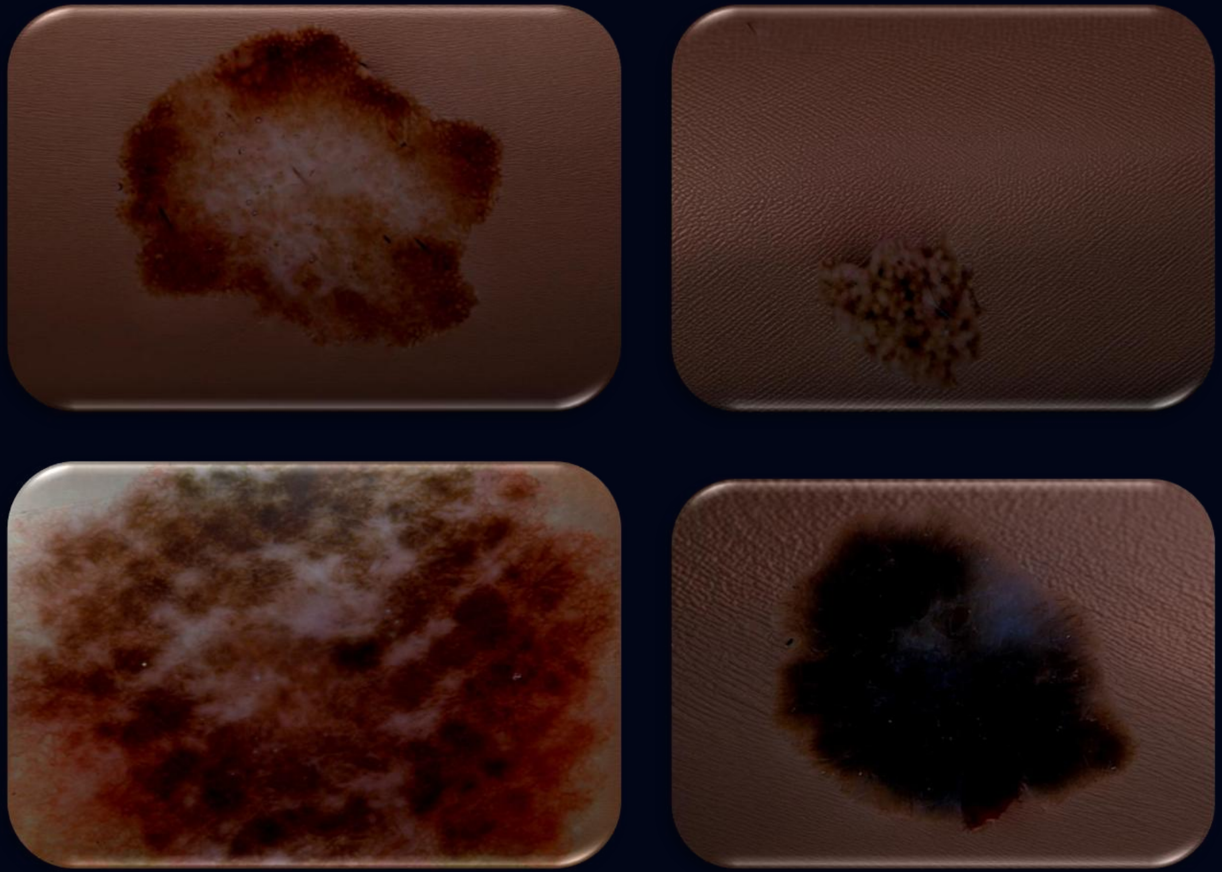
Phase 2: Synthetic Skin Synthesis

Building the 'Digital Skin Bank'

To solve the data scarcity of dark skin tones, we utilize Stable Diffusion XL (SDXL) to generate a diverse library of synthetic backgrounds.

- Medical Prompts: Custom prompt engineering ensures the generation of *clinical-grade* textures, including pores, fine lines, and epidermal ridges.
- Skin Fidelity: We target the Fitzpatrick Scale Type VI to create the most underrepresented skin tone patches.
- Precision: Images are generated at 1024x1024 resolution and downscaled to match clinical input sizes.

Phase 3: Intelligent Poisson Blending



Seamless Image Fusion

The core of our augmentation is the Smart Blend function. It merges real malignant features with synthetic contexts without creating visual artifacts.

- Histogram Matching: We use `skimage.exposure` to synchronize the mole's lighting with the new dark skin background.
- Seamless Cloning: Implementing cv2.seamlessClone (Poisson Blending) to merge edges perfectly, maintaining diagnostic integrity.
- Result: A high-fidelity, medically valid dataset that represents cancer as it appears on dark skin.

Phase 4 & 5: Biased vs. Diverse Training

Establishing the Baseline

We first trained a **ResNet50 model** exclusively on original ISIC 2016 data. This confirmed our hypothesis: while accuracy was high on light skin, it achieved only **63.8% recall** on dark skin, creating a dangerous clinical bias.

Weighted Diverse Retraining

We retrained the model on our **Hybrid Dataset**. Crucially, we applied **Class Weights** in the loss function to force the model to prioritize malignant cases, regardless of the skin tone context.

Model Refinement

Final optimization involved 25 epochs of fine-tuning with a low learning rate (0.0001), allowing the model to learn subtle melanoma markers on dark skin without forgetting light-skin features.

Phase 6: Empirical Results & Impact

The Safety Win

By diversifying the dataset through generative synthesis, we achieved a **31.5% absolute increase** in malignant recall for minority populations. **DERMASENSE** successfully transforms AI from a biased tool into a life-saving assistant for everyone.


Thank you for your attention.
We are happy to take any questions.