Deep Armocromia: A Novel Dataset for Face Seasonal Color Analysis and Classification

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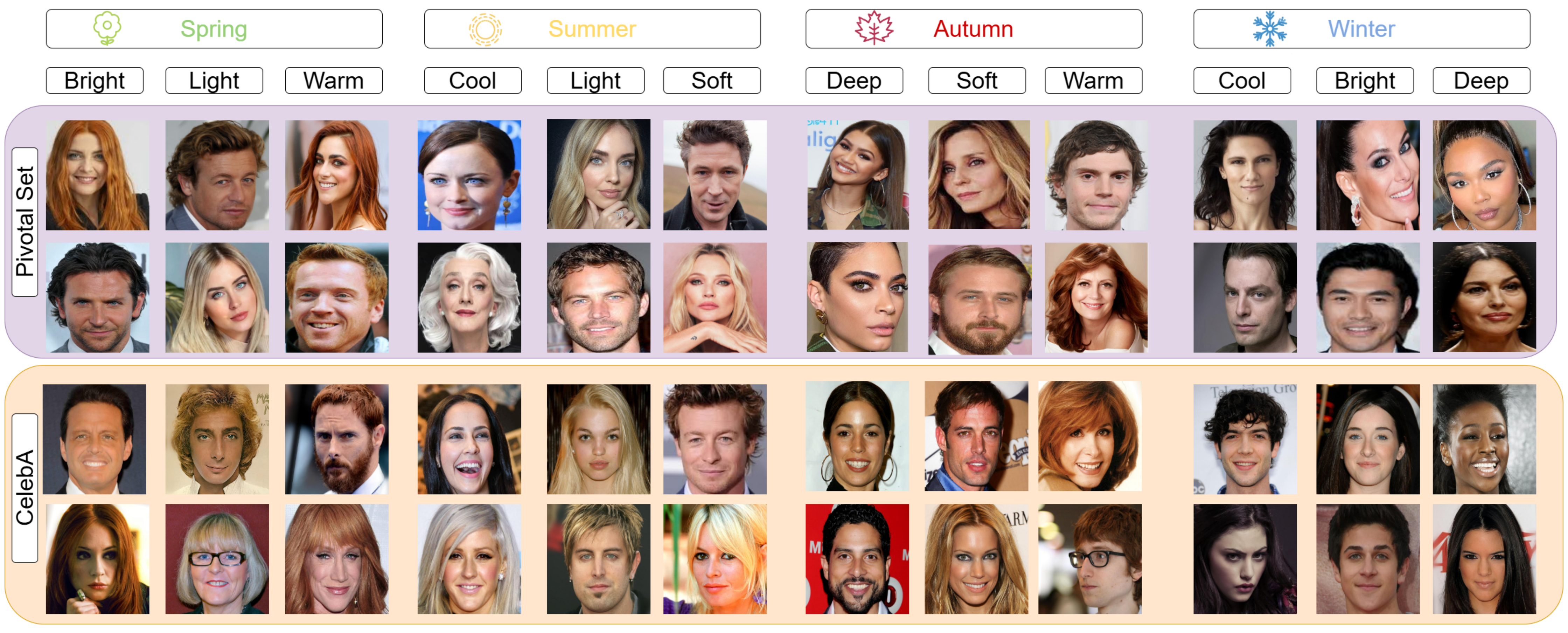


Deep Armocromia examples for Macro Season and Sub-Types.

Introduction

AI-based Face Season Color Analysis (Armocromia) is still under-explored [1, 2].

The Armocromia analysis process is mainly composed of two steps: (i) **Personal color properties**, to determine the skin's, hairs' and eyes' undertone, and lightness and evaluate contrasts; (ii) **Classification into Seasonal Types and Subtypes**, which analyzes those patterns to classify them into a Season and possible Sub-Type [2].

Considering this, such features and discriminative properties could be learned implicitly by DL models, but there is a lack of datasets for their optimization [2].

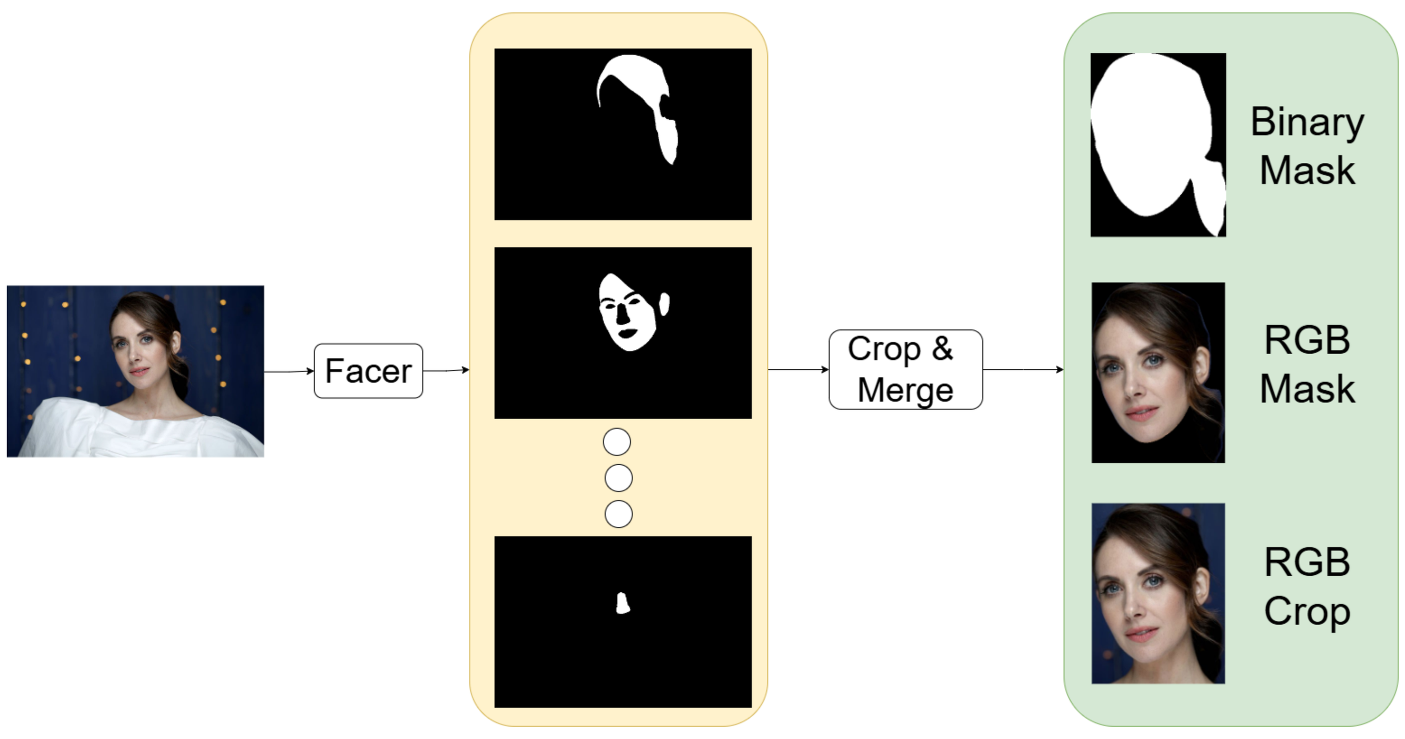
To this date, we here introduce **Deep Armocromia**, comprising labeled face images according to Armocromia Flow Theory [a]. This dataset was collected in collaboration with Moda Metrics S.R.L. [b].

Dataset Collection

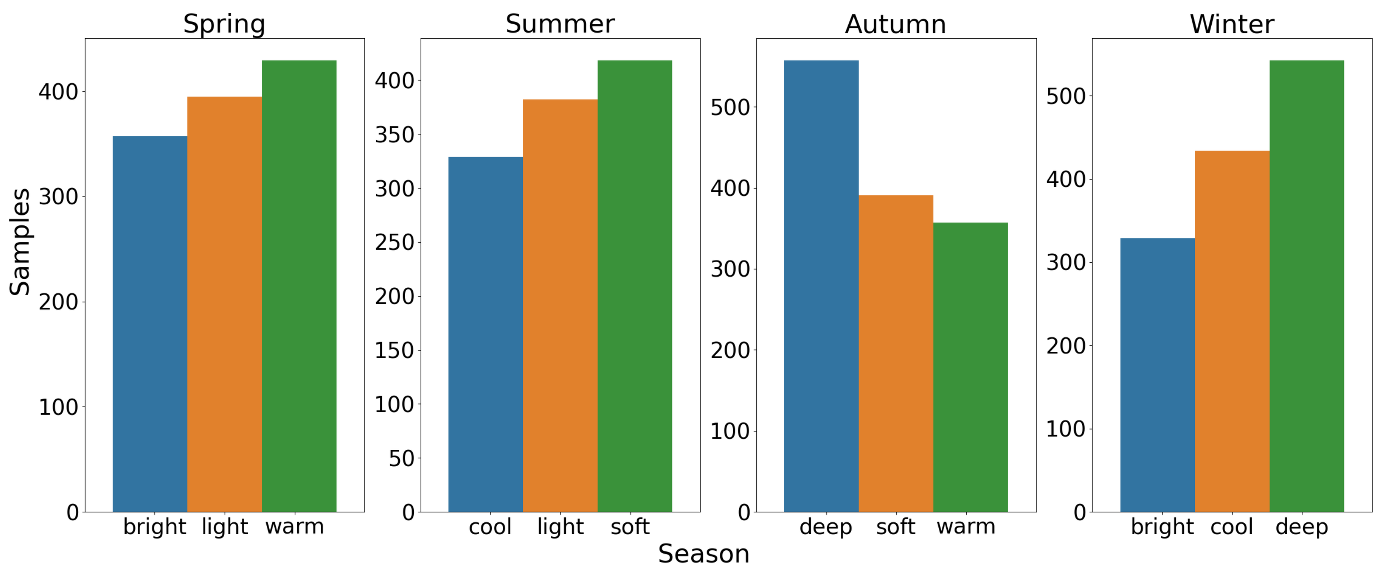
The annotation process follows a strict Armocromia protocol.

1. Students learn the Armocromia classification system through expert examples;
2. Images of celebrities with known Armocromia classifications are collected, labeled (Pivotal Set), and then used to annotate additional images from the CelebA dataset.

Finally, since the CelebA dataset already provides mask data, we isolated faces and their sub-parts within the Pivotal Armocromia set, exploiting the Facer toolbox , as visually reported in the following Figure .



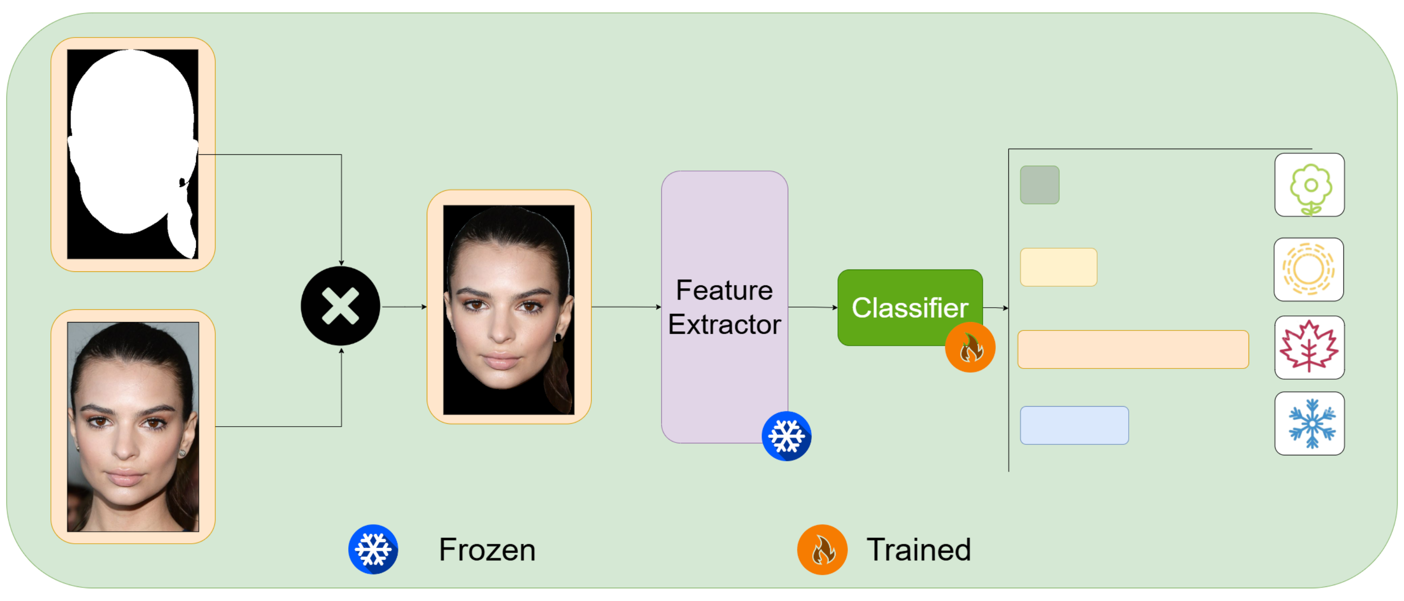
The Deep Armocromia dataset consists of 4920 samples categorized into four main season classes—Autumn, Winter, Spring, and Summer—further subdivided into 12 subtypes. The dataset includes 2981 samples from CelebA and 1939 from the Pivotal Armocromia Set, offering a diverse representation of seasonal and subtype variations.



The teaser figure reports qualitative examples taken from Deep Armocromia, according to both Season classes and relative Sub-Types. Spring individuals have warm undertones in their skin and hair, while Summer features cool, muted tones with soft colors. Autumn exhibits rich, warm tones with deep, saturated colors, and cool, intense traits with high contrast and icy or bright features that characterize Winter.

[a] `https://github.com/lorenzo-stacchio/Deep-Armocromia`
[b] `https://www.modametrics.it/`

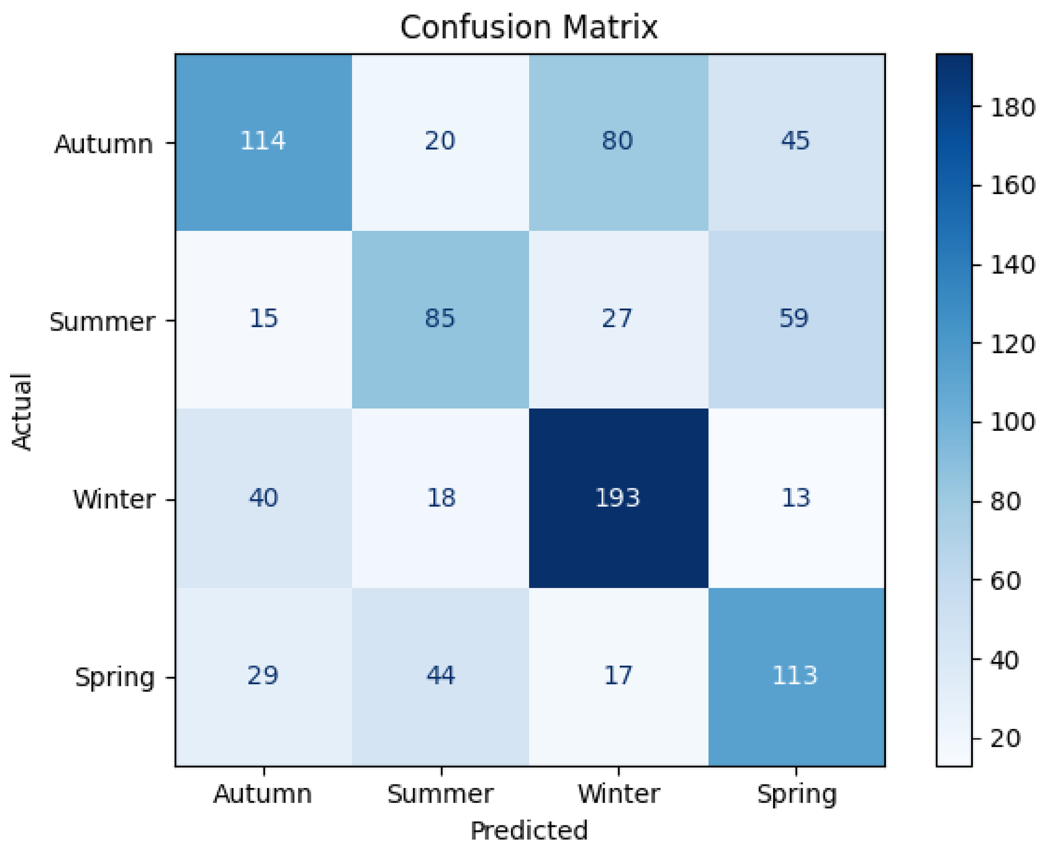
Experiments and Results



We explored a fine-tuning approach using two pre-trained visual backbones—FaRL (Vision Transformer) and ResNeXt50—with frozen weights for feature extraction, aiming to assess whether Armocromia analysis relies on specific learned facial features or more general ones. The same classifier (two FC layers with ReLU and dropout), replaced the classification head for fine-tuning. The image dataset was resized to $3 \times 224 \times 224$ pixels, applying data augmentation (not color-related) to reduce overfitting. We optimized all our models for 50 epochs using the AdamW optimizer (lr = 1e-3, weight decay = 1e-5), using a Cosine Annealing scheduler with warm restarts (every 10 iterations, min lr = 1e-5) and a batch size of 64.

The following table and Figure presents the evaluation metrics for our backbones on the Armocromatic 4 Season task.

Name Exp	Accuracy	Precision	Recall	F1 Score	Top-2
FaRL16	<u>0.525</u>	<u>0.518</u>	<u>0.525</u>	<u>0.516</u>	<u>0.815</u>
FaRL64	**0.554**	**0.553**	**0.554**	**0.548**	**0.808**
ResNeXt50	0.513	0.516	0.513	0.502	0.789



Conclusions

This work introduces the Deep Armocromia dataset, a collection of 5000 celebrity face images labeled using strict Armocromia and Flow Theory protocols, focusing on the 4 Season classes and their sub-types.

Future efforts will expand the dataset and explore novel deep learning techniques, including hierarchical and ordinal learning, to improve classification accuracy and compare DL approaches with classical computer vision methods for Armocromia classification.

References

[1] Wen-Huang Cheng, Sijie Song, Chieh-Yun Chen, Shintami Chusnul Hidayati, and Jiaying Liu. Fashion meets computer vision: A survey. *ACM Computing Surveys (CSUR)*, 54(4):1–41, 2021.

[2] Xueping Su, Jiawei Duan, Jie Ren, Yunhong Li, Michael Danner, Matthias Rätsch, and Jinye Peng. Personalized clothing recommendation fusing the 4-season color system and users' biological characteristics. *Multimedia tools and applications*, 83(5):12597–12625, 2024.