Advancing Facial Aging Assessment: Machine Learning in High-Resolution Imaging for Photoaging Prediction

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Abstract

Facial aging is a complex process influenced by multiple factors, including UV exposure (photoaging). The Glogau scale, a subjective method for classifying photoaging, varies with professional assessments. To enhance objectivity, this study aims to develop a machine-learning model to predict aging levels using high-resolution facial images. To produce the dataset, high-resolution facial images of women with at least level I on the Glogau scale were captured using Visioface® equipment. Then, a dermatologist classified the images according to the Glogau scale (Type I-IV). The study was ethically approved (13367219.5.0000.5404). Supervised machine learning algorithms predicted aging levels from the images. The model was validated independently, with 75% of images for training and 25% for validation. The algorithm accurately predicted aging levels, aligning well with human assessments. The study shows the feasibility of using imaging systems to predict Glogau photoaging. Future research will aim to improve classification accuracy for real-time applications. Machine learning reduced analysis time and improved facial aging assessment quality, supporting further research into facial aging and skin rejuvenation treatments with objective outcome assessments.

Keywords: automated image analysis; machine learning; facial photoaging detection; photoaging.

1. Introduction

Facial aging is a complex, multifactorial process, by multiple factors, including UV exposure (photoaging). Intrinsic aging is the result of internal factors, such as natural wear and tear on the body, while extrinsic aging, also known as photoaging, is influenced by external factors, such as exposure to ultraviolet radiation and lifestyle [1]. Both lead to the formation of free radicals and the fragmentation of collagen in the dermal matrix, resulting in changes in the elasticity and appearance of the skin, marking the continuous cycle of skin aging [2].

There is difficulty in classifying the severity of facial aging due to its multifactorial origin. Historically, the best evaluation for photoaging has been subjective analysis by the trained eye [3]. The conventional Glogau scale, a subjective analysis method performed by experienced professionals, can be influenced by variability in both inter- and intraobserver assessments.

To address this limitation, non-invasive systems are being explored for more objective evaluations of facial aging. Modern digital technologies have the potential to provide both professionals and consumers with more precise evaluations.

Despite continued research on the topic of facial aging, there are still no studies on predicting the severity of photoaging through photographic images. In this context, this study aimed to develop a model based on machine learning capable of predicting the level of aging through the analysis of high-resolution facial images.

It is a multidisciplinary study that brings together formulators, doctors, and computing professionals. It was also quite challenging, as many photos of different age groups and degrees of aging were necessary. This work contributes to the advancement of cosmetic science, as it will allow for a more objective analysis of formulation efficacy, and consequently with greater scientific rigor, guiding formulators in the development of formulations with ingredients that truly contribute to people aging with more beauty, self-esteem, and health.

2. Materials and Methods

2.1. Data preparation

In general, the high-resolution facial images of women exhibiting signs of aging, with at least level I on the Glogau scale, were captured using the Visioface® (Courage & Khazaka, Germany) equipment (item 2.1.1). The dataset images were subsequently assessed by a dermatologist and classified according to the Glogau photodamaged scale, which categorizes aging from early to advanced based on the progression of wrinkles, dyschromia, telangiectasias, and keratoses (Type I – early photoaging; type II - early to moderate photoaging; type III - advanced photoaging; type IV - severe photoaging) (item 2.1.2.).

The study was approved by the ethics committee under the number 13367219.5.0000.5404.

2.1.1. Evaluation of skin visual characteristics by high-resolution imaging

The high-resolution image dataset was constructed from images of the women's faces exhibiting signs of aging, with at least level I on the Glogau scale. These images were captured at different times and separated for further analysis in this dataset. The capture was performed on the front view of 397 women, between 20 and 70 years old, all skin phototypes.

The high-resolution images were obtained with the Visioface® RD (Courage & Khazaka, Germany) device for the evaluation of the visual characteristics related to aging such as the presence of wrinkles and hyperpigmentation [4,5].

Before the acquisition, the subjects remained for 20 min in an environment with controlled air temperature and relative humidity, 20–22°C and 45–55%, respectively, for acclimatization. All participants were advised to avoid washing their faces for at least 3 hours before the measurement.

Images were read and resized to 2279x3051 pixels to ensure consistency across the dataset. Subsequently, the images were converted to grayscale to simplify feature extraction.

2.1.2. Clinical analysis of photoaging

The method consisted of a subjective clinical assessment conducted by the dermatologist at the beginning of the study. This assessment involved a clinical anamnesis carried out by the dermatologist to evaluate the photoaging of the research subjects, ranging from moderate to advanced, according to the Glogau scale [6]. It is used to determine the stage of facial skin photoaging, considering Types I, II, III, and IV, based on the presence and type of wrinkles, spots, and pre-cancerous changes, among others. The definitions for each type are in Table 1.

Table 1. Photoaging Glogau scale classification.

Type I	Type II	Type III	Type IV
No wrinkles - early photoaging; slight pigmentation changes; minimal wrinkles; no visible age-related changes.	Wrinkles in motion - early to moderate photoaging; the appearance of lines only during facial movements; early appearance of brown spots; most notable skin pores.	Wrinkles at rest - advanced photoaging; prominent brown pigmentation; visible age spots; small, noticeable blood vessels; wrinkles now evident even when the face is at rest.	Wrinkles only; severe photoaging; wrinkles visible regardless of facial movement; yellow-gray skin tone; history of previous skin cancers; precancerous skin changes (actinic keratosis).

2.2. Data modeling and evaluation

2.2.1. Feature Extraction using Local Binary Pattern (LBP)

Local Binary Pattern (LBP) was employed for feature extraction [7]. This technique captures texture information by comparing each pixel with its neighboring pixels. This process resulted in the creation of a local binary pattern for each pixel, encoding its texture characteristics. Following the computation of LBP for all pixels in the image, a histogram was constructed to represent the distribution of the 256 different LBP patterns within the image. Each bin in the histogram corresponded to a unique LBP pattern, while the bin count denoted the frequency of occurrence of that pattern in the image. Consequently, for each image, we have a 256-dimensional feature vector. The frequency values of the LBP features were transformed using a logarithmic function.

2.2.2. Model Training and Evaluation

The dataset was split into training and test sets using an 80-20 ratio to ensure model generalizability. The training set was used to train a predictive model, while the test set was reserved for evaluating the model's performance.

The following steps were undertaken for model training and evaluation:

- **Model Training:** A multinomial logistic regression model with Elastic-Net regularization, implemented using the 'glmnet' package, was fitted using the training dataset. The dataset was pre-processed using Principal Component Analysis (PCA) to reduce dimensionality and improve computational efficiency. Leave-one-out cross-validation (LOOCV) was used to select the tuning parameters.
- **Model Evaluation:** The model was tested on an independent test dataset to evaluate its generalization capability. Confusion matrices and performance metrics were generated to analyze the model's classification accuracy.
- **Software Implementation:** The entire analysis was implemented using the R programming language with packages ‘EBImage’, ‘caret’, ‘wvtool’, and ‘glmnet’.

3. Results

Examples of images obtained and classified by an expert are presented in Figure 1.

Figure 1. Standard Visioface® photographs of 4 subjects placed on the Glogau Photoaging Scale as follows: (A) a subject classified as Glogau I, (B) a subject classified as Glogau II, (C) a subject classified as Glogau III, and (D) a subject classified as Glogau IV. Subject range is provided to exemplify the clinical spectrum seen in this study.

The best-performing model was selected through an independent validation set. The training dataset comprised 75% of the facial images, while the remaining 25% was used for validation. The general performance data of the model can be found in Table 2. The performance of the machine learning algorithm by Glogau scale level is described in Table 3.

Table 2. Overall performance of the machine learning algorithm using Visioface® images data for the classification of photoaging in women.

Training sets		
	Accuracy	0.7855
	95% CI	(0.7362, 0.8294)
Testing/validation sets		
	Accuracy	0.5844
	95% CI	(0.4664, 0.6957)

Table 3. Performance by level of the machine learning algorithm for the Glogau classification of photoaging in women.

Glogau classification	Training dataset				Testing dataset			
	I	II	III	IV	I	II	III	IV
Sensitivity	0.8023	0.7708	0.7160	0.8889	0.7143	0.4783	0.600	0.5385
Specificity	0.9437	0.8778	0.9237	0.9620	0.9286	0.7778	0.8070	0.9219
Balanced Accuracy	0.8730	0.8243	0.8199	0.9254	0.8214	0.6280	0.7035	0.7302
Recall	0.8023	0.7708	0.7160	0.8889	0.7143	0.4783	0.600	0.5385
Precision	0.8415	0.7327	0.7632	0.8276	0.7895	0.4783	0.5217	0.5833
F1 Score	0.8214	0.7513	0.7389	0.8571	0.7500	0.4783	0.5581	0.5600

4. Discussion

The aging of facial skin is a growing concern among consumers and patients. With a growing interest in preventing or reversing skin aging, numerous new and promising treatments for facial rejuvenation are emerging. Despite its simplicity, the Glogau Scale remains one of the most widely used tools by researchers studying skin photoaging [3].

The study results highlight the feasibility of using an imaging system to predict Glogau photoaging assessments. However, new images continue to be obtained by our research group, as the mathematical model employed requires many images to achieve adequate precision. Our research group is continuously working to improve the accuracy of photodamage classification for real-time applications, as this will contribute to the advancement of cosmetic science. These findings contribute to future investigations on facial aging and therapeutic options for facial skin rejuvenation, allowing for an objective evaluation of treatment results.

5. Conclusion

Multidisciplinary work is challenging and pushes us out of our comfort zone, but it can significantly contribute to the advancement of cosmetic science and innovation. In the case of this presented study, we can conclude that the development of prediction models contributes to future investigations of facial aging, and therapeutic options for facial skin rejuvenation, and enables an objective assessment of treatment outcomes.

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Conflict of Interest Statement

NONE.

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