

CAD Project: A SKIN LESION CLASSIFICATION APPROACH WITH MACHINE LEARNING

By

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Skin Lesion Dataset

- The dataset contains high resolution and different sizes of images.

CAD Challenge 1: Binary Dataset

Types	Number of Images	
	Train	Validation
Nevus	7725	1931
Others	7470	1865
Total	15195	3796



Balanced dataset

CAD Challenge 2: Multiclass Dataset

Lesion Types	Number of Images	
	Train	Validation
BCC	1993	498
Melanoma	2713	678
SCC	376	94
Total	5082	1270



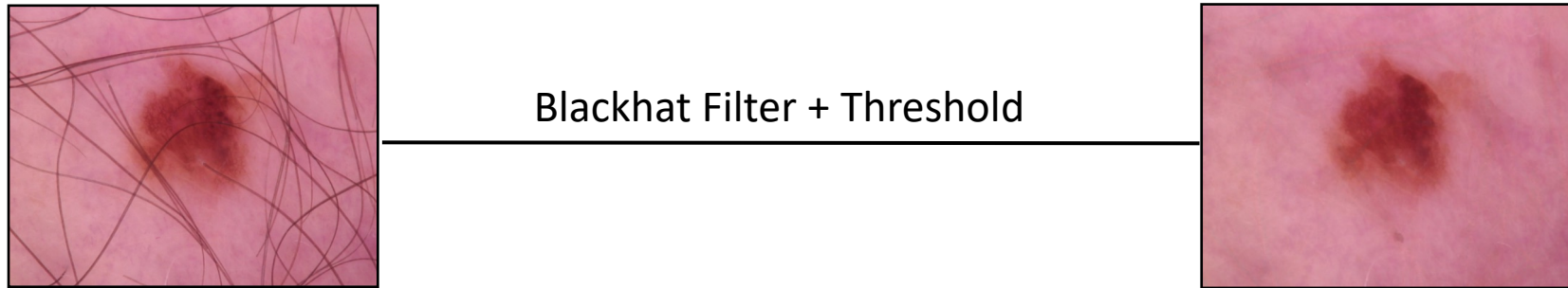
Imbalance dataset

- To address class imbalance in Challenge 2, a two-step approach is employed: firstly, the minority class (1694 samples) is oversampled using Synthetic Minority Oversampling Technique (**SMOTE**), and subsequently, the other classes are randomly undersampled to match the same quantity.

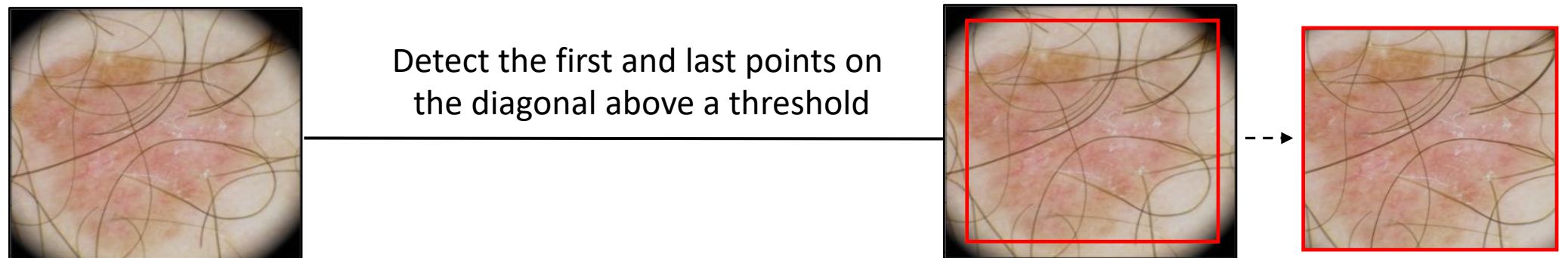
Project Design: Preprocessing

For each skin lesion image the following preprocessing pipeline is applied:

- **Hair Removal**

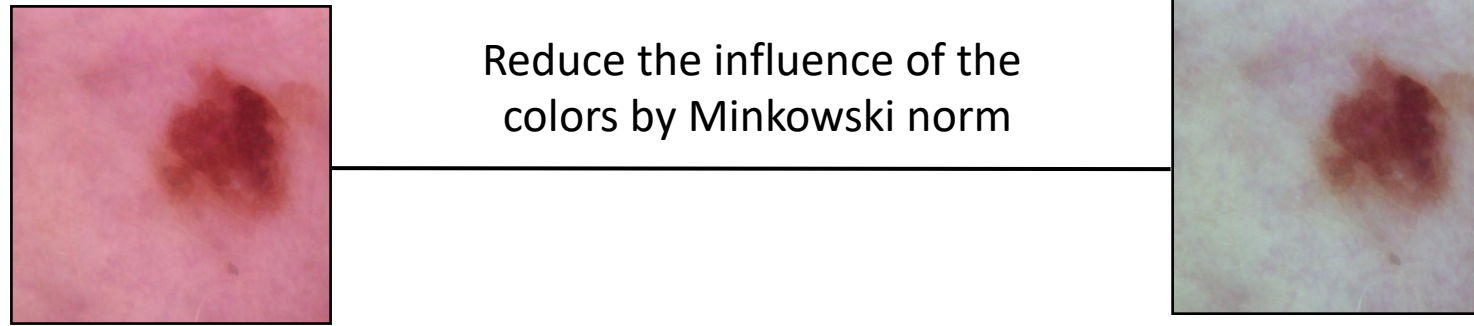


- **Region of Interest**

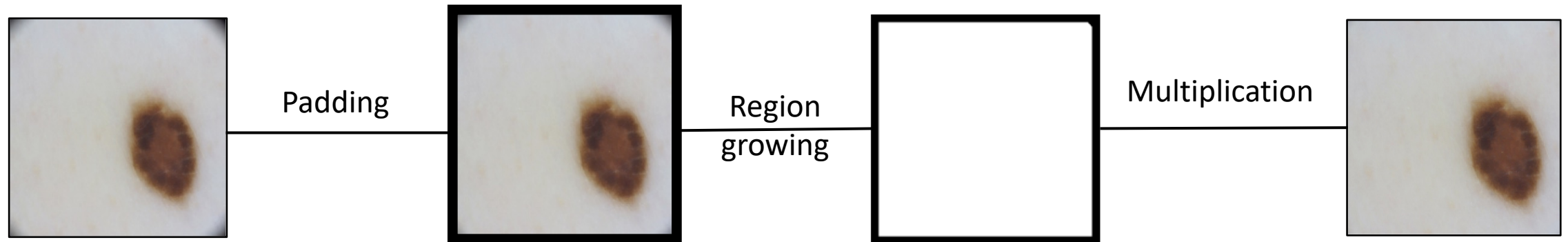


Project Design: Preprocessing

- **Color Normalization**

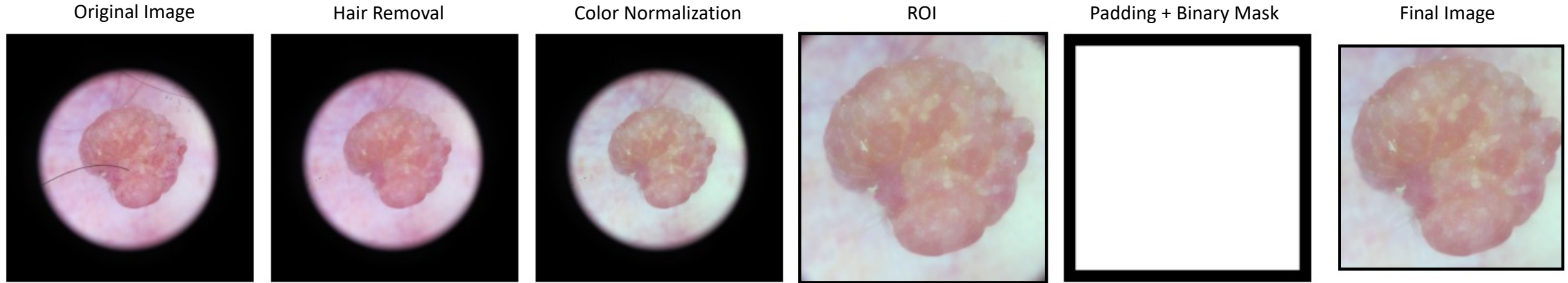


- **Padding + Mask**



Project Design: Preprocessing

Example of the preprocessing approach:



- Finally, after several experiments, only the ROI step was kept for the final pipeline of this project.

Project Design: Feature Extraction

- **Texture Features**
 - LBP (**Local Binary Patterns**) with a configuration of $P=16$ and $R=2$.
 - GLCM (**Gray-Level Co-occurrence Matrix**) calculates five characteristics for four distinct angles based on homogeneity, contrast, energy, and dissimilarity.
- **Color Features**
 - **Color moments** encompass four parameters that describe the color distribution within images: mean, standard deviation, skewness, and variance.
 - **Color histograms** are created for each channel in three different color spaces: RGB, HSV, and Lab.
 - **Color variegation** is determined by assessing the normalized standard deviation of the red, green, and blue components within the image.

Note: After extracting the features, the entire feature vector was normalized to a range $[0,1]$ using Min-Max normalization.

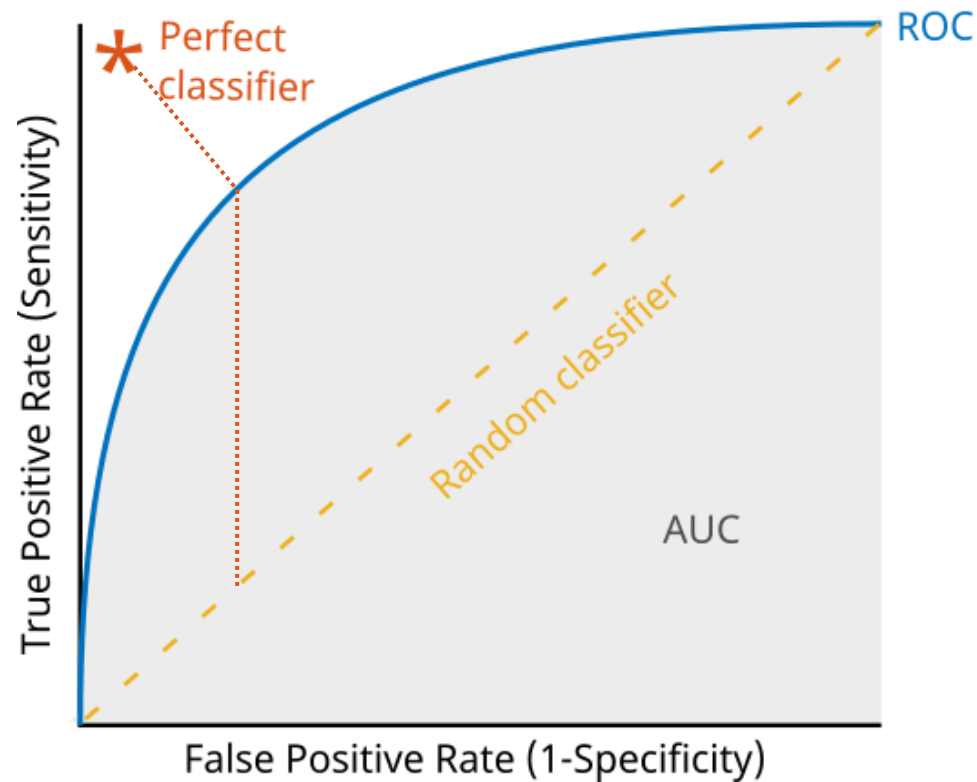
Project Design: Parameters and Classification

Before feeding the images to the classifier for training, these configurations were taken into account:

- **Image size** = 256x256.
- Training and Validation sets were merged to perform Cross Validation (CV).
- **A CV of 5 folds was utilized** to assess the performance of the machine learning model.
- The final results was the **average** of the performance of the model in each of the folds.
- The following classifiers were implemented:
 - **Random Forest**
 - **XGBoost**
 - **Ensemble of the previous classifiers (sum of predictions >1)**

Project Design: Parameters and Classification

- The classifier's probabilities to belong to each of the classes were acquired when predicting the validation set, and the optimum threshold was chosen using the **Youden index**.



Evaluation Criteria for Challenges

Binary challenge

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

		True Labels	
		Nevus	Other
Predicted Labels	Nevus	TP	FP
	Other	FN	TN

Multiclass challenge

$$\text{kappa}(\kappa) = \frac{P_o - P_e}{1 - P_e}$$

$$\text{Balanced Accuracy} = \frac{1}{3} \left(\frac{TP}{TP+FN} \right)$$

		True Labels		
		Mel	Bcc	Scs
Predicted Labels	Scs	TN	FP	TN
	Bcc	FN	TP	FN
	Mel	TN	FP	TN

Binary and Multiclass Approach Results

CAD Binary Results (Avg of the CV) : Nevus vs. Others Cases

Model	Computational Time (s)	Number of features	Accuracy	F1-Score
XG Boost	12.02	642	0.834	0.832
Random Forest	71.58	642	0.829	0.828
Ensemble	-	642	0.833	0.834

CAD Multiclass Results (Avg of the CV) : Melanoma vs. BCC vs. SCC Cases

Model	Computational Time (s)	Number of features	Balanced Multiclass Accuracy	Kappa Score
XG Boost	15.36	642	0.698	0.702
Random Forest	20.77	642	0.672	0.630

Conclusion and Future Scope

- The methods used in this projects demonstrated a robust performance, with an **accuracy of 0.83** and a **kappa score of 0.70** for binary and multiclass classification tasks, respectively.
- Despite experimenting with a variety of strategies, we discovered that **simplicity in our model was key**; extensive preprocessing and feature selection did not yield significant improvements in classifier performance.
- This project highlighted both the **advantages and disadvantages of standard machine learning** methodologies. It emphasized the effectiveness of traditional procedures while also highlighting the difficulties they provide.
- In the future, we intend to expand upon this work by utilizing the full power of artificial intelligence. Our future efforts will include the creation of a comparable pipeline that will leverage the capabilities of **deep learning models to improve binary and multiclass segmentation challenges**.

References

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- [6] https://github.com/nickshawn/Shades_of_Gray-color_constancy_transformation/blob/master/color_constancy.py
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*Thank
you*

