INFORMATICA MULTIMEDIALE E INTELLIGENZA ARTIFICIALE
Docente: *Marina Paolanti*
Studentesse: *Beatrice Offidani, Samanta Doka, Veronica Neroni*

TASK.1 – COLOR ANALYSIS OF FACES

ABSTRACT

This paper aims to define a color analysis classifier starting with faces. Color analysis is one of the most fashionable trends in recent years, as well as a real discipline that makes it possible to identify the chromatic palette of so-called "friendly colors," i.e., the colors that most enhance a person, through analysis of the combination of skin, eyes and hair. The software used for this project was *Orange Data Mining* in its version *3.36.2* by training on the convolutional Neural Network (*CNN)* model, performing classification on the *SqueezeNet* [1]network.

After analyzing several authoritative articles in which the color class of various celebrities was reported and downloading their respective images, each member of the group classified 300 images from an existing dataset of faces (*Celeb-A),* categorizing each of them according to their respective color class and trying to follow the basic rules of color analysis as closely as possible. After the cataloging phase, we uploaded the images within *Orange Data Mining*, already divided into Train and Test sets, through a *CNN* we extracted the Feature, then we performed a *Fine-Tuning FC Layer,* finally on the Test data the evaluation was done. This process was conducted following a supervised approach.

From the results, several misclassifications emerged, which were analyzed and discussed.

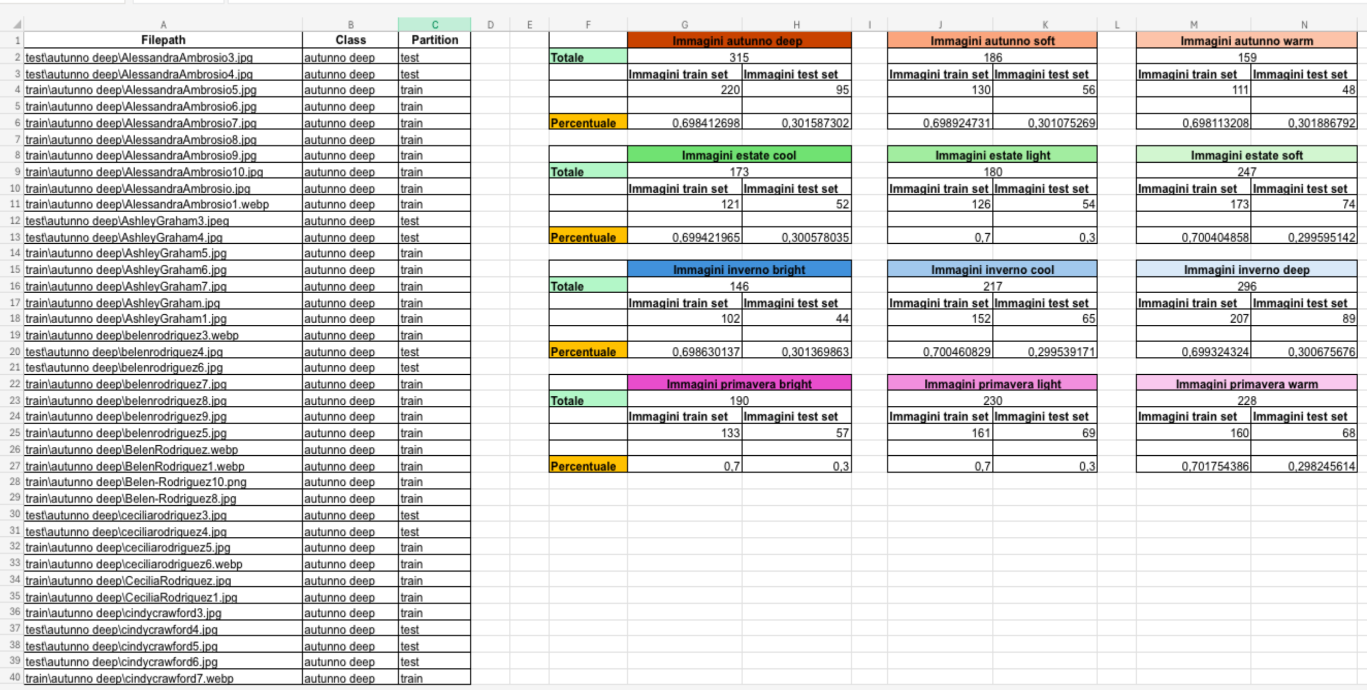
INTRODUCTION

The theory of seasons divides individuals into four groups: summer, autumn, winter and spring. This classification is not about wardrobe, but about the individual's natural colors, which recall those of the respective seasons, and each corresponds to a color palette that harmonizes with the individual's natural colors. These colors can be warm or cool, bright or more muted, and each of the four seasons is characterized by the extent to which certain variables (undertone, value, intensity and contrast) are present.
The work was divided into several steps: initially, several authoritative articles in which the color class of various celebrities was defined were analyzed and their respective images were downloaded. Fifteen to 25 celebrities were identified for each color season, and multiple face photos were downloaded for each celebrity. Then, trying to follow as closely as possible the rules of color analysis each group member categorized 300 images (for a total of 900 images) that were added to the previous images downloaded online. While categorizing the 900 images, we tried to adhere to the basic rules of color analysis as much as possible. The table below summarizes the color characteristics of each class.

[1] **SqueezeNet** is a deep model for image recognition that achieves Alex Net-level accuracy on ImageNet with 50x fewer parameters. The model is trained on the ImageNet dataset.

Autumn deep Warm skin undertones (olive, beige, brown), dark hair (dark brown to black with warm highlights), dark brown, hazel or dark green eyes.	*Autumn soft* Warm skin undertones (beige, peach, golden), dark blond to golden brown hair, green, hazel or brown eyes.	*Autumn warm* Warm skin undertones (golden or orange), red or light brown hair with golden highlights, green, hazel or brown eyes.
Winter deep Cool skin undertones (light, olive or dark), very dark hair, brown, hazel or dark green eyes.	*Winter cool* Cool skin undertones, dark hair without warm highlights, blue, gray, green or dark brown eyes.	*Winter bright* Light skin with cool undertones, dark hair with cool highlights, bright clear eyes (blue, bright green, gray, hazel).
Summer cool Cool skin undertones, ash blond or light brown hair, blue, gray, light green or hazel eyes.	*Summer soft* Light to medium skin with cool undertones, dark blond or medium brown hair, gray, blue-green, hazel or light brown eyes.	*Summer light* Very fair skin with cool undertones, light blond or light brown hair, light blue, light green or gray eyes.
Spring bright Warm skin undertone, blond or light brown hair with golden highlights, bright clear eyes (blue, bright green, light hazel).	*Spring light* Very fair skin with warm undertones, blond or light brown hair with warm highlights, light and bright eyes (light blue, light green, light hazel).	*Spring warm* Peach, golden or ivory skin; blond, red or light brown hair with warm highlights; green, blue or hazel eyes with warm tones.

Once all the necessary images for each color class were obtained, the images were divided into 70% Train and 30% Test. To keep track of the work and avoid errors, an excel file was prepared divided into: filepath, class (autumn deep, autumn warm, autumn soft, winter deep, winter cool, winter bright, summer light, summer cool, summer soft, spring bright, spring light, spring warm) and partition (Train, Test). A total of 2567 photos were obtained from the cataloging phase (1796 used for Train set, 771 used for Test set).



	Filepath	Class	Partition
2	test\autunno deep\AlessandraAmbrosio3.jpg	autunno deep	test
3	test\autunno deep\AlessandraAmbrosio4.jpg	autunno deep	test
4	train\autunno deep\AlessandraAmbrosio5.jpg	autunno deep	train
5	train\autunno deep\AlessandraAmbrosio6.jpg	autunno deep	train
6	train\autunno deep\AlessandraAmbrosio7.jpg	autunno deep	train
7	train\autunno deep\AlessandraAmbrosio8.jpg	autunno deep	train
8	train\autunno deep\AlessandraAmbrosio9.jpg	autunno deep	train
9	train\autunno deep\AlessandraAmbrosio10.jpg	autunno deep	train
10	train\autunno deep\AlessandraAmbrosio.jpg	autunno deep	train
11	train\autunno deep\AlessandraAmbrosio1.webp	autunno deep	train
12	test\autunno deep\AshleyGraham3.jpeg	autunno deep	test
13	test\autunno deep\AshleyGraham4.jpg	autunno deep	test
14	train\autunno deep\AshleyGraham5.jpg	autunno deep	train
15	train\autunno deep\AshleyGraham6.jpg	autunno deep	train
16	train\autunno deep\AshleyGraham7.jpg	autunno deep	train
17	train\autunno deep\AshleyGraham.jpg	autunno deep	train
18	train\autunno deep\AshleyGraham1.jpg	autunno deep	train
19	train\autunno deep\belenrodriguez3.webp	autunno deep	train
20	test\autunno deep\belenrodriguez4.jpg	autunno deep	test
21	test\autunno deep\belenrodriguez6.jpg	autunno deep	test
22	train\autunno deep\belenrodriguez7.jpg	autunno deep	train
23	train\autunno deep\belenrodriguez8.jpg	autunno deep	train
24	train\autunno deep\belenrodriguez9.jpg	autunno deep	train
25	train\autunno deep\belenrodriguez5.jpg	autunno deep	train
26	train\autunno deep\BelenRodriguez.webp	autunno deep	train
27	train\autunno deep\BelenRodriguez1.webp	autunno deep	train
28	train\autunno deep\Belen-Rodriguez10.png	autunno deep	train
29	train\autunno deep\Belen-Rodriguez8.jpg	autunno deep	train
30	test\autunno deep\ceciliarodriguez3.jpg	autunno deep	test
31	test\autunno deep\ceciliarodriguez4.jpg	autunno deep	test
32	train\autunno deep\ceciliarodriguez5.jpg	autunno deep	train
33	train\autunno deep\ceciliarodriguez6.webp	autunno deep	train
34	train\autunno deep\CeciliaRodriguez.jpg	autunno deep	train
35	train\autunno deep\CeciliaRodriguez1.jpg	autunno deep	train
36	train\autunno deep\cindycrawford3.jpg	autunno deep	train
37	test\autunno deep\cindycrawford4.jpg	autunno deep	test
38	test\autunno deep\cindycrawford5.jpg	autunno deep	test
39	test\autunno deep\cindycrawford6.jpg	autunno deep	test
40	train\autunno deep\cindycrawford7.webp	autunno deep	train

	Immagini autunno deep		Immagini autunno soft		Immagini autunno warm	
Totale	315		186		159	
	Immagini train set	Immagini test set	Immagini train set	Immagini test set	Immagini train set	Immagini test set
	220	95	130	56	111	48
Percentuale	0,698412698	0,301587302	0,698924731	0,301075269	0,698113208	0,301886792

	Immagini estate cool		Immagini estate light		Immagini estate soft	
Totale	173		180		247	
	Immagini train set	Immagini test set	Immagini train set	Immagini test set	Immagini train set	Immagini test set
	121	52	126	54	173	74
Percentuale	0,699421965	0,300578035	0,7	0,3	0,700404858	0,299595142

	Immagini inverno bright		Immagini inverno cool		Immagini inverno deep	
Totale	146		217		296	
	Immagini train set	Immagini test set	Immagini train set	Immagini test set	Immagini train set	Immagini test set
	102	44	152	65	207	89
Percentuale	0,698630137	0,301369863	0,700460829	0,299539171	0,699324324	0,300675676

	Immagini primavera bright		Immagini primavera light		Immagini primavera warm	
Totale	190		230		228	
	Immagini train set	Immagini test set	Immagini train set	Immagini test set	Immagini train set	Immagini test set
	133	57	161	69	160	68
Percentuale	0,7	0,3	0,7	0,3	0,701754386	0,298245614

After dividing the images into Train set and Test set, we proceeded to use the *Orange Data Mining* software. The widgets we used were:

Import Images allowed us to import the file system of our dataset. The path to each image could be viewed through the Data Table widget. Initially we imported the Train folder to train the model, then we duplicated the Import Images widget, but this time we imported the Test folder to evaluate the model. This way we calculated metrics (e.g., accuracy).

Image Embedding allowed us to extract Features (numeric vectors that represent images in a small space and are used to do image classification) of selected images through the Image Export widget. These embeddings can be used for various tasks such as image similarity analysis, clustering or as in our case classification. From Image Embedding we selected the SqueezeNet Embedder.

Test and Score allowed us to evaluate our model based on Test. This widget, however, needs a neural network to work. In fact, to the Test and Score widget we connected the Neural Network widget that allowed us to do training, called *Fine-Tuning FC Layer.*

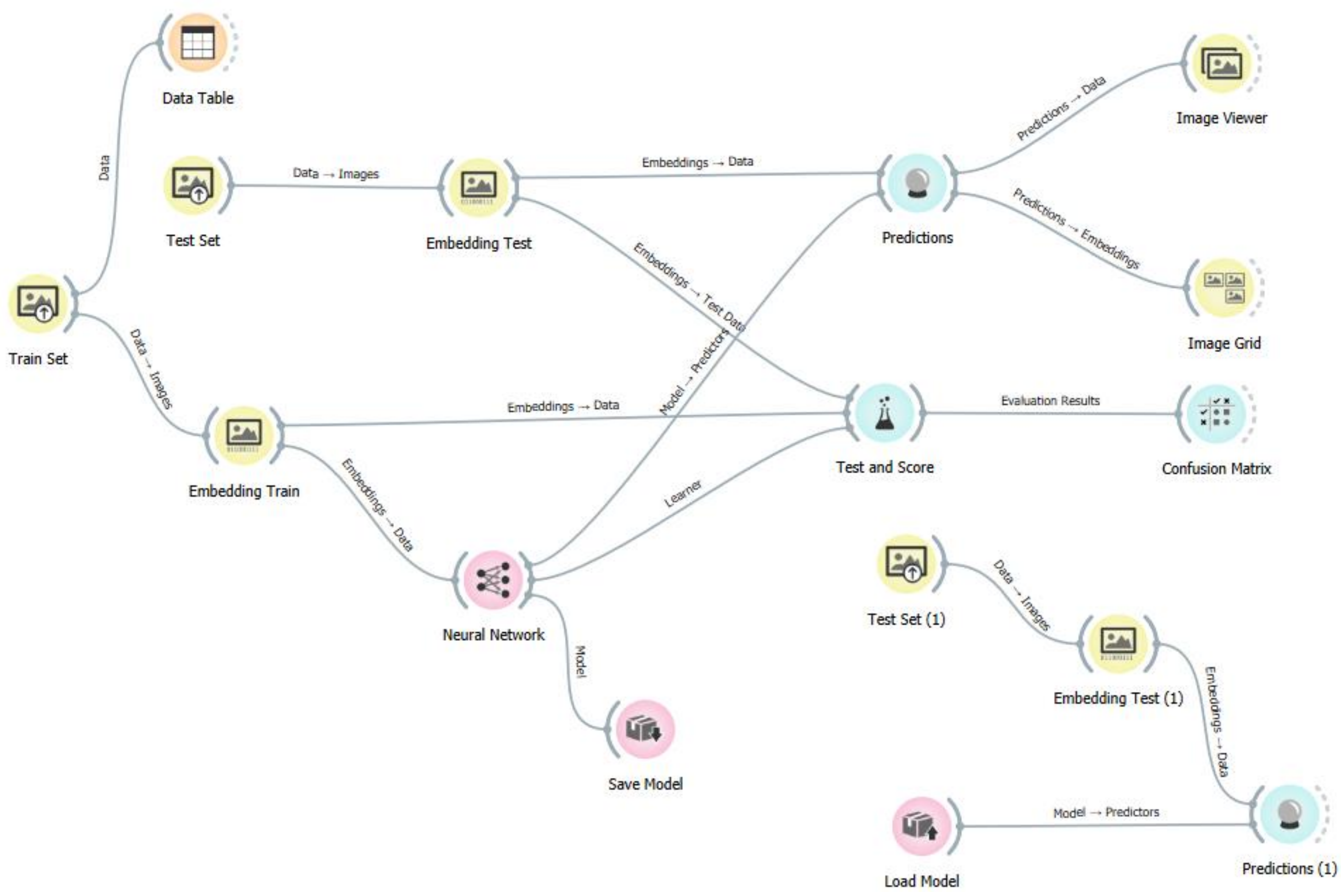
Predictions allowed us to pass data from Image Embedding to the Neural Network and compute predictions about the newly trained model. Thanks to this widget we could see all the predictions made by the model for each image.

Confusion Matrix allowed us to evaluate the performance of our classification model. This widget shows the number of correct or incorrect predictions made by the model on a Test dataset.

Orange provides an interactive visualization, so through the *Image View* widget we were able to view images from our dataset and investigate misclassifications.

Image Grid allowed us to do a qualitative analysis upon completion and see how the model merged the different images based on their similarity.

Save Model allowed us to save our trained model.



MATERIALS AND METHODS

The research was conducted using *Orange Data Mining* software in its version *3.36.2*, and the *Convolutional Neural Network (CNN)* selected was the pre-trained *SeqeezeNet*. The dataset was balanced following a division of 70% for the Training set and 30% for the Testing set. The widgets used were those related to Image analytics group (Import Images, Images Embedding, Image Viewer, Image Grid), Model group (Neural Network, Save Model), Evaluation group (Test and Score, Predictions, Confusion Matrix). Selected images were downloaded from: Google Images and Pinterest. The results of the task were evaluated through the Confusion Matrix.

RESULTS

Before reaching a fair percentage of accuracy of our classification model, we had to make several attempts. In the first attempt, using the 12 classes initially available, the accuracy achieved was only 22.7 percent, which was definitely insufficient. This could be because the Train and Test folders had not been properly balanced.

TEST	CA	IMMAGINI	EMBEDDER
autunno deep, autunno soft, autunno warm, inverno deep, inverno bright, inverno cool, estate soft, estate light, estate cool, primavera bright, primavera light, primavera warm	22.7%	771	SqeezeNet

Subsequently, after further rebalancing the Train and Test folders, we made a second attempt. The accuracy rate increased by almost 7 percentage points to 29.2%, but it was still unsatisfactory. As shown by the confusion matrix, only 227 of the 771 images in the test set were correctly predicted by the classification model, consequently 554 images were misclassified.

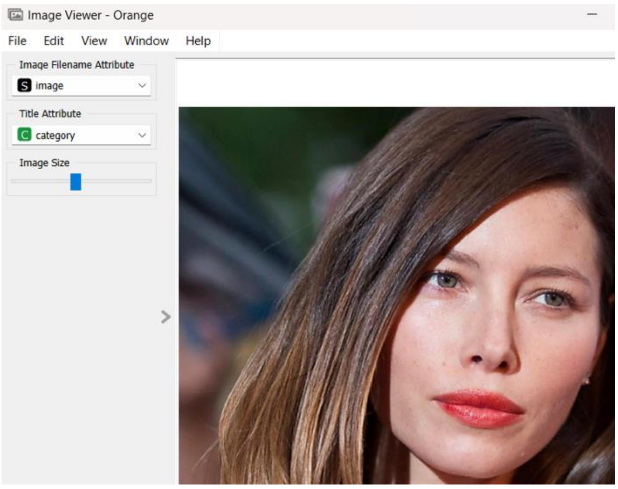
Actual \ Predicted	autunn...	autunn...	autunn...	inverno...	inverno...	inverno...	primav...	primav...	primav...	summe...	summe...	summe...	Σ
autunn...	37	4	4	3	1	23	0	1	6	6	5	5	95
autunn...	12	3	1	1	0	10	0	10	4	2	3	10	56
autunn...	6	0	13	0	1	7	0	7	8	1	1	4	48
inverno...	17	0	1	7	5	11	0	1	1	0	0	1	44
inverno...	12	2	3	2	6	17	0	8	2	8	0	5	65
inverno...	17	1	1	3	9	46	1	4	0	0	2	5	89
primav...	20	1	1	0	4	11	1	7	4	3	1	4	57
primav...	4	2	2	0	1	0	0	22	4	3	6	25	69
primav...	12	2	1	1	3	6	1	11	17	2	3	9	68
summe...	6	0	2	2	4	9	0	0	0	16	8	5	52
summe...	0	0	1	0	0	0	0	10	0	3	19	21	54
summe...	6	1	3	0	5	4	0	12	2	5	2	34	74
Σ	149	16	33	19	39	144	3	93	48	49	50	128	771

TEST	CA	IMMAGINI	EMBEDDER
autunno deep, autunno soft, autunno warm, inverno deep, inverno bright, inverno cool, estate soft, estate light, estate cool, primavera bright, primavera light, primavera warm	29.2%	771	SqeezeNet

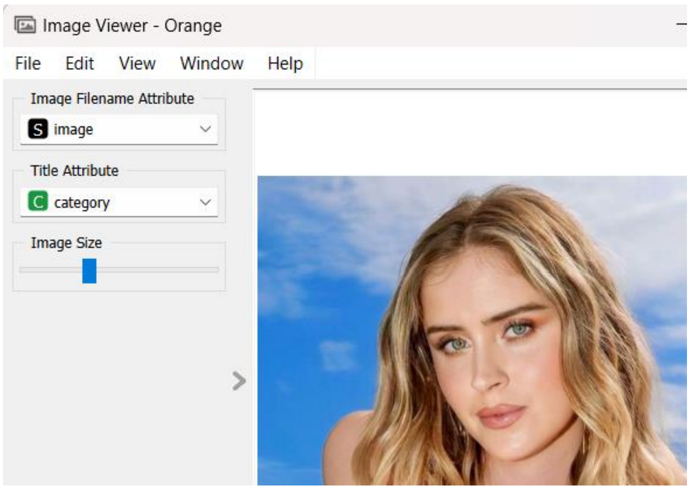
Evaluation results for target (None, show average over classes)

Model	AUC	CA	F1	Prec	Recall	MCC
Neural Network	0.760	0.292	0.272	0.313	0.292	0.220

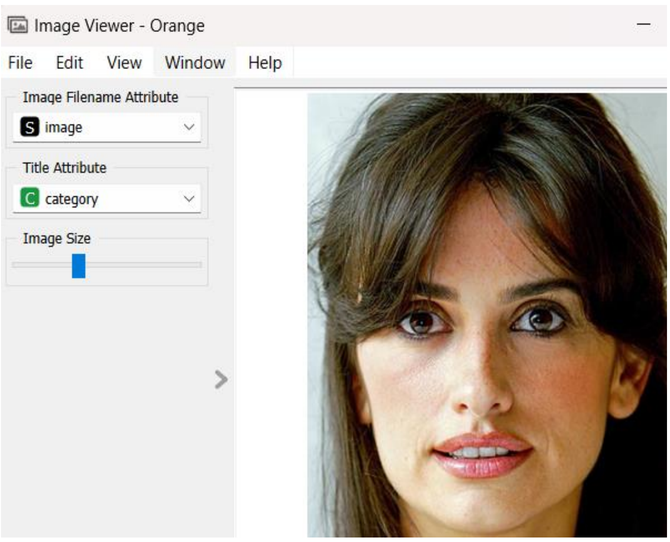
Examples of misclassification



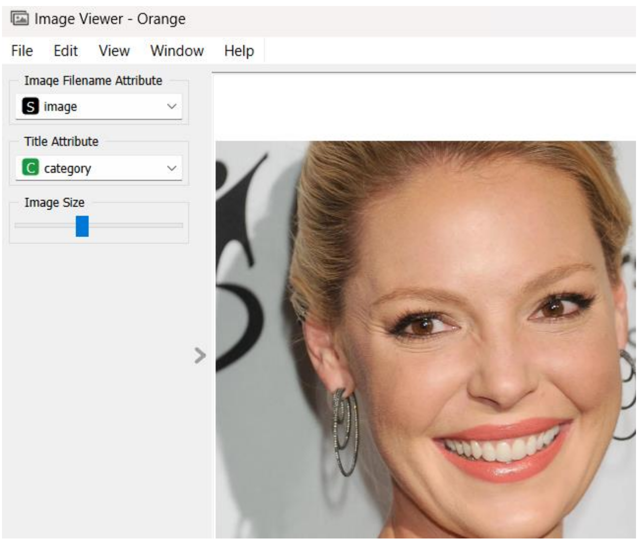
summer soft misclassified *in winter deep*



primavera light misclassified in *primavera warm*



inverno deep misclassiified in *estate soft*



summer soft misclassified in *inverno cool*

The reasons for the model's poor performance may have been as follows:

➢ insufficient amount of images → although 771 images were available for the Test, the amount of images for each class was still too low for the model to achieve good performance;

➢ domain problem → within the same class there were images of very different faces, images with visual characteristics that varied too much. This may have made it difficult to identify consistent patterns;

➢ overfitting → need to diversify and rescale the training data with a complete representation of possible values and types of input data;

➢ inconsistency in annotation → probably the annotation may not have been performed completely consistently, due to the subjectivity of the task. In this case, the model may have received mixed signals during training;

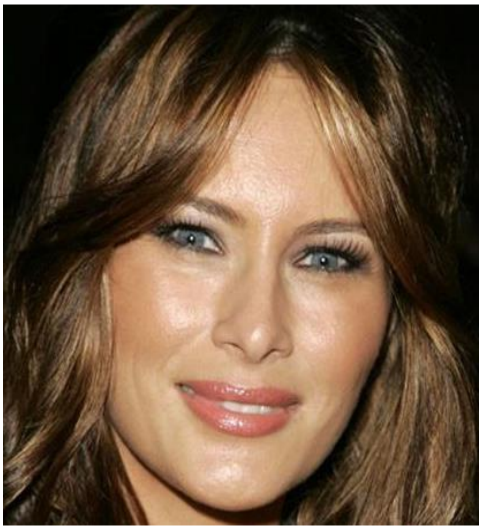
➢ ambiguity of classes → some classes may be very similar to each other, creating ambiguity in the classification process (e.g., summer light - spring light; autumn deep - winter deep);

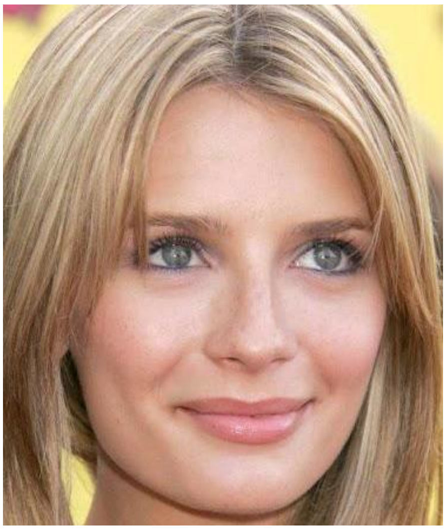
➢ image quality → there may be significant differences in lighting, resolution, and image quality. This can make it difficult for the model to recognize color features;

➢ topic subjectivity → besides being a recent and unpublished study especially, color analysis is an extremely detailed topic. In fact, the differences between different color classes are subtle and easily confused.

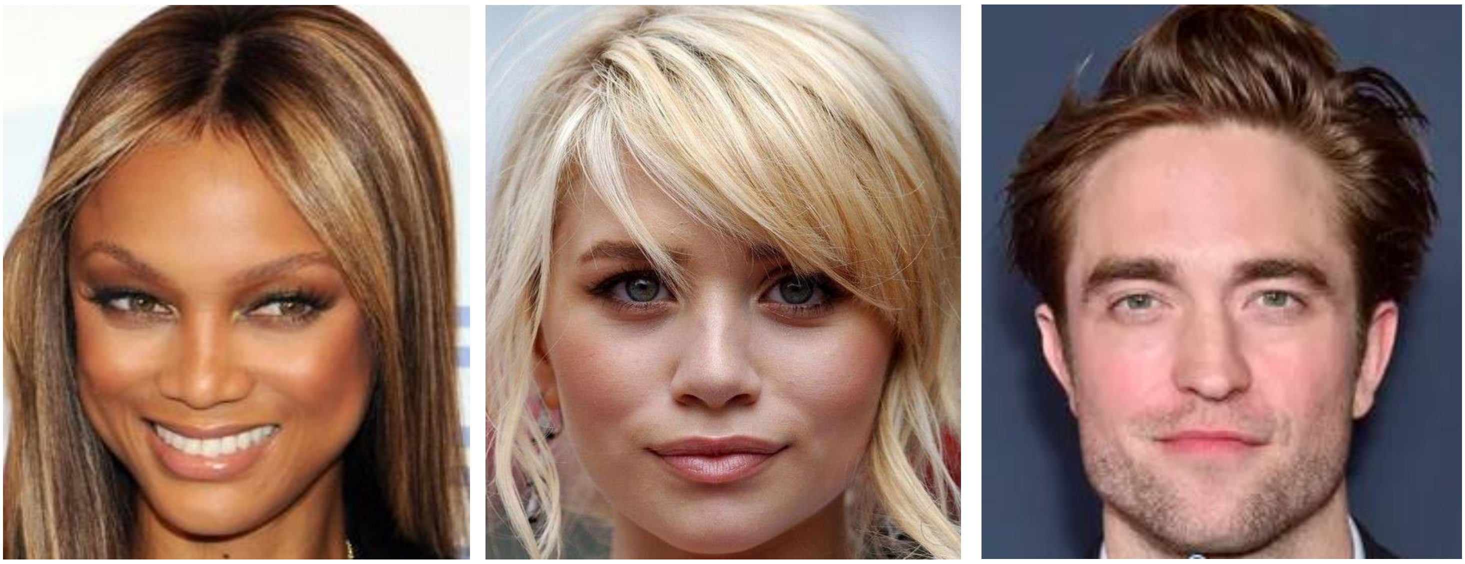
All these issues, particularly the diversity of visual features of images within the same class and the limited amount of images available for each class, prevented good performance with the 12 classes. Below are two examples to clarify the concept of diversity of visual features within the same class.

Summer soft





Autunno soft



As can be seen, in the first example of "Summer Soft," all three images belong to the "Summer Soft" category, but still present different characteristics to each other while being part of the same class. The same happens in the second example, in which all three images are classified as "Fall Soft," but they still present different characteristics despite being part of the same class. Therefore, this inherent diversity within the same category can make it complex for our model to identify and classify images, especially if the amount of available images is limited.

Therefore, to improve the performance of our model, we reduced the 12 classes to 4 macro-classes (*AUTUMN, SUMMER, WINTER, SPRING).*

The reduction in the number of classes led to a significant improvement in model performance: the accuracy rate doubled to 61.1%. As evidenced by the confusion matrix, the classification model correctly predicted 471 of the 771 images in the Test set. Reducing the classes from 12 to 4 increased the number of images in each class, allowing the model to better capture the distinctive features of each class. In addition, the lower diversity of images within each class contributed to a greater balance between classes, further improving the model's performance.

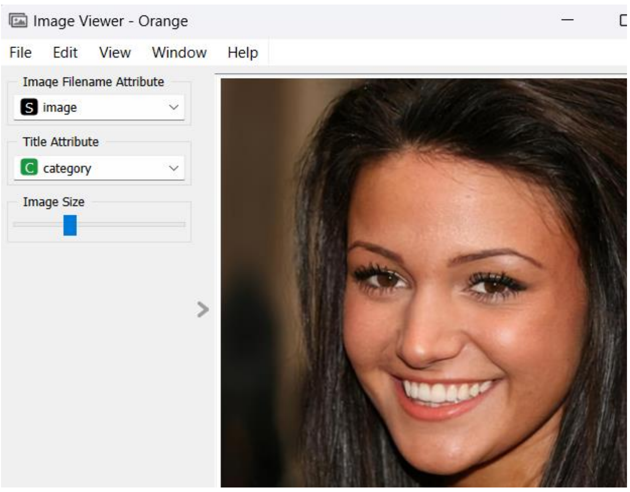
		Predicted				
		AUTUNNO	**ESTATE**	**INVERNO**	**PRIMAVERA**	**∑**
Actual	**AUTUNNO**	86	24	34	37	**181**
	ESTATE	17	157	16	26	**216**
	INVERNO	26	14	141	20	**201**
	PRIMAVERA	28	29	29	87	**173**
	∑	**157**	**224**	**220**	**170**	**771**

TEST		CA	IMMAGINI	EMBEDDER
AUTUNNO, INVERNO, ESTATE, PRIMAVERA	61.1%		771	SqeezeNet

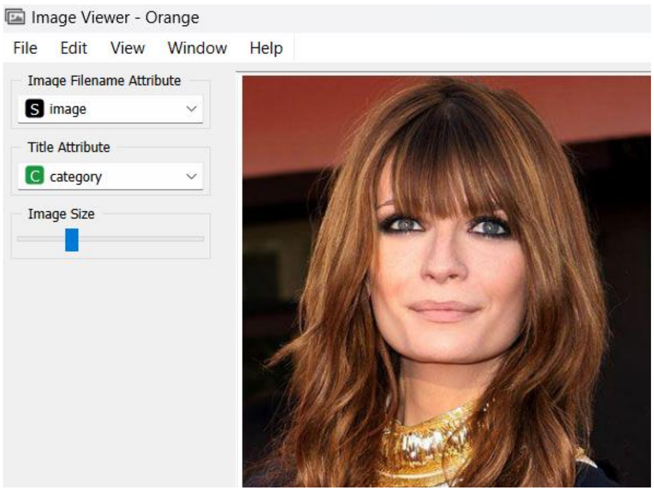
Evaluation results for target (None, show average over classes)

Model	AUC	CA	F1	Prec	Recall	MCC
Neural Network	0.804	0.611	0.608	0.607	0.611	0.480

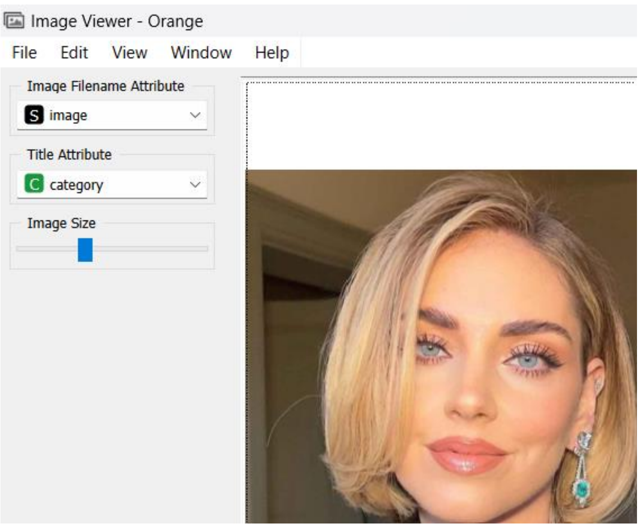
Although reducing the classes to 4 improved the performance of the model, out of a total of 771 images in the Test set, 300 were misclassified. Examples of misclassifications are given below.



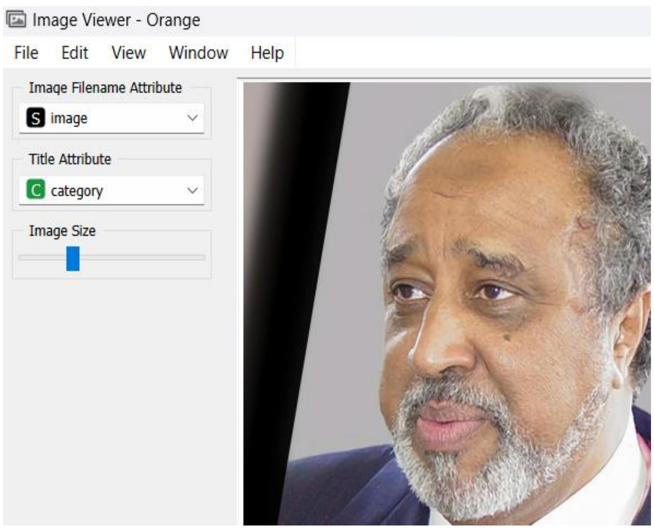
AUTUNNO misclassified in *ESTATE.*



ESTATE misclassified in *AUTUNNO*



PRIMAVERA misclassified in *ESTATE*



AUTUNNO misclassified in *PRIMAVERA*

Summary tables

	CLASSI	CA	EMBEDDER
ATTEMPT #1	12	23.7%	SqueezeNet
ATTEMPT #2	12	29.2%	SqueezeNet
ATTEMPT #3	4	61.1%	SqueezeNet

Although the most suitable *Convolutional Neural Network (CNN)* for our task should have been the pre-trained *OpenFace,* providing the best accuracy rate in all three trials conducted was *SqueezeNet.* However, in order to understand which network gave us the best performance, we tried several available networks. Below are the results obtained with the various *CNNs* in the three attempts performed.

	SQUEEZENET	OPENFACE	INCEPTION V3	DEEPLOC	PAINTERS
ATTEMPT #1	23.7%	22.8%	20.6%	18.1%	23.4%
ATTEMPT #2	29.2%	27.5%	25%	19%	25.8%
ATTEMPT #3	61.1%	46.1%	47.6%	39.8%	47.9%

CONCLUSION

Reducing the classes from 12 to 4 has led to an improvement in the performance of the cataloging model, with an accuracy of 61.1% however, this figure is not yet to be considered fully satisfactory. To further increase the accuracy of the model, there are some strategies to be implemented: certainly, first, increase the number of images that make up the dataset. It is necessary to have a large and diverse dataset to train the model; the more training data you have, the better the model can learn to generalize and capture variations in data features. In addition, it is critical to balance the classes correctly, that is, to make sure that each class has a similar number of images. This is important because balance could lead the model to focus more on the dominant class, neglecting the less represented classes and thus reducing the model's performance on them. Annotation should also be done as consistently as possible. The images that make up the dataset must be of high quality and resolution.