Algorithm development for wrinkle evaluation based on artificial intelligence (AI) technology

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Background: The visual evaluation of wrinkles is a form in which the subjective point of view of the evaluator enter although it is broadly used in the fields of skin evaluation such as cosmetics and dermatologic research. In this study, we developed a wrinkle detection algorithm based on a AI technique. This system can accurately and rapidly detect wrinkles

Methods: Grades classified by visual assessment were used as references and we chose the control-learning method provided with the algorithm (Visual assessment vs AI evaluation). Five hundred images were submitted to a machine learning algorithm for reading. Acquired images are preprocessed by Face Mesh solution using MediaPipe platform on Google. The process provided 9 ROI from one photograph, and we have acquired consecutively five thousand ROIs based on machine learning. Data augmentation was performed through the image conversion process such as image rotation, brightness and contrast adjustment, and then we analyzed over one hundred thousand images augmented.

Results: Out of 500 volunteers, the pickup rate for major wrinkles was 100%, although it for whole wrinkle grade was approximately 70%.

Conclusion: In this study, we could verify that the performance AI-based wrinkle grade is useful and actuatable to evaluate showing efficacy results for preventing wrinkle formation by providing only images. This enables researchers to track the progress of anti-wrinkling techniques such as anti-aging cosmetics.

Keywords: (Artificial intelligence (AI); wrinkles; visual assessment; machine learning; image recognition).

Introduction. Wrinkle formation is considered as a major indicator for skin ageing. Although there are the methodological evaluations for preventing wrinkle formation, it is important for clinicians to be able to grade wrinkles objectively. Unfortunately, the results as definitively classified criteria are unclear depending on each researcher due to visualized degree. Recently, artificial intelligence (AI) strategies are providing a potential solution to the growing demand in health care fields for diagnosis and are potent to redefine how researchers can deliver efficacy evaluation methodology to the next generation.

Methods. Facial photographs were acquired from VISIA CR (Canfield Scientific, Inc., USA). Acquired images are preprocessed by Face Mesh solution using MediaPipe platform on Google. The process provided 9 ROI from one photograph, and we have acquired consecutively 4518 ROIs based on machine learning. The AI model was designed to learn the characteristics of each grade, such as the shape and depth of wrinkles in the facial photos for each area, and classify them into the corresponding grade. Based on the Convolutional Neural Network (CNN), the pattern corresponding to each class feature was extracted and learned from the first input image from each convolutional layer, and the learning was carried out in the direction of increasing the accuracy of classification. Batch normalization and Max-pooling layers were inserted between convolution layers to prevent over-fitting in the learning process and to increase learning efficiency.

Results.

MediaPipe's Face Mesh solution is based on machine learning-based 3D surface shape inference, it is possible to obtain a uniform region of interest (ROI) from facial photos with various characteristics for each individual. We acquired a facial landmark consisting of a total of 468 points using Google's MediaPipe platform from a facial photograph (Figure 1 A). In cosmetics and anti-aging research, representative areas of interest where significant changes can be observed are the forehead, eye area, nasolabial folds, and neck (Figure 1 B).

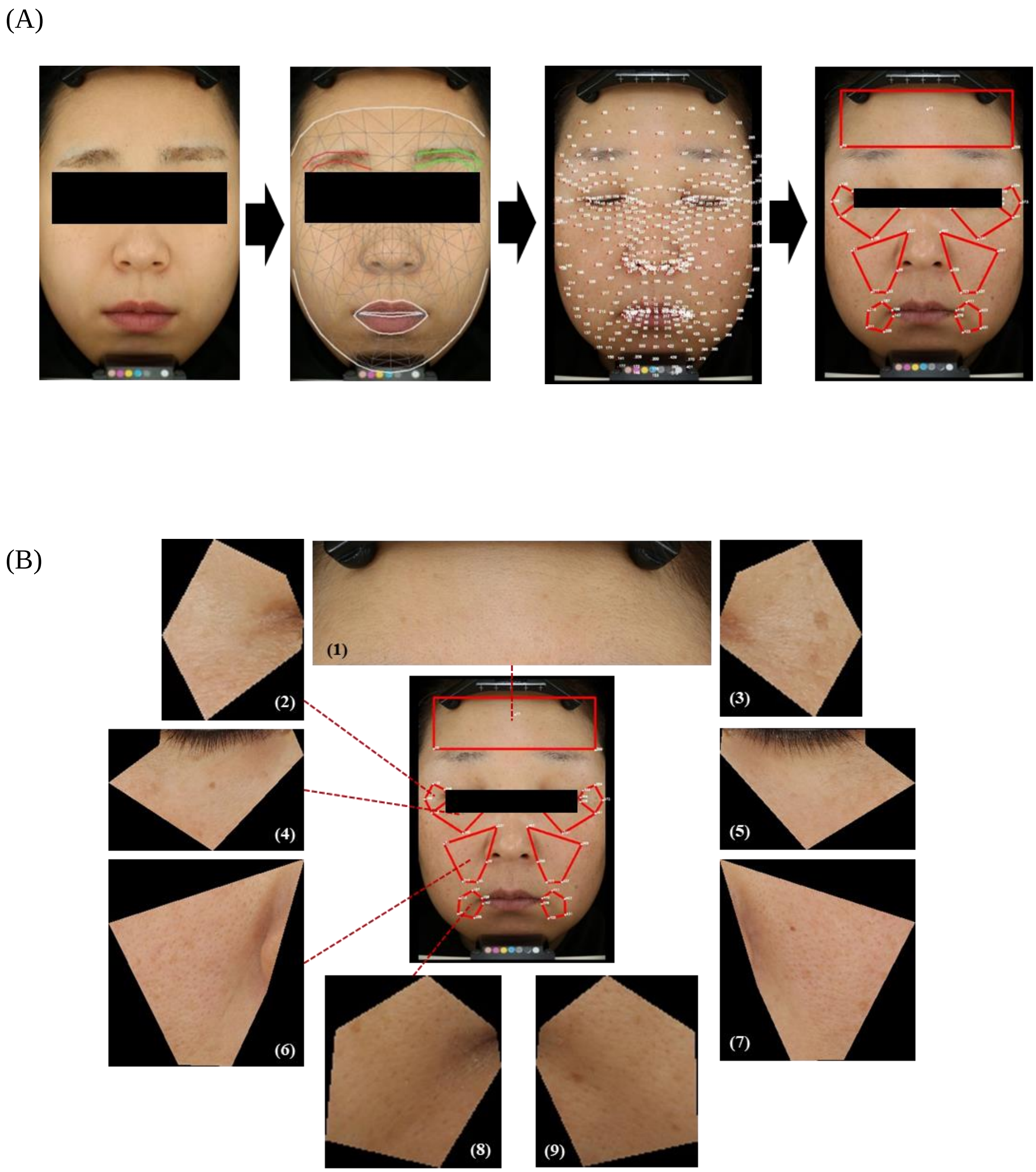

Figure 1. Pre-processing for A.I training

In order for the AI model to evaluate the grade using the wrinkle photos, training should be conducted based on the skin wrinkle image and the grade evaluation results. In order to reduce the bias between the evaluation results, two experts evaluated the wrinkle photos of 502 subjects as visual assessment grade (Figure 2 A). A total of 2888 face photos were used, and among them, 4518 ROI images were used for the first AI training. Accordingly, we can check the wrinkle grade data for each ROI in the graph (Figure 2 B).

(A)

Grade	Description	Grade	Description
0	Essentially unwrinkled	5	A little moderate wrinkles
1	Appearing shallow wrinkles	6	Several moderate wrinkles
2	Minimal shallow wrinkles	7	Development of deep wrinkles
3	Average roughness	8	Several deep wrinkles
4	Appearing moderate wrinkles	9	Numerous large deep wrinkles

(B)

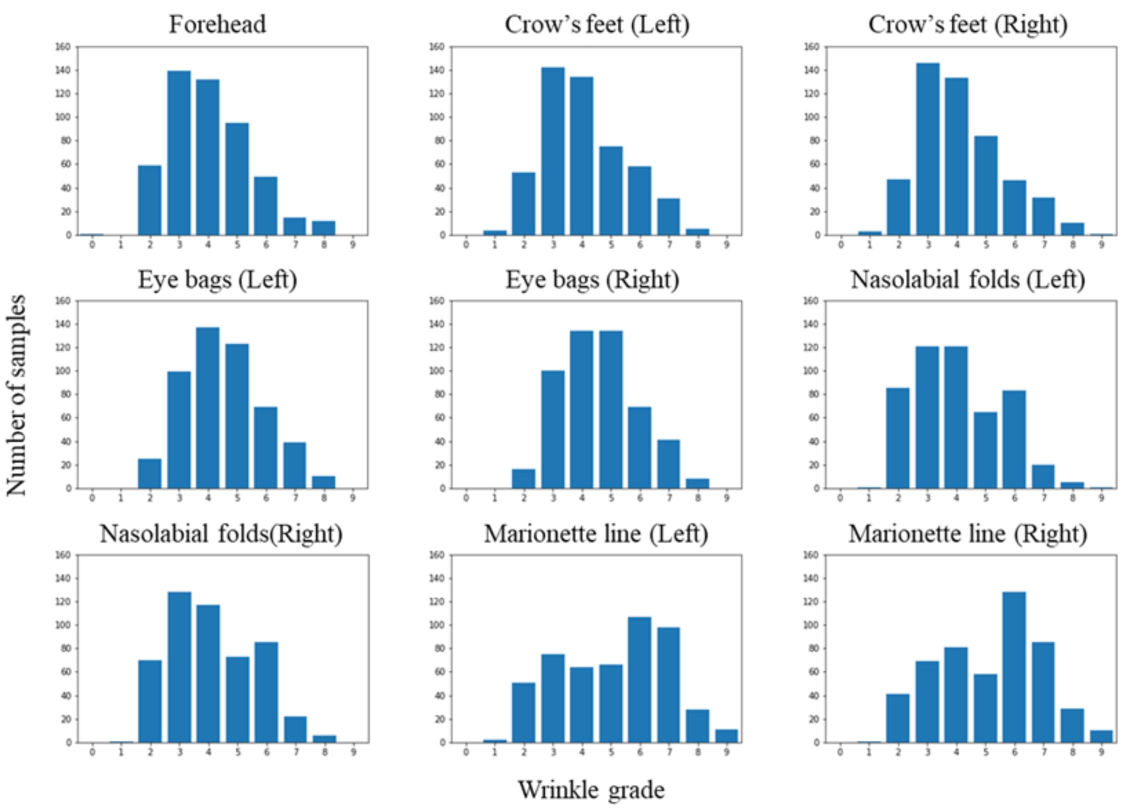

Figure 2. The distribution by visual assessment results as ROI

Data augmentation is a method of applying various image transformations to increase the amount of data. In this study, the augmented data was used for model training in order to secure the number of data insufficient for training and to respond to different skin characteristics for each individual. In the case of ROIs that exist on the left and right, data was unified into the right region through left and right inversion, and data augmentation was performed through image conversion processes such as image rotation, brightness and contrast adjustment, and CLAHE (Contrast limited adaptive histogram equalization). For all ROIs, 100,000 for training and 10,000 for evaluation were obtained for each class group (0-3, 4-6, 7-9) through data augmentation (Figure 3).

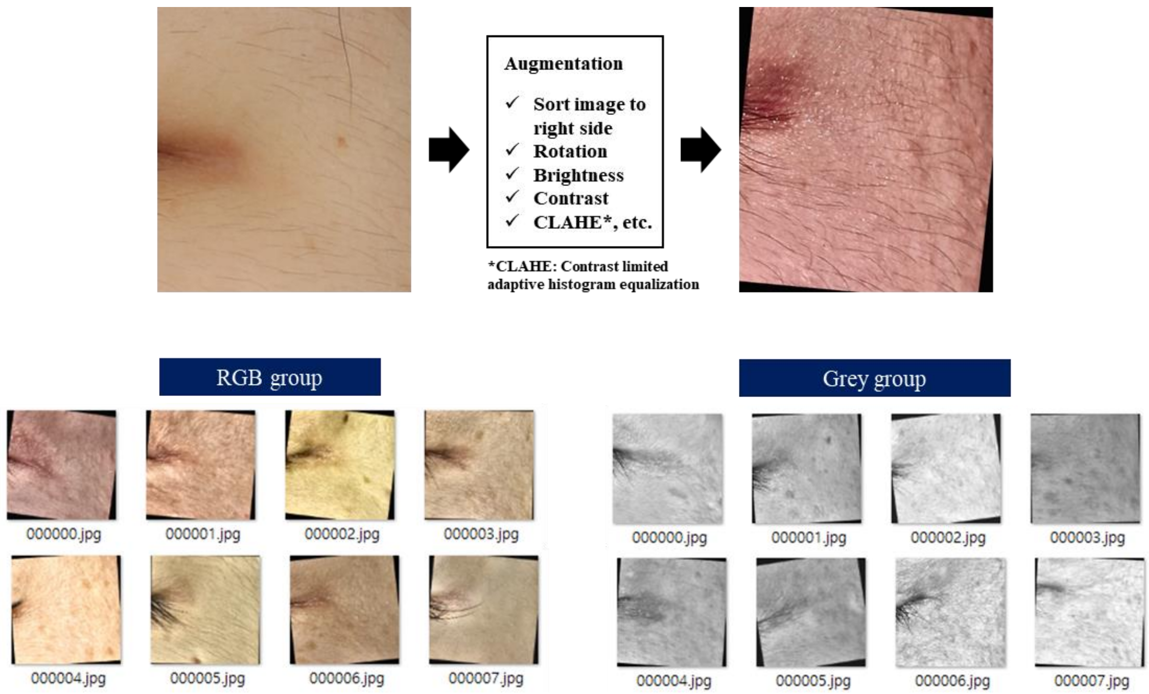

Figure 3. Data Augmentation Process for Artificial Intelligence Training

For grades 0 to 1 with very low wrinkles and grades 8 to 9 with very high levels of wrinkles, the number of data was insufficient to be used for AI training. Grades 0 to 3 were grouped into one group, grades 4 to 6 and grades 7 to 9 were grouped into one group, respectively, and the grades were reorganized and used for AI training (Figure 4 A).

The AI model was individually trained for a total of 10 conditions, including 5 areas under the eyes, nasolabial folds, around the lips, and on the forehead for RGB and gray images (Figure 4 B).

(A)

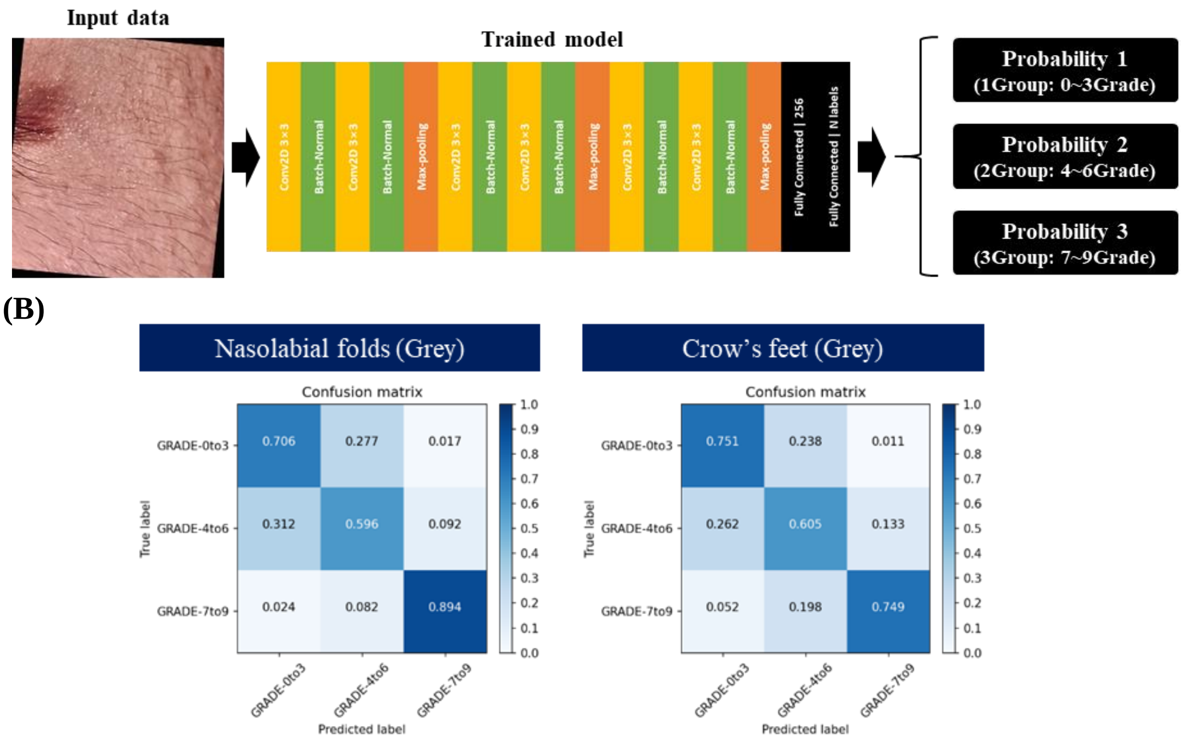

Figure 4. Grouping for deep learning. (A) Model structure, (B)Confusion matrix

As the performance result of the classification model for wrinkle around the eyes, which is one of 10 AI models, it is possible to check how the model predicted results match well the actual results. It was confirmed that the accuracy of the region of interest was around 70% (Figure 5).

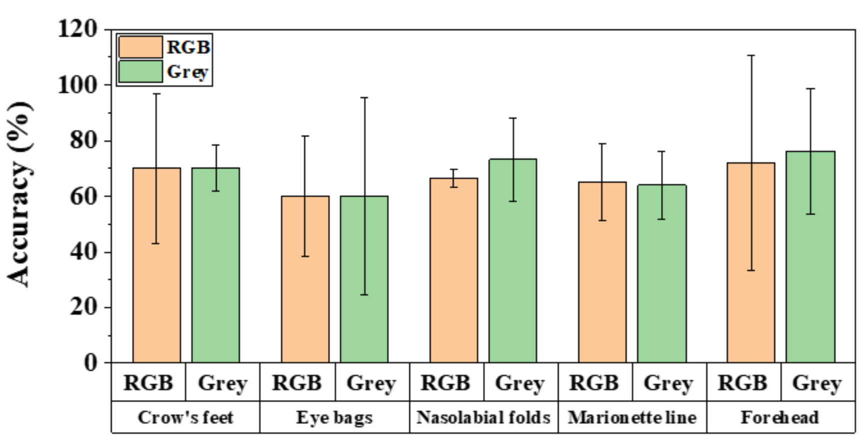

Figure 5. The accuracy of the AI model for each ROI

Discussion.

This study intends to establish an objective index to evaluate the degree of wrinkles using artificial intelligence. In order to improve accuracy and develop from the current model that classifies three class groups to a model that classifies 10 subclasses, it is considered that it is most important to additionally secure a sufficient number of data for each subclass.

Conclusion.

In this study, we could verify that the performance AI-based wrinkle GRADE is useful and actuatable to evaluate showing efficacy results for preventing wrinkle formation by providing only images. This enables researchers to track the progress of anti-wrinkling techniques such as anti-aging cosmetics. The algorithm gives a chance to apply photographs from mobile device, showing the results similar expert grading. Moreover, our system is low cost as the wrinkle detection can be simply based on photographs.

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Conflict of Interest Statement. NONE.

References.

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