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Predicting skin aging clinical signs evolution using dermatological knowledge and image generative models

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Abstract

Cosmetic companies are developing rigorous models to predict aging according to consumer lifestyles. Given the complex interplay of lifestyle, environment, and intrinsic factors on aging, these models offer valuable support for consumers. They provide guidance for making choices aligned with public health recommendations, filling a gap where scientifically robust tools are often lacking. We present a novel, expert-developed, and validated visual multi-ethnic predictive model to visualize the effects of lifestyle choices, specifically sun exposure and smoking, on facial aging. By generating comparative images, this model projects a consumer's potential future appearance based on their habits, offering personalized insights, and supporting

broader longevity initiatives promoting healthy aging by giving information to customers on consequences of tobacco use and excessive sun exposure.

The proposed model addresses the challenge of predicting long-term facial aging changes, which take decades to manifest and are difficult to assess in clinical studies.

The proposed model is based on published research. Firstly, elicited models predict the cumulative impact of lifestyle and chronological aging on specific skin aging signs over a 15-year period, starting at age 18. These models, developed by 28 experts dermatologist, across France, USA, China, Brazil, South Africa, and Senegal, focus on wrinkles, skin tone

heterogeneity, and ptosis in women of European, Asian, and African descents. The output provides a probability distribution of all possible clinical aging grades for each sign, along with a mean predicted score. Secondly, the AgingMapGAN (AMGAN) describes a model that modifies the clinical sign grade of high-resolution facial images, incorporating

ethnicity-specific aging information. This methodology provides new images of the face at targeted clinical sign grades.

By combining AMGAN with the mean score derived from the elicited predictive models, our model generates simulated images forecasting facial aging from age 18 to 65, considering personalized intrinsic and extrinsic factors. To demonstrate the potential of this combined approach, simulations are presented illustrating the impact of smoking and sun exposure on the face.In [9], the AgingMapGAN (AMGAN) leverages the generative adversarial network (GAN) methodology to produce a model that modifies the clinical signs [10] of high-resolution facial images, incorporating ethnicity-specific aging information. This allows for the generation of new images of the face at targeted clinical sign scores.

By combining AMGAN [9] with the mean score derived from the elicited predictive models [7-8], our model generates simulated images forecasting facial aging from age 18 to 65, considering personalized intrinsic and extrinsic factors. To demonstrate the potential of this combined approach, simulations are presented illustrating the impact of smoking and sun exposure on the face.

Keywords : Longevity, Dermatology, Tobacco, ,Aging, Generative AI, Elicitation, GANs

1. Introduction

Facial skin aging is affected by intrinsic (chronologic) aging, triggered mainly by genetic and extrinsic aging caused by environmental factors [1-6]. Dermatologists recognize the impact of medical history, lifestyle (tobacco/alcohol use, UV exposure/sensitivity), and clinical presentation (pigmentation, perceived/chronological age discrepancy, facial morphology) on facial aging. However, the influence of these factors varies with age, specific clinical signs, and extrinsic factor intensity, necessitating the development of personalized, predictive tools.

Currently, software that predicts and modifies digital photographs to visualize facial aging can be easily accessed. However, these programs do not consider the complex interplay of the various factors that contribute to facial skin aging. Thus, in a reliable and objective matter for a given individual, it is impossible to obtain compiled information about specific facial skin aging. Developing a method, using expert knowledge elicitation and image generation approach that allows the creation of a predictive model validated by dermatologists in a multiethnic population and to build a facial skin aging model usable in all individuals, is of great interest.

We've developed and validated a novel and photo-based predictive model to empower consumers in making informed lifestyle choices and mitigate the effects of exposome (UV, pollution, etc.). The proposed model addresses the challenge of predicting long-term facial aging changes, which take decades to manifest and are difficult to assess in clinical studies.

2. Material and Methods

The predictive model is composed of two elements: Causal Belief Bayesian Networks which quantify dermatological expertise [7-8] and generative adversarial network (GAN) methodology [9] to produce a model that modifies the clinical signs [10] of high-resolution facial images, incorporating ethnicity-specific aging information.

a. Elicitation of Causal Belief Bayesian Networks using dermatological expertise

Causal Bayesian Belief Networks (CBBNs, Figure 1) are probabilistic graphical models [11], representing the causal relationships between risk factors and their influence on skin aging progression. They provide a framework for assessing the impact of various lifestyle habits. Their intuitive representation, made of nodes and arcs, makes them both user-friendly and

easy to interpret. Clinical signs that are considered are wrinkles (forehead, crow's feet, …), pigmentary disorders and face ptosis (lower face ptosis and eye bags).

CBBNs are aimed to objectively predict the evolution of facial skin aging in all phototypes 15 years after their initial assessment, by leveraging the knowledge and experience of an international group of 28 experienced dermatologists across France, USA, Brazil, China, South Africa and Senegal, through a causal modelling method with expert knowledge elicitation.

The model predicts how a baseline grade of facial aging signs is likely cumulatively impacted by environmental (extrinsic) and intrinsic modulators, using evolution probability elicited using the Delphi approach and constituting prior state-of-the-art knowledge. The output is a distribution of possible aging sign grades, each associated with a probability of occurrence.

This model generates mean clinical scores (Figure 2) and probabilities of reaching a defined clinical score at a given age, depending on photoprotection and smoking from age 18, for women of European, Asian, and African descent, as well as women with three different tones of SOC. It provided results consistent with existing literature.

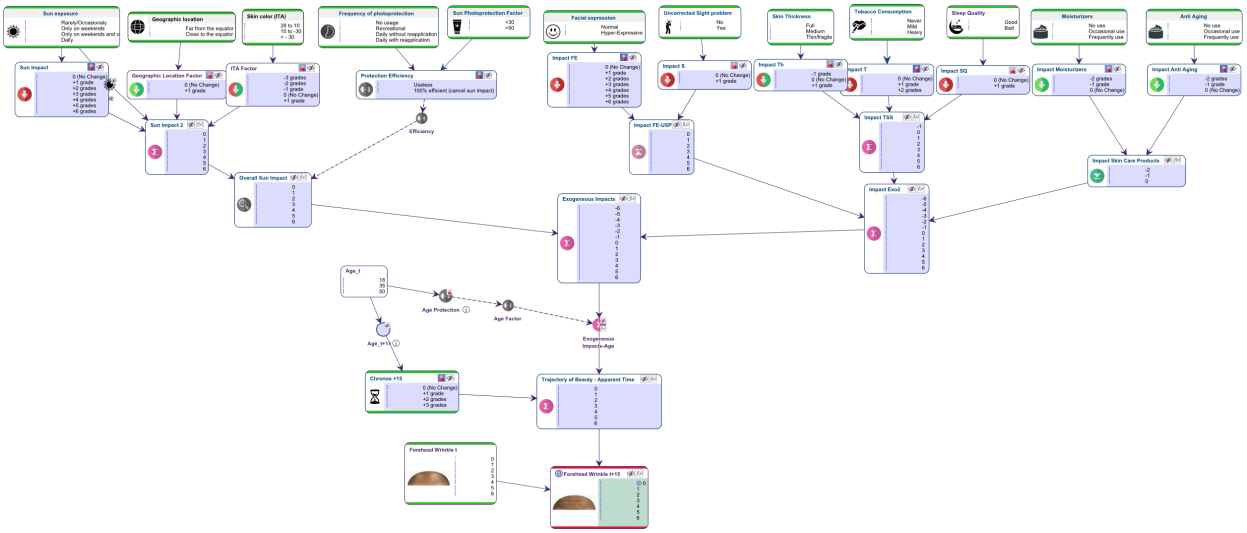


Figure 1: Example of CBBN of forehead wrinkles prediction on African-descent skin

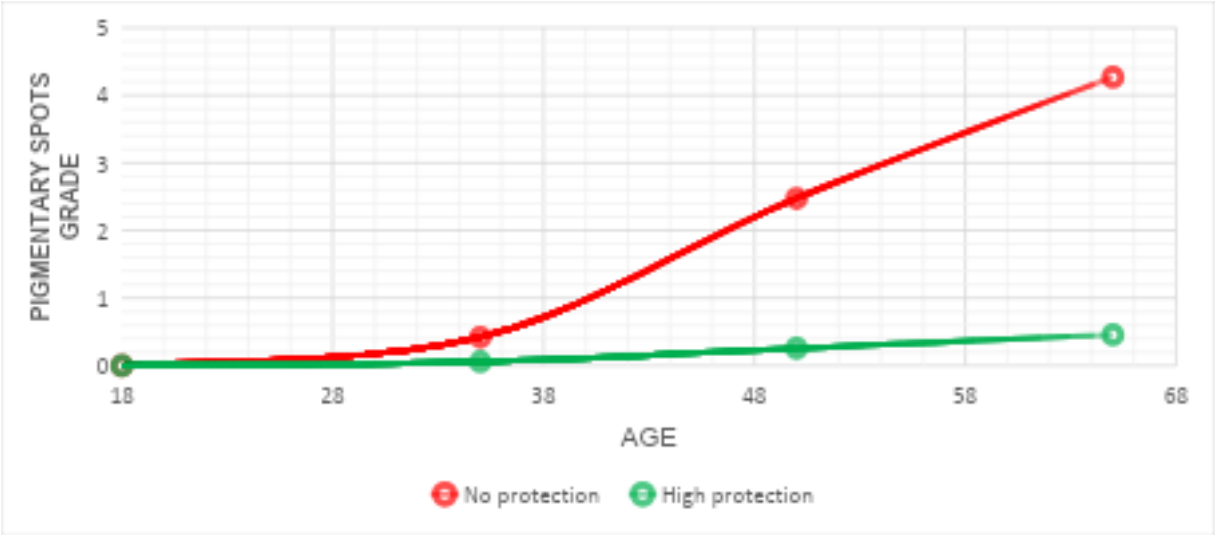


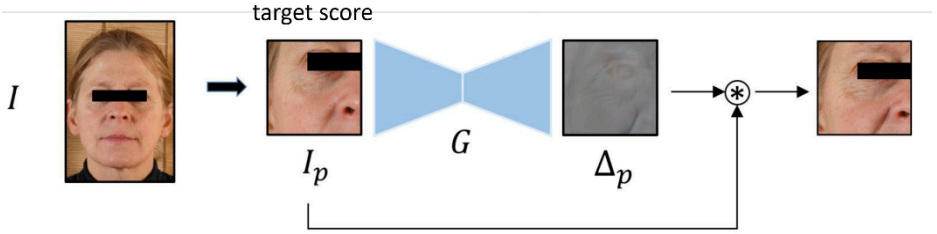
Figure 2: Example of aging trajectory simulation on pigmentary disorders of European-descent skin from mean scores derived from elicitation model

b. AgingMapGAN (AMGAN) : aging effects visualization on photos

Generative adversarial networks (GANs) are machine learning models used for generation [14]. A GAN is composed of two models. A generator that generates samples, and a discriminator that assesses the realism of samples generated by the generator. GAN has been extended to conditional generation where the generator generates samples conditionally to given inputs [14].

Our model AMGAN [9] is a conditional GAN where the generator receives as inputs a source image, and a target sign score, and generates a target image (see Figure 3(a)). The source image is a skin ageing sign image crop such as glabellar, nasolabial, inter-ocular, forehead wrinkles. The source image crop is defined according to the aging sign region as defined by skin atlases in [10]. The target sign score is also defined according to skin atlas grading in [10]. The discriminator controls generator quality by scoring generator generation realism, and accuracy of target scores (see Figure 3(b)).

(a) GAN generator G taking input a source image Ip cropped from an image I, and a target score and generating an increment Δp that added to source image gives target image with sign score corresponding to the target score.



(b) Discriminator D assessing whether target image score is realist (real/fake) and it's sign score matches target sign score.

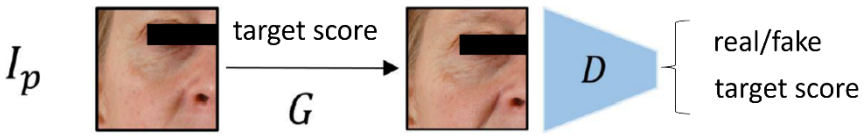


Figure 3: GAN generator G and discriminator D pipelines.

AMGAN model is trained using a dataset of 600 persons which have their sign scores graded by 15 experts. For each sign, the source image scores are taken to be the average of the scores given by the 15 experts. Figure 4 gives sample results of score evolution results generated by AMGAN on two individuals. Scores evolved from lowest to maximum scores. These results show that AMGAN generates highly realistic images.

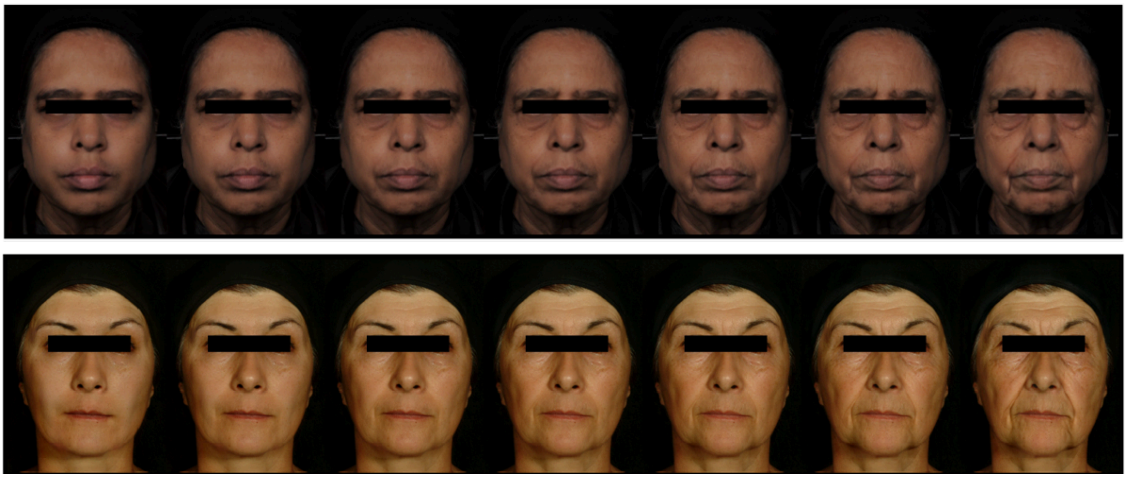


Figure 4: Score evolution produced by AMGAN on two test individuals.

c. Application to Sun exposure and Tobacco consumption

By combining AMGAN with the mean score derived from the elicited predictive models, the final model generates simulated images forecasting facial aging from age 18 to 65, considering personalized intrinsic and extrinsic factors.

Here, we have chosen to present two results (Figure 5b and 5c) generated by our predictive model to illustrate the personalization tool and the effects of smoking and sun exposure.

Figure 5 a shows the image of a 43-year-old woman.

Figure 5 b presents a projection 15 years later (at age 58), setting the smoking parameters to less than 10 cumulative pack-years by that age, and with moderate daily and recreational sun exposure (30 minutes to 2 hours per day between 10 a.m. and 4 p.m., in a location far from the equator), combined with daily use of SPF 50+ photoprotection.

Figure 5 c shows an alternative projection at age 58, based on more than 20 cumulative pack-years of smoking and with important daily and recreational sun exposure (more than 2 hours per day between 10 a.m. and 4 p.m., in a location far from the equator), without photoprotection.

3. Results

Simulation results are shown in Figure 5, comparing the original photograph (age 43, Figure 5a) with two simulations (Figure 5b, 5c) varying sun exposure, photoprotection, and smoking parameters.

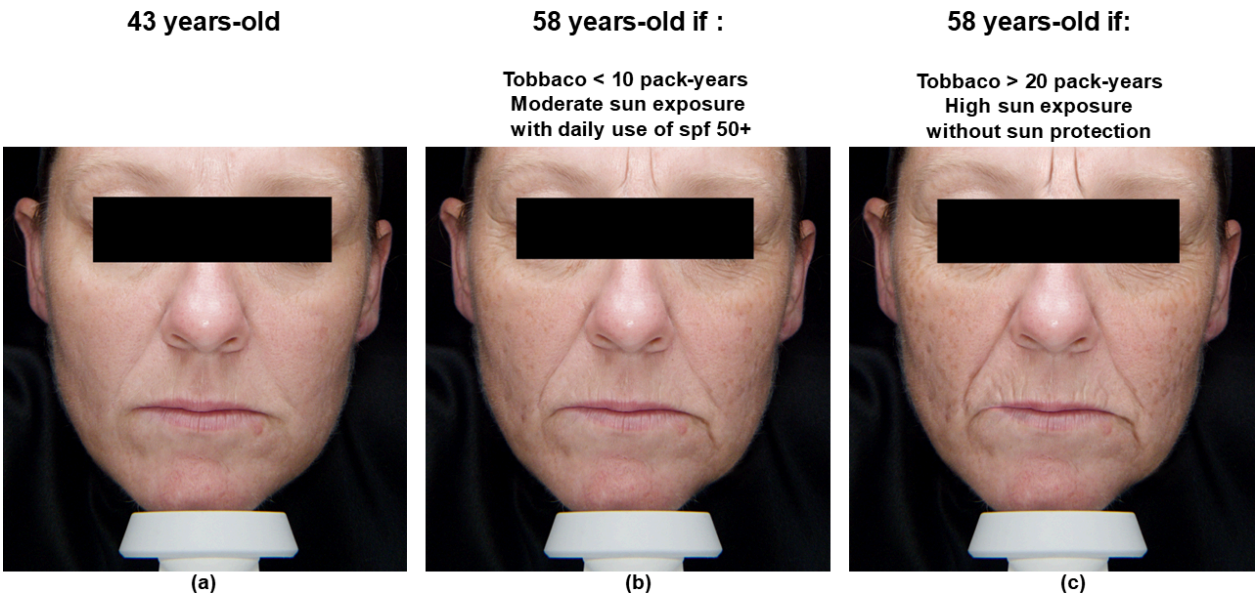


Figure 5: a) image of a 43 years old woman, and b)-c) score evolution generated by the proposed model

4. Discussion

This innovative method combines expert knowledge quantification, causal modeling, and image generation to offer personalized, visual, and inclusive aging simulations. It allows for recommendations of products or lifestyle adjustments to mitigate the worsening of clinical signs for well-aging.

As the aim of the project is to obtain personalized simulations that closely reflect real life, the simulations presented in this document exhibit less marked effects than those typically used to illustrate the impact of smoking or sun exposure [12]. This is due both to the simulator being grounded in dermatologists' real-life observations of aging, and to the fact that the predictions cover only a 15-year period for these extrinsic aging factors.

Concerning CBBNs, harnessing expert-reviewed empirical data remains essential to enhance these models further. The use of this data supports the update of probabilities, resulting in predictions of even greater accuracy.

A limitation of GANs is the difficulty to train such models. During training, the generator tries to generate samples that cannot be identified by the discriminator. This competition between generator and discriminator can induce training instabilities.

Conclusion

This paper presents a model for predicting and visualizing the effects of extrinsic aging factors (sun exposure and smoking) by combining elicited dermatological expertise with GANs. Elicitation predicts skin aging scores evolution driven by chronoaging and extrinsic factors. While GANs generate visualizations based on scores predicted by evolution. Presented results show that proposed models generate very realistic results that can be used for customers' awareness about the potential impacts of extrinsic factors on skin aging.

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Conflict of interest

HJ, FF, SB, JD, are employees of L'Oréal. ER and ASM are consultants for L'Oréal.

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