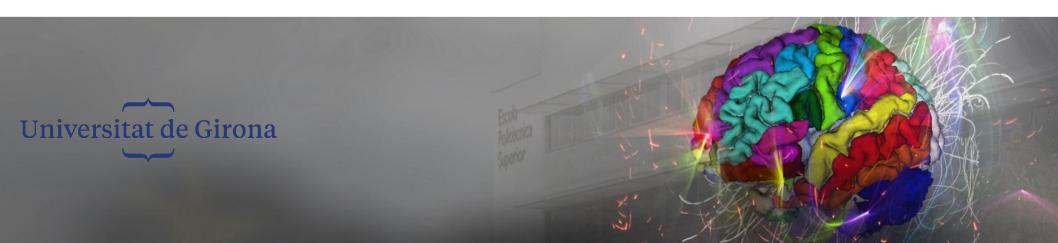


CAD Project: Skin Lesion Classification

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Objectives

Skin Lesion Classification: Binary and Three-Class Problem Questions to be solved. What is the best pipeline for classification?

- With or without pre-processing?
- Hair Removal and/or vignette removal?
- Data Augmentation or Over Sampling/SMOTE? (for imbalanced class Problem)
- Feature Extraction Techniques?
- Feature Selection?
- Classifier Selection?
- Ensemble Classifiers?





Overview

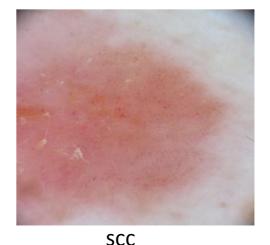
- Binary problem: nevus vs others
- Three class problem: mel (melanoma), bcc (basal cell carcinoma), scc (squamous cell carcinoma)
- Two main ways of tackling the problems: classification with raw images and with preprocessed images.
- 11 different classifiers trained on 7 different feature set.
- Class Imbalance treatment: Data augmentation and oversampling.



melanoma



bcc







Preprocessing (Hair Removal)

- Sum of rotating Top-Hats Transforms
- Morphological Operation
- Image Inpainting

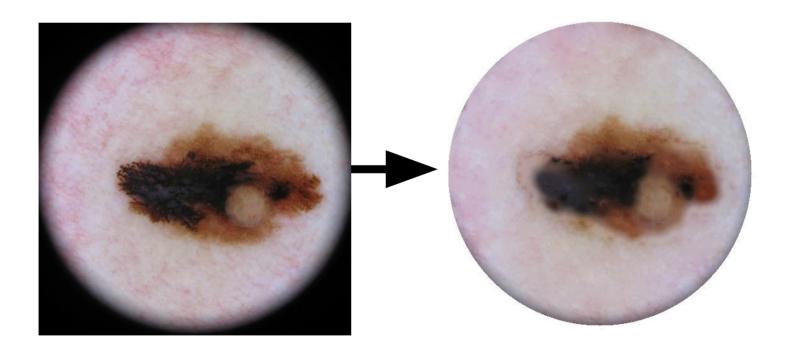






Preprocessing (Vignette Removal)

- Creating Circular Mask
- Counting the number of black pixels around the mask
- Reduce the radius according to a threshold

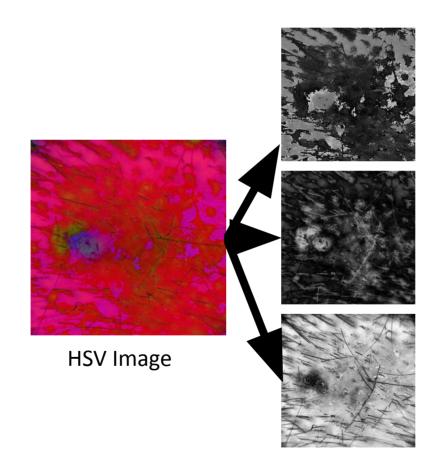






Preprocessing (Histogram Equalization)

- Contrast limited adaptive histogram equalization.
- Histogram equalization on smaller tiles of images(8*8).

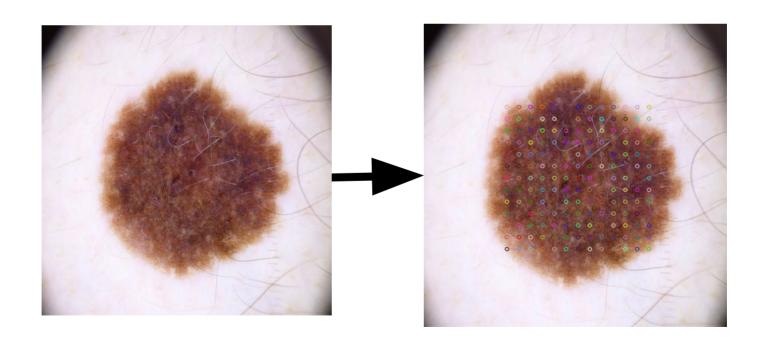






Feature Extraction: SIFT + BoW

- 200 randomly chosen images are used for vocabulary creation
- The number of clusters for BoW was kept 200
- Dense sift descriptors were used







Feature Extraction: Color Histograms

- Concatenated histogram of R, G and B channels
- Histogram bins: 64
- Number of features: 192
- For each channel, the following statistics were extracted: min, max, mean, std, skew. Channels analyzed (RGB and HSV)
- Number of features: 30
- In some experiments for the three class problem, histogram equalization was performed in the image.





Feature Extraction: GLCM Texture features

- GLCM Matrix along 3 distances (1,2,3 pixels) and 4 angles $(0, \frac{\pi}{4}, \frac{\pi}{2}, 3\frac{\pi}{2})$
- Mean and std of GLCM Matrix properties (contrast, dissimilarity, homogeneity, energy, correlation) along the chosen configuration.
- Number of features: 10





Feature extraction: LBP Texture features

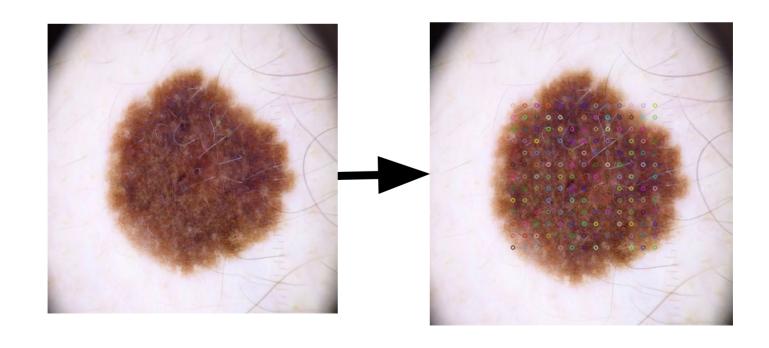
- LBP concatenated histograms for 3 cases (P,R): (8,1), (16,2), (24,3).
- Number of features: 54
- Statistics of LBP histograms for the 3 chosen cases: mean, std, kurtosis, skew, entropy:
- Number of features 15





Feature Extraction: SIFT + BoW

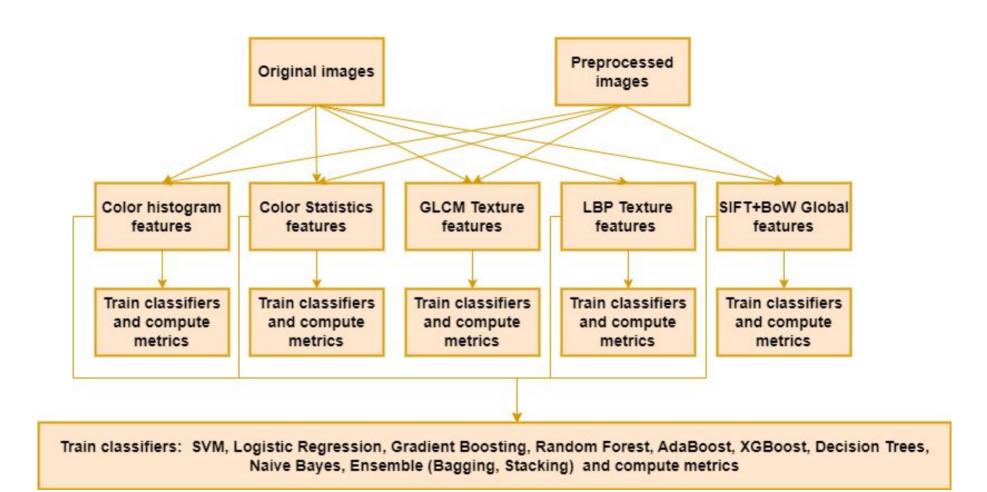
- 200 randomly chosen images are used for vocabulary creation
- The number of clusters for BoW was kept 200 (Features)
- Dense sift descriptors were used
- Total number of features: 500







Two class Problem: Scheme Diagram







Two class problem: Results (I)

Case – 1: Without Preprocessing

								Naive		Ensemble	
Features	SVM	LR	Gboost	RF	Adaboost	Decision Trees	XGBoost	Naive Bayes	KNN	Bagging	Stacking
СН	0,750	0,674	0,768	0,801	0,730	0,713	0,765	0,628	0,750	0,803	0,804
CS	0,782	0,739	0,768	0,793	0,734	0,716	0,763	0,629	0,753	0,793	0,795
GLCM	0,696	0,649	0,696	0,717	0,649	0,641	0,688	0,574	0,682	0,725	0,728
LBPH	0,734	0,726	0,713	0,745	0,699	0,666	0,715	0,653	0,722	0,745	0,761
LBPS	0,672	0,667	0,685	0,712	0,661	0,660	0,700	0,588	0,682	0,713	0,715
SIFT + BoW	0,757	0,743	0,749	0,762	0,738	0,676	0,745	0,726	0,739	0,756	0,768
All	0,822	0,804	0,807	0,820	0,773	0,728	0,805	0,723	0,788	0,820	0,830





Two class problem: Results (I)

Case – 2 : With Preprocessing

								Naive		Ense	mble
Features	SVM	LR	Gboost	RF	Adaboost	Decision Trees	XGBoost	Naive Bayes	KNN	Bagging	Stacking
СН	0,767	0,671	0,778	0,801	0,738	0,695	0,770	0,684	0,736	0,795	0,800
CS	0,784	0,714	0,774	0,793	0,741	0,700	0,773	0,630	0,763	0,786	0,795
GLCM	0,725	0,691	0,717	0,727	0,706	0,641	0,721	0,634	0,698	0,734	0,736
LBPH	0,748	0,724	0,737	0,745	0,714	0,665	0,737	0,657	0,722	0,750	0,754
LBPS	0,699	0,694	0,696	0,714	0,673	0,643	0,692	0,570	0,696	0,722	0,715
SIFT + BoW	0,760	0,739	0,743	0,759	0,733	0,664	0,741	0,714	0,731	0,750	0,768
All	0,817	0,793	0,805	0,815	0,778	0,711	0,806	0,743	0,779	0,817	0,830





Two class problem: Results (III)

- Taking only the original images, an ensemble of classifiers with majority voting was constructed under the following three scenarios:
- Ensemble of the 3 best standalone classifiers for each feature set, and then ensemble of the resulting ensemble classifier from each feature set.
- Ensemble of the best standalone classifier for each feature set
- Ensemble of the best overall classifier for each feature set (ensemble of stacking classifiers)

Ensemble Model	Balanced accuracy
Model 1	0,781
Model 2	0,802
IVIOGEI 2	0,802
Model 3	0,824





Two class problem: results (IV)

 Another experiment was carried out, where the best standalone model for the best feature set (dataset without preprocessing, SVM, all features), was retrained on all possible combinations of features to determine the optimum number of features using SelectKBest function. It was obtained that with 415 features, SVM obtains an accuracy score of 0.8245 as opposed to 0.822 with 500 features.





Two class problem: results (V)

 Overall, results are very similar with and without preprocessing. However, models trained on dataset without preprocessing perform slightly better results and it is computationally less expensive, so it was decided to use this approach for the final pipeline selection.





Two class problem: results (VI)

• Random Forest classifier proved to be the best model along all experiments as a standalone classifier. However, for all cases **Stacking classifier** gets the highest performance, so it was decided to keep this model for the final pipeline selection.





Two class problem: results (VII)

• Finally, when evaluating all experiments, using a **Stacking classifier** with **all features** yields the highest balanced accuracy, therefore, this is used as the final pipeline for generating predictions on test set.





Two class problem: Best model

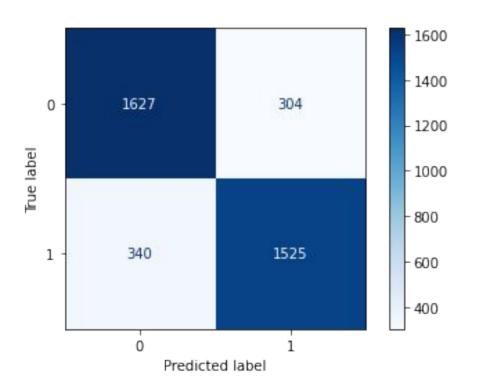
- Stacking of classifiers trained on data without preprocessing and using all features.
- Stacking of classifiers: using the output of each individual classifier as input of a final classifier
- Classifiers used for the stacking: LR, KNN, Decision Tree, SVM, Bayes, Gboost, RF, Adaboost
- Final Classifier: LR

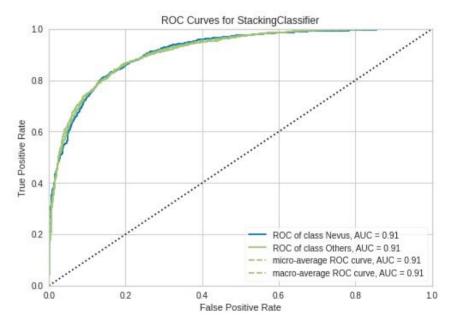




Two class problem: Best model

Class	Precision	Recall	F1-Score
0	0.83	0.84	0.83
1	0.83	0.82	0.83









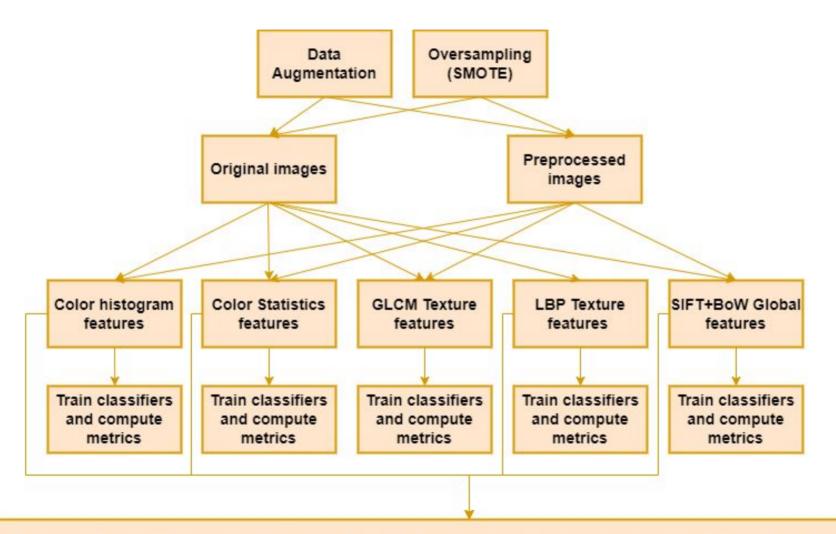
Two class problem: conclusions

- The overall results for the validation set are good. The misclassification errors for both classes are very similar, which is theoretically correct as the classes are balanced.
- Using an ensemble of stacking classifiers trained on each feature set did not perform better than a single stacking classifier trained on all features.





Three class Problem: Scheme Diagram



Train classifiers: SVM, Logistic Regression, Gradient Boosting, Random Forest, AdaBoost, XGBoost, Decision Trees, Naive Bayes, Ensemble (Bagging, Stacking) and compute metrics





Three class Problem: Results(I)

 Case – 1: Without Preprocessing + Data Augmentation (Balanced Accuracy)

Feature						Decision		Naive		Ensemble	
Extractor	SVM	LR	GBoost	RF	Adaboost	Trees	XGBoost	Bayes	KNN	Bagging	Stacking
CHF	0.667	0.54	0.686	0.744	0.565	0.621	0.651	0.428	0.674	0.746	0.756
CSF	0.648	0.534	0.627	0.696	0.581	0.588	0.622	0.429	0.651	0.688	0.71
GLCM	0.507	0.464	0.51	0.562	0.476	0.514	0.508	0.454	0.518	0.539	0.564
LBPH	0.464	0.457	0.467	0.515	0.402	0.475	0.446	0.419	0.473	0.51	0.522
LBPS	0.409	0.372	0.408	0.451	. 0.401	0.433	0.432	0.34	0.431	0.441	0.462
CIFT .											
SIFT + BoW	0.587	0.56	0.57	0.586	0.527	0.473	0.561	0.517	0.596	0.566	0.614





Three class Problem: Results(I)

 Case – 2: Without Preprocessing + Smote (Balanced Accuracy)

Feature						Decision		Naive		Ensemble	
Extractor	SVM	LR	GBoost	RF	Adaboost	Trees	XGBoost	Bayes	KNN	Bagging	Stacking
CHF	0.69	0.543	0.682	0.71	. 0.592	0.591	0.635	0.457	0.698	0.731	0.733
CSF	0.634	0.541	0.643	0.673	0.574	0.558	0.635	0.458	0.631	0.693	0.645
GLCM	0.546	0.506	0.558	0.615	0.506	0.527	0.548	0.41	0.578	0.625	0.613
LBPH	0.598	0.575	0.567	0.592	0.523	0.498	0.571	0.405	0.557	0.611	0.588
LBPS	0.521	0.466	0.496	0.507	0.478	0.439	0.496	0.362	0.509	0.525	0.501
SIFT +											
BoW	0.589	0.518	0.482	0.517	0.458	0.475	0.494	0.499	0.589	0.521	0.576





Three class Problem: Results(I)

 Case – 3: With Preprocessing + Data Augmentation (Balanced Accuracy)

Feature						Decision		Naive		Ense	mble
Extractor	SVM	LR	GBoost	RF	Adaboost	Trees	XGBoost	Bayes	KNN	Bagging	Stacking
CHF	0.619	0.501	0.65	0.682	0.595	0.572	0.644	0.459	0.645	0.702	0.706
CSF	0.602	0.52	0.584	0.652	0.536	0.543	0.576	0.437	0.632	0.636	0.669
GLCM	0.55	0.503	0.568	0.59	0.492	0.477	0.55	0.446	0.552	0.611	0.595
LBPH	0.572	0.579	0.548	0.589	0.514	0.495	0.535	0.463	0.556	0.597	0.599
LBPS	0.497	0.472	0.527	0.554	0.459	0.46	0.523	0.349	0.492	0.546	0.562
CIET .											
SIFT + BoW	0.577	0.541	0.562	0.591	. 0.508	0.442	0.554	0.484	0.575	0.588	0.599





Three class Problem: Results(III)

Case – 4: With Preprocessing + Smote (Balanced Accuracy)

Feature						Decision		Naive		Ensemble	
Extractor	SVM	LR	GBoost	RF	Adaboost	Trees	XGBoost	Bayes	KNN	Bagging	Stacking
CHF	0.647	0.518	0.637	0.658	0.57	0.545	0.623	0.458	0.656	0.666	0.661
CSF	0.622	0.511	0.611	0.644	0.54	0.549	0.616	0.434	0.629	0.654	0.623
GLCM	0.575	0.496	0.534	0.58	0.504	0.505	0.531	0.43	0.541	0.582	0.557
LBPH	0.581	0.591	0.576	0.555	0.537	0.482	0.538	0.451	0.539	0.549	0.558
LBPS	0.504	0.489	0.523	0.528	0.48	0.441	0.483	0.353	0.507	0.538	0.524
CIET .											
SIFT + BoW	0.555	0.52	0.482	0.507	0.477	0.427	0.481	0.47	0.552	0.521	0.558





Three class Problem: Results(IV)

- Without any Processing yields better results
- Data Augmentation provides better results so far than SMOTE Oversampling
- Color Histogram (BGR) is the best Feature Extractor so far
- Case 5 (Hair Removal Only with Data Augmentation, CHF)

Feature						Decision		Naive		Ensemble		
Extractor	SVM	LR	GBoost	RF	Adaboost		XGBoost	Bayes	KNN	Bagging	Stacking	
CHF	0.635	0.495	0.644	0.716	0.562	0.579	0.641	0.409	0.642	0.701	0.723	

- Standalone hair removal is better than combined with vignette removal
- Still without any preprocessing is better performer, so decided to stick with it





Three class Problem: Results(IV)

- Case 6 : Features Combined (Balanced Accuracy)
- Combined the feature extractors (CHF, CSF, GLCM, SIFT, LBP)
- Different combinations were tried but the best one was using CHF,
 CSF, GLCM

Decisio	n Naive	Ensemble
		KNIN Bagging Stacking
GBOOST RF Adaboost frees	Adduosi dayes	KININ Dagging Stacking
583 576 0.647 0.525 0.6	01 0 568 0 <i>11</i> 13	0.643
GBoost RF Adaboost Trees 583 576 0.647 0.525 0.6	XGBoost Bayes	KNN Bagging Stack 0.643 0.624 0

- SelectKBest Features was used, the highest accuracy received was
 0.731 combining 286 Features
- Improved the overall result but still lacks behind standalone CHF





Three class Problem: Results(IV)

- Case 7 : Ensemble Classifiers (Balanced Accuracy)
- Majority and Average voting was used
- 3 best models from each case-I per feature extractor was used
- Equal votes are untied choosing the lower class

Ensemble Model	Balanced Accuracy
CHF (RF, Gboost, SVM)	0.714
CSF (SVM, Gboost, RF)	0.656
GLCM (RF, KNN, Gboost)	0.553
Ensemble of Ensemble	0.681
Average Voting	0.743

 Average Voting gives improved performance with CHF (RF, Gboost, SVM), still not the best





Three class Problem: Results(V)

- Case 8 : Color Histogram Analysis (Balanced Accuracy)
- As color histogram yields the best result, so other color spaces were also explored with adaptive histogram equalization

Footure					Desision	Neive			Ense	mble	
Feature Extractor	SVM	LR	GBoost	RF	Adaboost	Decision Trees	XGBoost	Naive Bayes	KNN	Bagging	Stacking
CHF_BGR	0.656	0.552	0.668	0.738	0.614	0.617	0.670	0.450	0.689	0.739	0.741
CHF_HSV	0.679	0.561	0.685	0.751	0.587	0.594	0.670	0.457	0.674	0.740	0.758
CHF_Luv	0.654	0.546	0.687	0.729	0.575	0.606	0.675	0.387	0.676	0.744	0.748
CHF_XYZ	0.641	0.563	0.677	0.713	0.578	0.585	0.668	0.451	0.652	0.723	0.634

HSV color space overcomes the best result of BGR color space





Three class Problem: Results(V)

- Case 8: Color Histogram Analysis (Cohen Kappa Score)
- As the problem is imbalanced class problem, cohen kappa score was also measured for the best case scenario

Footuro						Decision		Naive		Ensemble	
Feature Extractor	SVM	LR	GBoost	RF	Adaboost		XGBoost	Bayes	KNN	Bagging	Stacking
CHF_BGR	0.508	0.396	0.533	0.658	0.423	0.439	0.523	0.282	0.534	0.640	0.674
CHF_HSV	0.545	0.374	0.572	0.679	0.434	0.401	0.556	0.283	0.537	0.655	0.708
CHF_Luv	0.521	0.349	0.564	0.658	0.422	0.439	0.549	0.063	0.514	0.661	0.693
CHF_XYZ	0.486	0.394	0.529	0.617	0.414	0.395	0.502	0.287	0.499	0.612	0.634

HSV Color space Histogram is the best!

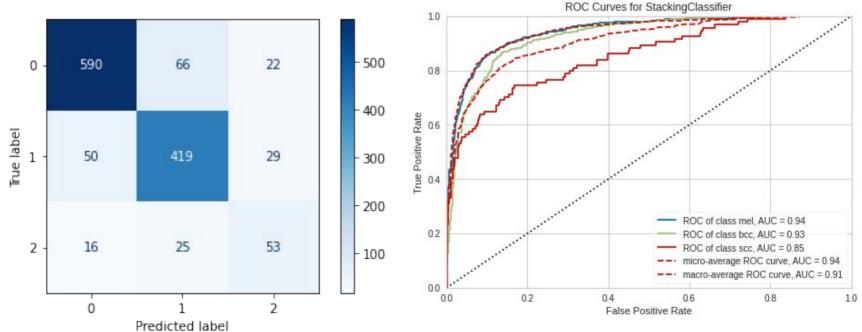




Three class Problem: Best Model

Classification Report on Validation Set (Best Model)

Class	Precision	Recall	F1-Score
0	0.9	0.87	0.88
1	0.82	0.84	0.83
2	0.51	0.56	0.54







Three class Problem: Conclusions

- Winner of Three Class Classification Problem Configuration:
 - Without preprocessing (Hair/Vignetter Removal)
 - Contrast Enhancement by Histogram Equalization
 - Using Data Augmentation
 - Feature Extraction: Color Histogram
 - Color Space: HSV
 - Classifier: Stacking (Ensemble) / Random Forest (StandAlone)
- The overall balanced accuracy is decent but due to very low number of samples from scc class, it hampers the overall performance.

