Skin Cancer Lesion Image Classification

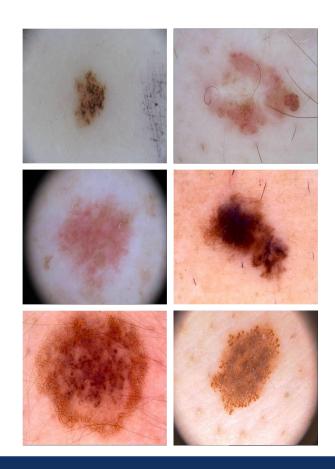
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Introduction

- Skin cancer is among the most common cancers globally, early detection is crucial for effective treatment.
- We leverage computer vision and Machine Learning techniques to support dermatological assessment and diagnosis.





Dataset: ISIC 2019 Challenge dataset

Class Name	Class Label	Training Dataset	Resampled Training
Melanocytic Nevus	NV	12876	1000
Melanoma	MEL	4522	1000
Basal Cell Carcinoma	всс	3323	1000
Benign Keratosis	BKL	2624	1000
Actinic Keratosis	AK	867	1000
Squamous Cell Carcinoma	SCC	628	1000
Vascular Lesion	VASC	253	1000
Dermatofibroma	DF	239	1000

- **25,331** images for **training**
- **6,091** images for **testing**,
- 8 diagnostic categories.
- Resolution: **450×450** to **6000×4000** pixels
- Channels: **RGB**
- Compression: **JPEG**
- Variations:
 - Lighting,
 - Skin tone,
 - Vignettes,
 - Artifacts (hairs, rulers)



Feature Selection

Feature	Melanoma	Carcinoma	Vascular Lesion	Nevus			
Asymmetry	✓ High	✓ Moderate	X Rare	X Absent			
Border Irregularity	✓ High	✓ Possible	X Usually smooth	X Absent			
Color Variation	✓ Significant	X Minimal	✓ Distinct (red/purple)	X Minimal			
Texture Variation	✓ Significant	✓ Possible	X Homogeneous	XAbsent			
Specific Dermoscopic Signs	✓ Pigment network, veil, streaks	Telangiectasia, keratin)	✓ (Lacunae, vessels)	✔ (Regular patterns)			
Growth Pattern	✓ Rapid	✓ Variable	✓ Can be fast	X Stable			

Edges & Gradients:

- HOG
- Laplacian

Texture and Patterns:

- Local Binary Pattern (LBP)
 - GLCM
 - Wavelet decomposition

Color Features:

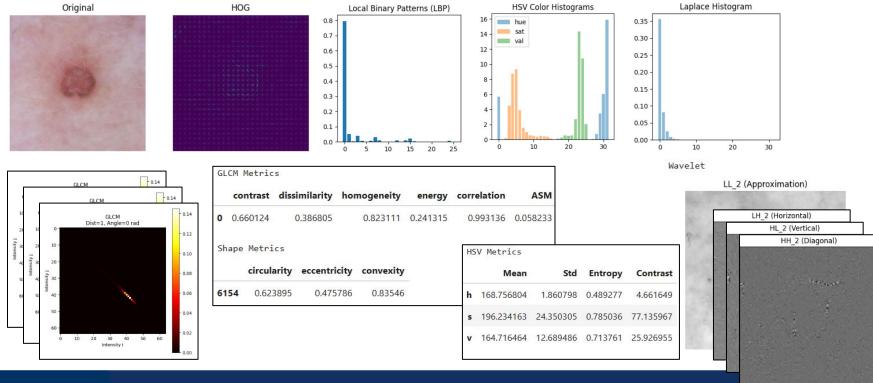
- o HSV color histograms
- HSV metrics (mean, std, entropy)
- HSV contrast

Shape Features:

- Circularity
- Eccentricity
- Convexity



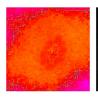
Feature Examples



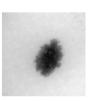


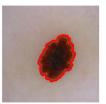
Feature Extraction - Color & Shape Metrics

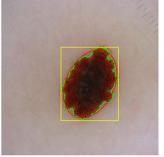


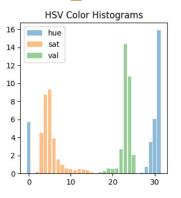












Mean	STD
h: 53.5	h: 80.63
s: 95.52	s: 15.64
v: 165.16	v: 13.4
Entropy	Contrast
h: 0.49	h: 39.27
s: 0.74	s: 31.44
v: 0.71	v: 19.85

Contrast Magnitude: 54.08

Shape Metrics

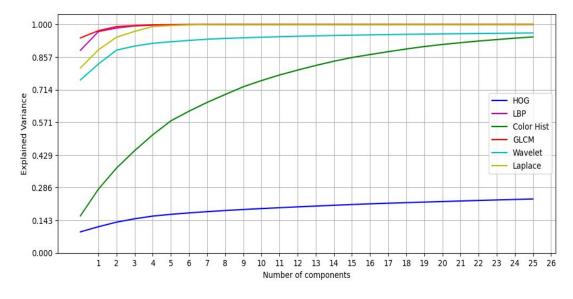
	circularity	eccentricity	convexity
2634	0.426892	0.343492	0.707103



Dimensionality Reduction

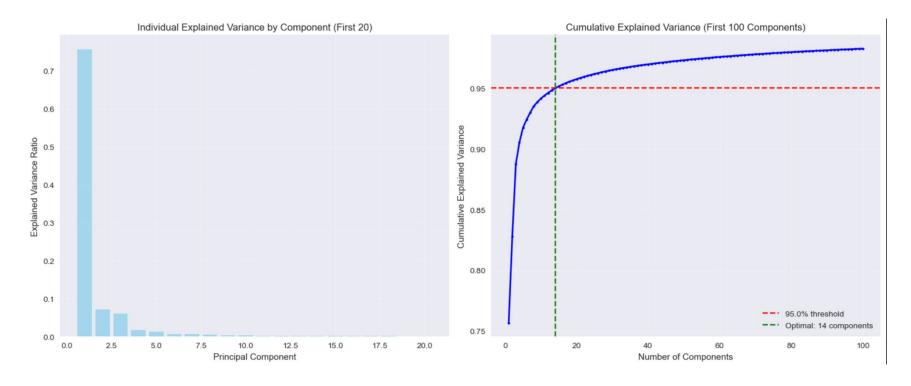
For each feature, we identified the optimal number of components by two methods.

- Cumulative Variance: The number of components is the one that reaches a cumulative variance of 95% of the total variance.
- **Cross Validation:** The number of components that returns the best cross-validation score when fitting a logistic regression to the data.



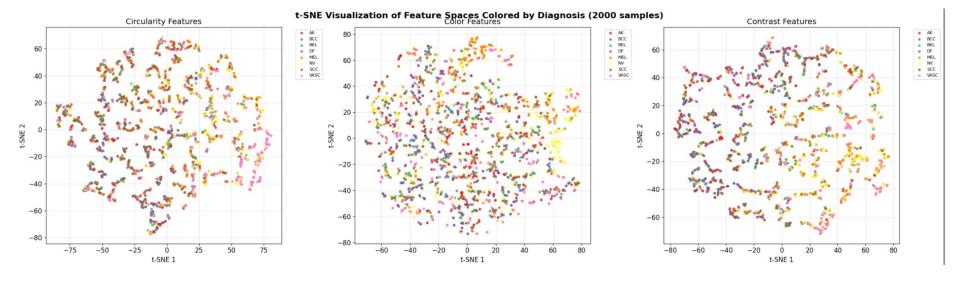


PCA Reduction - Wavelet (from 1,000 to 14)





t-SNE Visualization





Edges & Gradients: Modeling HOG Laplacian **Texture and Patterns:** Local Binary Pattern (LBP) Model 1 Model 2 Model 3 XGBoost **GLCM XGBoost** XGBoost XGBoost Wavelet decomposition **Color Features:** HSV color histograms Model 1 Model 2 Model 1 **HSV** metrics SVM HSV contrast **SVM SVM SVM Shape Features:** Circularity Eccentricity Convexity CNN High dimension Complex Simple Features PCA Reduced **Features** Texture Features kaggle Color Features CNN second last • Edge & Gradient Pre-Trained Shape Features layer Features CNN Top Layer **ISIC 2019** Fine - Tuning Preprocessing **PCA** EfficientNet-B3

Features Summary



Model Performance - SVM

```
DETAILED SVM MODEL COMPARISON
 Model Features CV Accuracy Test Accuracy Test F1 Test ROC-AUC
Model 1 16 0.4686 ± 0.0115
                                  0.4806 0.4717
                                                    0.8371
Model 2 195 0.5120 ± 0.0083
                                                   0.8659
                                  0.5262 0.5262
Model 3 244 0.5861 ± 0.0100 0.5969 0.5966
                                                   0.9018
Best performing SVM model: Model 3 (All features)
Test accuracy: 0.5969
```



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Ž	8	5	14	3	32	132	3	3		40		0.52											0.50					_					
SCC	31	31	8	4	17	4	105	0		20		0.50											0.48		T	7							
VASC	4	4	3	6	6	4	2	171				0.48	● ^{Mc}	odel 1									0.46		4	_							
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Model Performance - XGBoost

DETAILED XGB MODEL COMPARISON

Model Features CV Accuracy Test Accuracy Test F1 Test ROC-AUC

Model 1 16 0.6514 ± 0.0076 0.6506 0.6417 0.9067

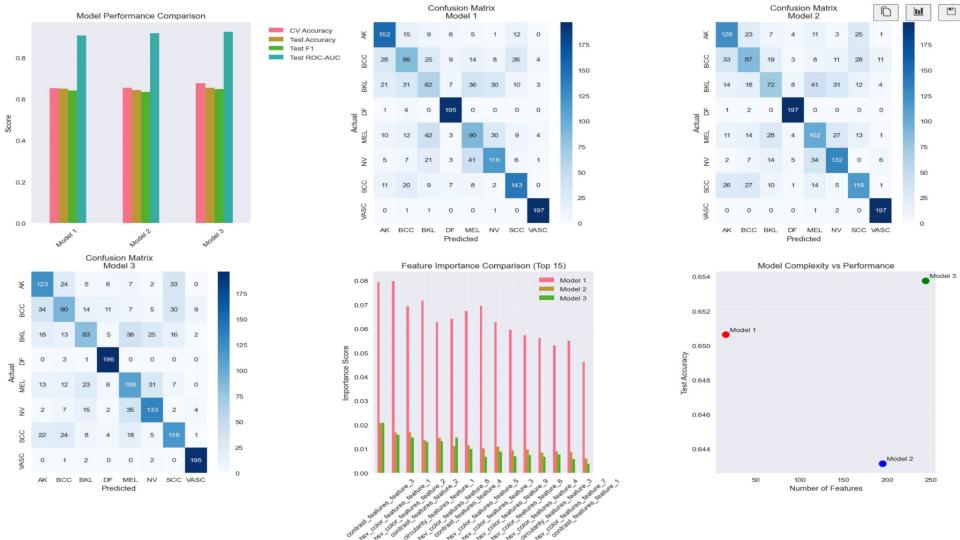
Model 2 195 0.6539 ± 0.0100 0.6431 0.6349 0.9183

Model 3 244 0.6773 ± 0.0156 0.6538 0.6470 0.9250

Best performing model: Model 3 (All features)

Test accuracy: 0.6538



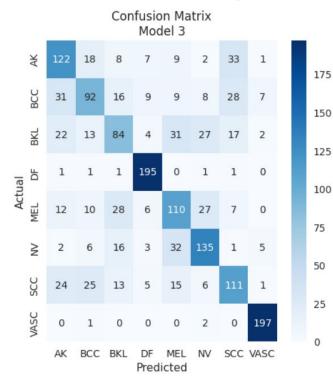


Best Performance Model - XGBoost Model 3

Features : 244

Accuracy : 0.6538 F1 : 0.6470 ROC-AUC : 0.9255

	Class	Recall	Precision	Accuracy	F1
Actinic Keratosis	AK	0.7000	0.6422	0.9138	0.6699
Basal Cell Carcinoma	BCC	0.4950	0.5789	0.8919	0.5337
Benign Keratosis	BKL	0.4600	0.5644	0.8881	0.5069
Dermatofibroma	DF	1.0000	0.8696	0.9813	0.9302
Melanoma	MEL	0.5450	0.5533	0.8881	0.5491
Melanocytic Nevus	NV	0.6950	0.6814	0.9213	0.6881
Squamous Cell Carcinoma	SCC	0.6600	0.6600	0.9150	0.6600
Vascular Lesion	VASC	0.9900	0.9124	0.9869	0.9496



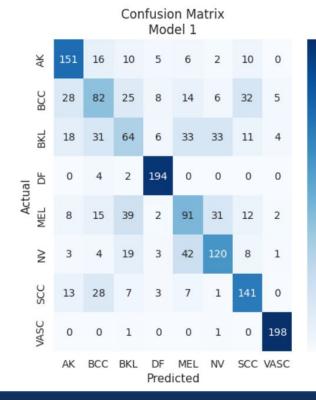


Best Efficiency Model - XGBoost Model 1

Features : 16

Accuracy : 0.6506 F1 : 0.6423 ROC-AUC : 0.9071

	Class	Recall	Precision	Accuracy	F1
Actinic Keratosis	AK	0.8050	0.7285	0.9381	0.7648
Basal Cell Carcinoma	BCC	0.4300	0.5150	0.8781	0.4687
Benign Keratosis	BKL	0.3550	0.4226	0.8588	0.3859
Dermatofibroma	DF	1.0000	0.9009	0.9863	0.9479
Melanoma	MEL	0.4450	0.4495	0.8625	0.4472
Melanocytic Nevus	NV	0.5850	0.6223	0.9038	0.6031
Squamous Cell Carcinoma	SCC	0.8350	0.7422	0.9431	0.7859
Vascular Lesion	VASC	1.0000	0.9479	0.9931	0.9732



175

150

125

100

75

50

25

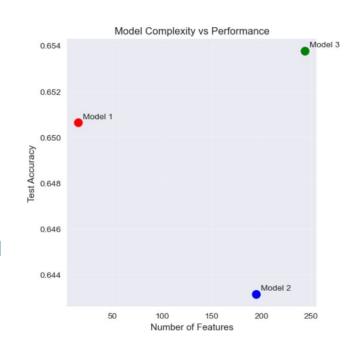


Conclusion

XGBoost models performed comparably across increasing dimensionality, and outperformed SVM models.

SVM models performed better with more complex feature sets.

Due to the high cost in compute time to fine-tune and get inferences from VGG16, and the small trade-off in performance, we would recommend using an XGBoost model with simple features, as Model 1.





Thank You



Appendix

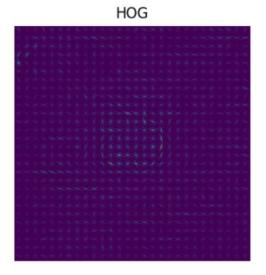


HOG

Hog was calculated using the following parameters:

- Orientations = 4
- Pixels per cell = 16 x 16
- Cell per block = 2 x 2
- Block Normalization Method = 'L2-Hys'





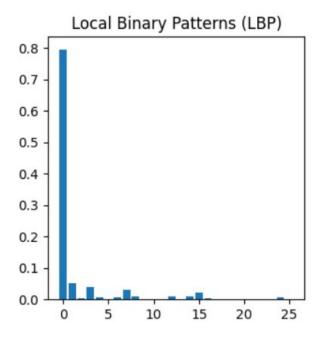


LBP

LBP was calculated using the following parameters:

- Radius = 3
- Points = 24

The graph below shows the histogram of binary patterns for the same image above.





GLCM

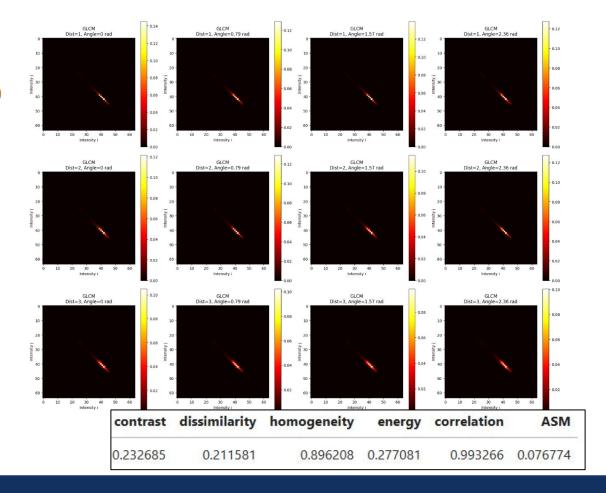
(Gray-Level Co-occurrence Matrix)

The GLCM features were extracted using the graycomatrix from the skimage package, using the following parameters:

- Distances = 1, 2, and 3.
- Angles = 0°, 45°, 90°, and 135°

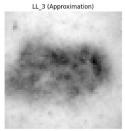
For each image we extracted the following metrics:

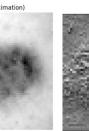
- Contrast
- Dissimilarity
- Homogeneity
- Energy
- Correlation
- ASM

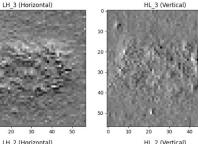


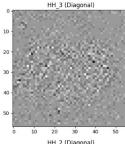


Wavelet









The Wavelet method helps to analyze the image in several frequencies, showing different levels of textures.

- For the final model we used two levels.
- Here is an example with 3 levels, and the respective LL, HL, LH, and HH filters.

