George Washington University

Classification of Skin Lesion Melanoma Detection

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The vision

Skin Cancer, particularly Melanoma, has a very high fatality rate globally, and if diagnosed at an early stage, is highly curable. To make accurate diagnoses, physicians typically rely on a combination of information sources, such as clinical images, dermoscopic images, and patient metadata. Deep learning algorithms have shown promise in assisting with skin lesion classification by integrating and analyzing these diverse data types. While several such algorithms are currently under development, further improvements are necessary to enhance their diagnostic accuracy before they can be reliably used in clinical settings.

Dataset

25,331 dermoscopic images: These images represent unique benign and malignant skin lesions collected from over 2,000 patients

Ground truth labels: Each image is labeled to indicate whether the lesion is benign or malignant, with malignant diagnoses confirmed via histopathology and benign diagnoses confirmed through expert agreement, longitudinal follow-up, or histopathology.

Dataset: https://challenge.isic-archive.com/data/#2019

Label Category

Lesion Category	Class Name
Melanoma	MEL
Melanocytic nevus	NV
Basal cell carcinoma	BCC
Actinic keratosis	AK
Benign keratosis	BKL
Dermatofibroma	DF
Vascular lesion	VASC
Squamous cell carcinoma	SCC
None of the above	UNK

OBJECTIVES

Cropping Image

- Remove unnecessary gray/black borders (pixels below a certain brightness threshold) around the main object in an image.
- tol = 7
- A mask is created based on the thresholded image. This mask identifies the rows and columns that contain significant pixels.

CLAHE

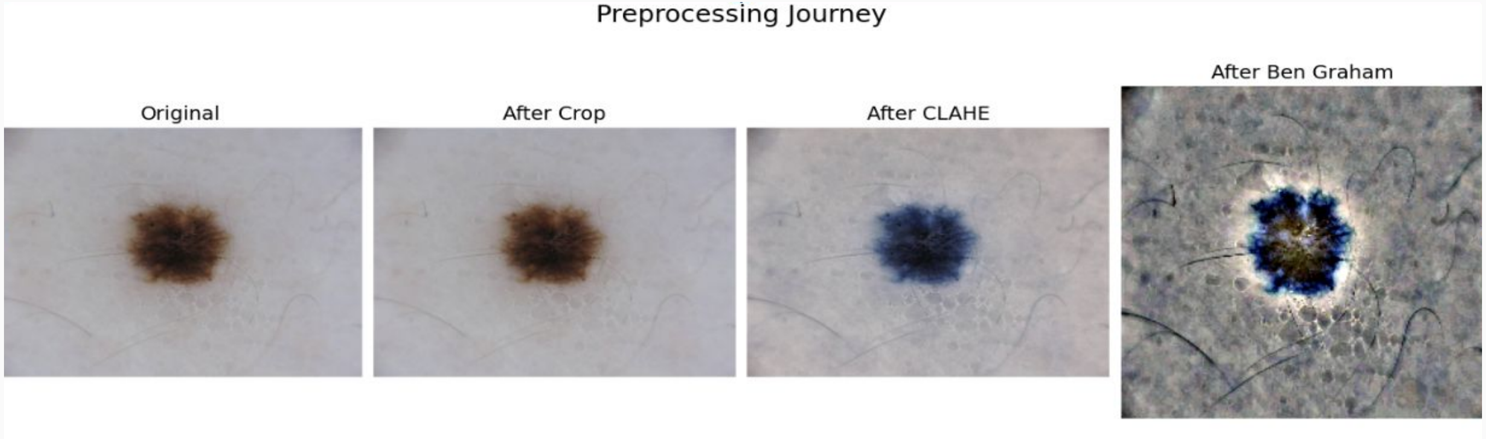
- Enhances the contrast of an input image by applying Contrast Limited Adaptive Histogram Equalization (CLAHE)
- BGR format, is converted to the Lab color
- CLAHE is then applied only to the L channel (lightness)

Ben Graham

- Enhance **contrast**.
- Remove noisy dark backgrounds.
- Soften lighting variations.
- Keep lesion or object details sharp.

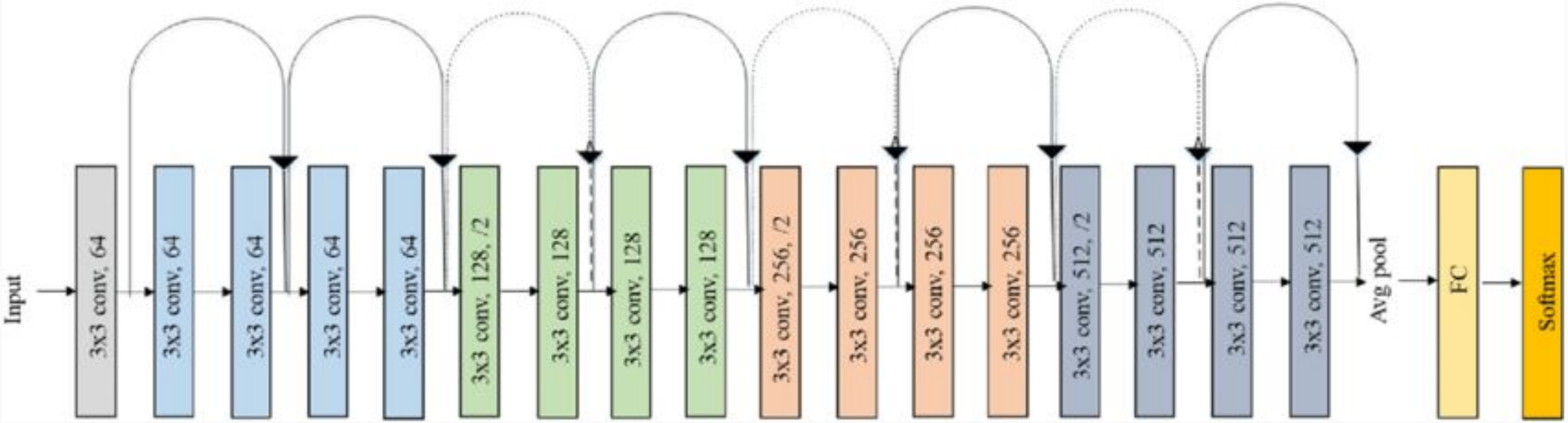
$$\text{Enhanced Image} = \frac{\text{Original}}{\text{Blurred Version}}$$

Preprocessing



Fg: Preprocessing Image of skin lesion

Resnet18



As the name suggests, ResNet-18 is a 18-layer convolutional neural network. It is well-suited for multi-label classification tasks, such as skin disease detection. In this setup, a ResNet-18 model pretrained on ImageNet.
The original fully connected (fc) layer is replaced with an identity layer to allow the addition of a custom classification head tailored to the specific task.
So, in contrast to a linear layer: f(x)=Wx+bf(x)=Wx+b, An identity layer is: f(x)=xf(x)=x

1

Input

Description: The model receives an image input of size **224×224×3** (RGB).

Preprocessing: Images are resized, normalized and converted into tensors using PyTorch transforms.

Purpose: Standardizes all images so the model can process them consistently.

2

Conv Layer+RELU

Description: The input is passed through **multiple convolutional layers** followed by **ReLU activations**.

Function: These layers extract local features like edges, textures, and lesion shapes by applying learnable filters.

Why ReLU?: It introduces non-linearity, helping the model learn complex patterns.

3

Avg Pooling

Description: Feature maps are **downsampled** using average pooling operations.

Function: This reduces spatial dimensions, helps in **reducing computation**, and adds translation invariance.

Why Avg Pooling?: It smoothens the feature maps, making them robust to small distortions.

4

FC

Description: Flattened features are passed through one or more dense layers.

Purpose: Combines all learned features to make class-level predictions.

Customization: In our model, we use a 256-node FC layer with dropout to prevent overfitting

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Output (Sigmoid)

Description: A final fully connected layer outputs **9 sigmoid values**, one per skin condition class.

Why Sigmoid?: Because it's **multi-label classification** — multiple skin conditions can co-exist — unlike softmax, which is for mutually exclusive classes.

Drawbacks & Future Enhancement

Model Improvements -

Upgrade backbone to **EfficientNet or ResNet50.**

Use **transfer learning** with dermatology-specific pretrained weights.

Explore **attention-based models** for better lesion focus.

Future Enhancement -

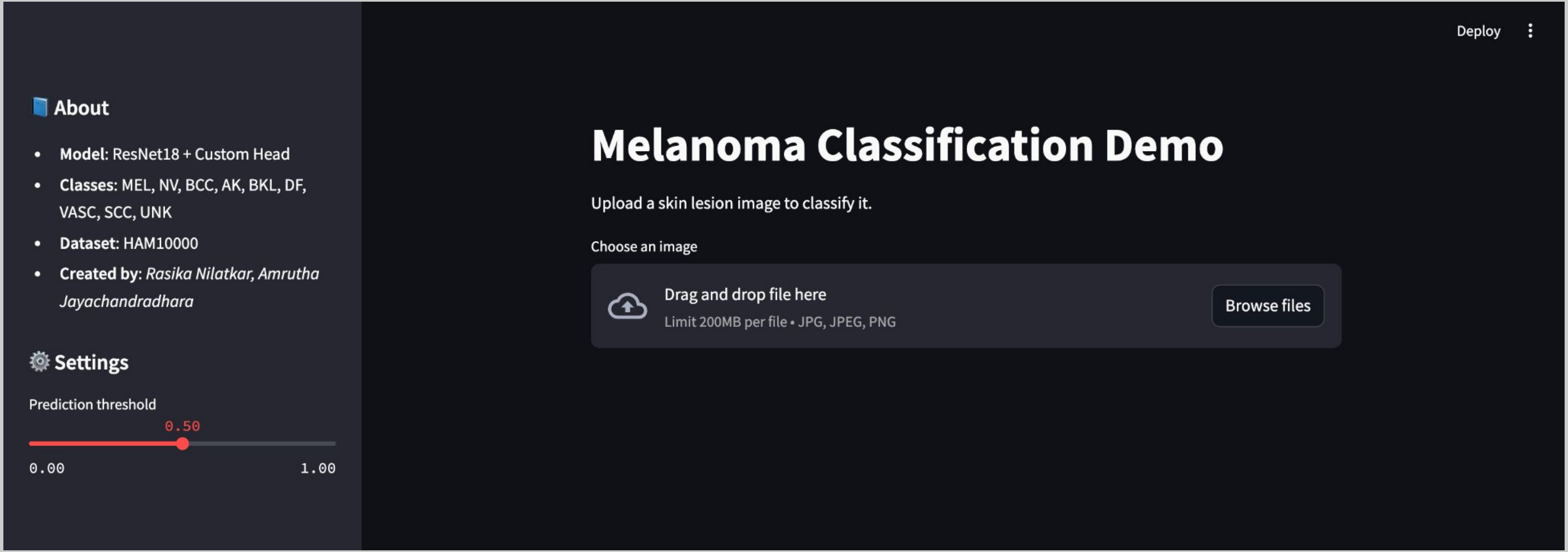
Add **heatmap overlays** using Grad-CAM to explain predictions

Multi-language support for wider accessibility

Add **user authentication** for secured access

Enable **feedback loop** from dermatologists to improve model iteratively

Melanoma Classifier: Streamlit Web Interface



http://localhost:8501/

Thank you!