



Optimizing On-Device Skin Cancer Detection

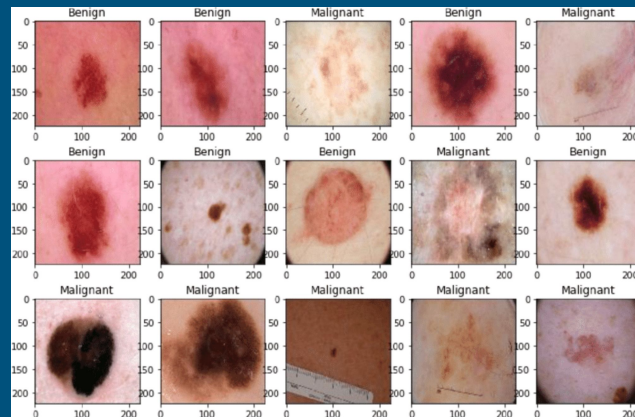


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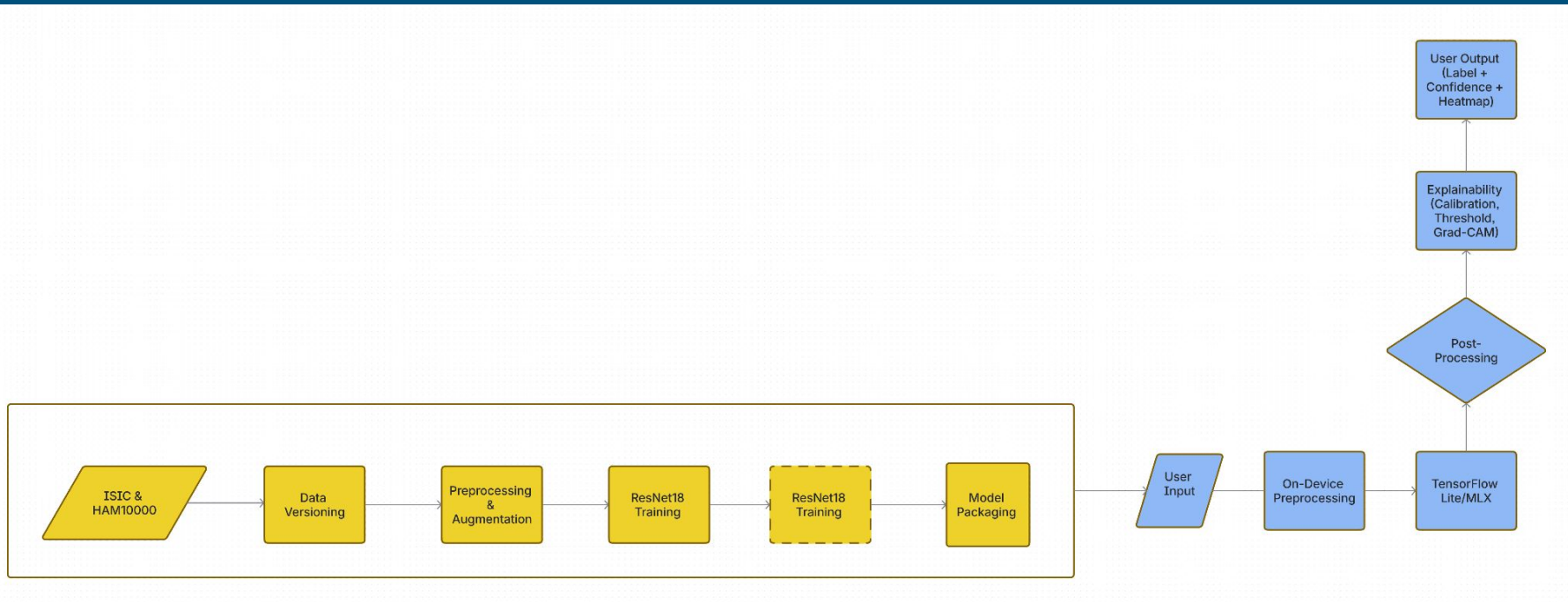


Problem

- Skin cancer is common; early detection saves lives.
 - 1/5
- Many people lack access to dermatologists or screening tools.
- Existing ML tools: research-only, cloud-based, or compute-heavy.
 - “Black box” interpretability
- How can we build a fast, lightweight, and interpretable skin lesion classification tool that performs reliably on small datasets and can run on-device for real-time use?



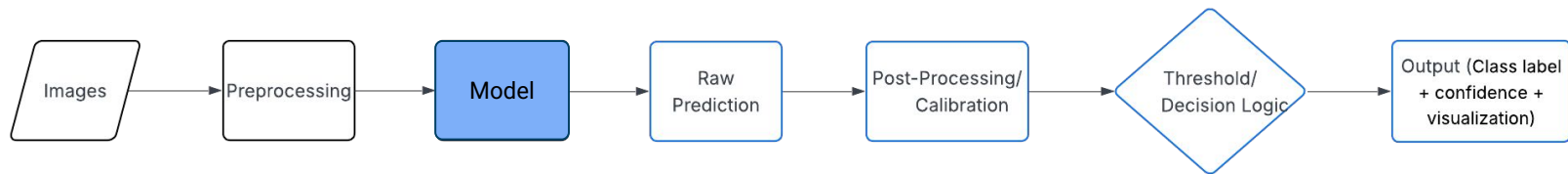
Solution



Method

- **Model & Training:** Pre-trained CNN, fine-tuned via transfer learning on datasets ISIC and HAM10000 with preprocessing and augmentation.
- **Optimization:** Model quantized (8-bit) to reduce latency and memory usage for on-device usage.

Solution

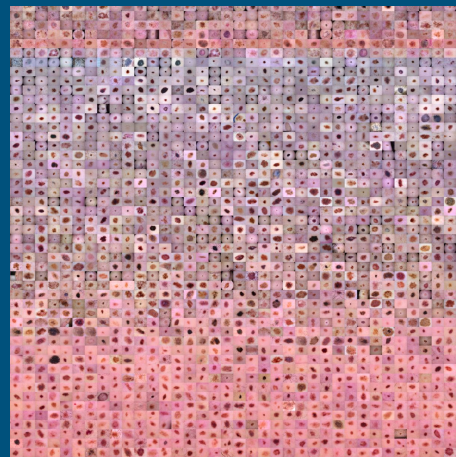


Hypothesis

We hypothesize that an end-to-end pipeline for on-device skin cancer detection can leverage a pretrained CNN to achieve high diagnostic accuracy while reducing latency and memory footprint through 8-bit quantization. This optimization will enable a practical prototype for preliminary screening for edge devices such as M1 or M2 Macbooks.

Data

- Public datasets: ISIC (dataset of skin lesion images for dermatology research) and HAM10000 (10k dermatoscopic images)
- Includes labeled skin lesion images (melanoma, benign, etc.)
Optional augmentation: lighting, rotation, zoom
- Supports training and evaluation of CNN models



Challenges

- Local compute may reduce model accuracy
- Skin lesions vary across skin tones → potential bias
- Lighting, angle, and image quality affect predictions
- Biopsy required for official diagnosis → model is preliminary only



Evaluation

- **ML Metrics**
 - Accuracy, Sensitivity, Specificity, F1 Score
- **Systems Metrics**
 - Full Precision vs. Quantized (8-bit) models
 - Inference latency & memory footprint
 - Energy usage
- **Explainability**
 - Grad-CAM heatmaps for interpretability