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Intersection of Skin Analysis Technology and Well-being: Utilizing Facial Skin Data for Stress Prediction and Management

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Effectively managing stress is essential for enhancing one's quality of life but requires a good understanding of one's stress levels. Nonetheless, the diversity and dynamic nature of stress symptoms can complicate this endeavor. In this study, we explored the potential of leveraging facial information to develop technologies for stress assessment. A prospective multicenter study was conducted in Tokyo, Japan, from January 2018 to December 2021, enrolling 2343 participants aged between 20 and 60 years. Participants completed a facial skin-related questionnaire, and their facial images and videos were collected for analysis. Stress levels were measured using both objective outcomes, including autonomic, blood, and urine markers, as well as subjective outcomes, such as fatigue scales and quality of life questionnaires. Various machine learning techniques were employed to create separate evaluation models to predict the 5 categories of stress outcomes from the 3 sources of facial data. The criteria for model accuracy were set at >0.7. The models using facial image data emerged as the most accurate models for predicting various static stress states derived from questionnaires or from blood/urine biomarkers. Facial skin data from subjective questionnaires also accurately predicted static stress states. Facial video data accurately predicted dynamic stress states reflected by autonomic nervous system-based biomarkers such as the heart rate, coefficient of variation of R–R, and the ratio of the low- and high-frequency bands in heart rate variability. In this study, we developed several machine learning-based prediction models to assess static and dynamic stress levels using facial information, including images, videos, and questionnaires. The ease of capturing and analyzing facial data with readily available camera-equipped devices, such as smart devices and personal computers, makes this facial skin-based stress analysis promising for organizational health management and individual well-being. It enables early stress detection through self-assessment, exemplifying the application of cosmetics research knowledge to overall well-being.

Key words: well-being, stress management, machine learning, deep learning, stress evaluation, smart device, biomarkers, facial information, organizational health management, facial skin-based stress analysis

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1. Introduction

The surge in mental health awareness, particularly accentuated by the COVID-19 pandemic, drives an increasing demand for enhanced mental well-being and quality of life. "Good Health and Well-being" is a target within "Sustainable Development Goal 3," adopted by the World Health Organization in 2015, which calls upon countries to guarantee healthy lives and well-being for people of all ages.

To achieve this goal, a significant emphasis is placed on stress management, as stress can manifest in physical and mental health issues, impacting performance, emotional well-being, and skin conditions. Effective stress management is crucial but often challenging to implement. There are 2 primary challenges: (i) recognizing the need for self-care and (ii) having access to effective self-care methods that are easily accessible and yield noticeable results. The foremost challenge revolves around identifying one's stress levels. When individuals are aware of their stress, they can more effectively tend to their well-being by incorporating rest and mental self-care into their routines. However, recognizing one's stress state can be elusive, leading to a lack of awareness and subsequently neglecting self-care, which can result in various health problems. Stress symptoms vary widely among individuals, encompassing mental and physical fatigue, stress markers in the blood, or fluctuations in the autonomic nervous system. Some of these symptoms can change dynamically, such as shifts in the autonomic nervous system, making it challenging to gauge one's stress level precisely. Therefore, there is a pressing need for a comprehensive and user-friendly stress monitoring technology.

In addressing this challenge, we sought to tap into the wealth of knowledge and expertise within the beauty and cosmetics industry, as numerous reports have highlighted potential connections between an individual's stress levels or stress risk and the condition of their facial skin. Research indicates that the accumulation of psychological stress correlates with the worsening of skin conditions,[1] a decline in the barrier function of stratum corneum cells,[2] and an increase in skin saccharifying substances.[3] The underlying in vivo mechanism suggests that mental stress can lead to an overproduction of glucocorticoids, ultimately resulting in a reduction in the stratum corneum's barrier function.[4] Furthermore, studies investigating the relationship between stress levels and skin health have found that sleep deprivation can impair the barrier function of stratum corneum cells, reduce their resilience to damage, and diminish their anti-inflammatory properties.[5,6]

Previously, we developed a technique that employed machine learning to infer an individual's stress and fatigue levels based on the characteristics of their facial stratum corneum cells.[7] This technology demonstrated the ability to accurately identify individuals surpassing predefined thresholds for various subjective and physical fatigue states, achieving an accuracy rate exceeding 70%. Nevertheless, this technology necessitates the collection, staining, and microscopic analysis of stratum corneum cells, rendering it unsuitable for widespread public use.

In addition to microscopic alterations, prolonged exposure to mental and physical stress has induced noticeable macroscopic changes in the skin, including the development of wrinkles and a reduction in skin thickness.[8] Furthermore, insufficient sleep can also manifest in distinct macroscopic changes, such as the emergence of dark circles, wrinkles, and a sagging mouth.[9] Based on these observations, we hypothesize the potential for evaluating various stress states through a reverse analysis of facial and skin characteristics. Leveraging the widespread adoption of devices with cameras, such as smartphones, tablets, and personal computers, we aimed to develop a user-friendly technology that utilizes machine learning methods to capture and analyze facial data, enabling stress level estimation that can be accessible to everyone.

2. Materials and Methods

2.1. Study design

A prospective multicenter study was conducted in Tokyo, Japan, from January 2018 to December 2021. The study enrolled Japanese men and women aged between 20 and 60 years. Participants with serious cardiovascular, hepatic, renal, respiratory, endocrine, or metabolic disorders, or having a medical history of these disorders, or those taking pharmaceuticals that have the possibility of affecting the autonomic nervous system, or those deemed unsuitable by the investigator were excluded. Participants completed a questionnaire related to their facial skin, and facial images and videos were obtained using a smartphone for analysis. Stress levels were measured using objective outcomes, such as autonomic, blood, and urine markers, and subjective outcomes, such as fatigue scales and quality of life questionnaires. All studies were conducted after obtaining approval from the POLA Ethics Committee, and informed consent was obtained before participation in the research.

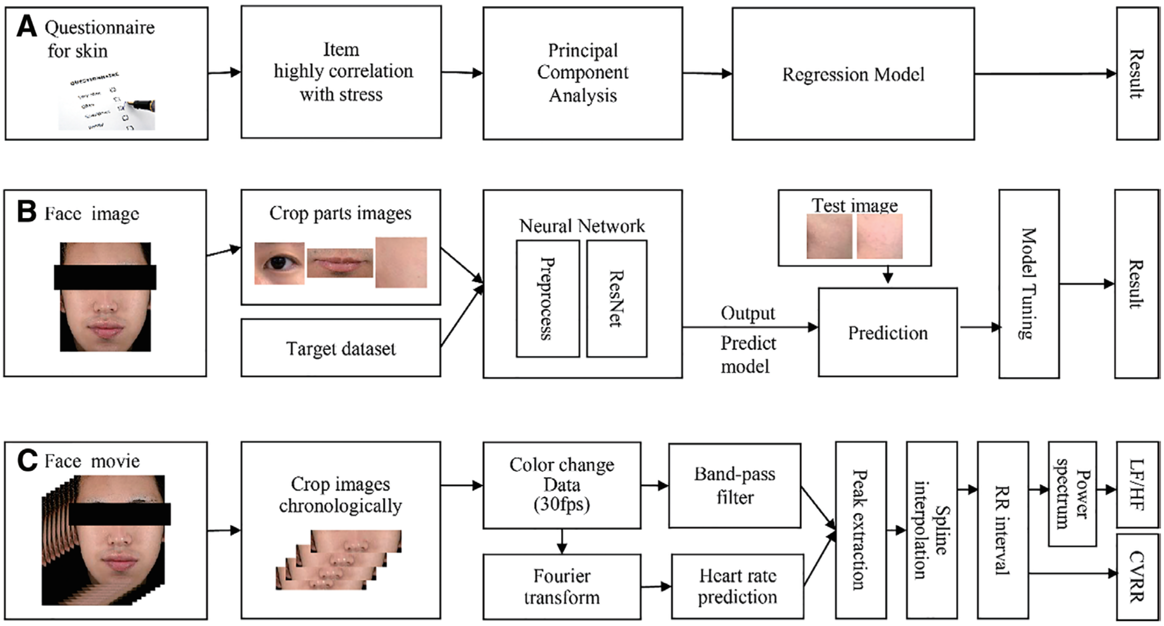

Fig. 1 Flow of stress state evaluation process and result output using 3 kinds of facial/skin data. (A) Questionnaire for skin, (B) facial image, and (C) facial movie.

2.2. Predictor variables

Three types of facial data, commonly used in cosmetics research, were used as predictors to develop the models for stress evaluation (Fig. 1).

2.2.1. Facial skin questionnaire

A 25-item questionnaire was administered to all participants in Japanese (Table 1, translated into English). Items that highly correlated with stress outcomes were chosen for inclusion in the regression models.

2.2.2. Facial photos

Photos were captured using a smartphone (iPhone 7) fixed to a pedestal approximately 30 cm away from the participant. High-resolution networks for facial landmark detection (HR nets),[10] a method for detecting facial parts, were used to crop and extract images of the whole face and specific parts, including the eyes, cheeks, and mouth sites, from the facial image for use in the models.

2.2.3. Facial videos

The videos were acquired with a smartphone (iPhone 7) fixed to a pedestal. The filming duration was 1 minute. After removing the first 10 s, the next 30 s were cropped chronologically and used for further study.

2.3. Stress outcomes

Five stress measures served as outcomes in the study.

2.3.1. Subjective status

Subjective status was measured using (a) the Chalder Fatigue Scale,[11] which is widely used to measure fatigue worldwide, and (b) the Mental and Physical Fatigue Scales,[12] which are the standards developed by a research group of the Japanese Ministry of Education, Culture, Sports, Science and Technology.

2.3.2. Quality of life status

Quality of life was measured using the Athens Insomnia Scale,[13] Pittsburgh Sleep Quality Index,[14] and the individual's frustration scale, scored using a 10-point scale, assessed using questionnaires.

2.3.3. Blood markers

Derivatives of reactive oxygen metabolites (d-ROMs)[15] and Oxidative Stress Index[16] were analyzed using blood samples collected from the participants. Blood was obtained in the morning to eliminate the effects of diurnal variation.

2.3.4. Urine markers

Isoprostane,[17] 8-OHdG (8-hydroxy-2′-deoxyguanosine),[18] vanillylmandelic acid,[19] and homovanillic acid[20,21] were analyzed using urine samples collected from the participants. Urine was obtained upon waking to eliminate the effects of diurnal variation. In addition, to eliminate the influence of the sex cycle, urine was not collected from those menstruating.

Table 1 25-Item questionnaire* for subjective assessment of facial skin condition.

1. Do your skin or lips dry out easily?
2. Do your cheeks become inflamed and hot?
3. Does your skin have urticaria easily?
4. When you scratch your skin, do you tend to get marks on it?
5. Do you have reddish-purple dots or patches on your skin?
6. Do you sweat without doing anything?
7. Do you bruise easily?
8. Does your upper eyelid swell easily?
9. Do you have dark circles under your eyes?
10. Do you develop age spots easily?
11. Do you have pale lips?
12. Is your forehead greasy?
13. Do you have redder lips compared to other people?
14. Is your nose greasy and shiny?
15. Do you get pimples easily?
16. Do you see capillaries on the cheeks?
17. Do you feel a fuzzy, uneven coloration in your complexion?
18. Do you feel stiffness when you touch your face?
19. When you touch your face, does your hand feel like it is being sucked?
20. Do you feel a sense of dryness immediately after washing your face?
21. Do you feel that your face is more yellowish than before?
22. Is there redness in the cheeks?
23. Does your face ever get chapped?
24. Does your skin get acne?
25. Have you ever had a problem with your facial skin or experienced symptoms of skin problems?

*The actual questionnaire was presented to the participants in Japanese.

2.3.5. Autonomic status

Heart rate and heart rate variability (CVRR: coefficient of variation of R–R interval and LF/HF: the ratio of the low- and high-frequency bands in heart rate variability)[22,23] were collected using wearable heart rate sensors (myBeat, UNION TOOL, Shinagawa-ku, Tokyo). To obtain data on different variations of autonomic status, data were collected in both sitting and standing positions.

2.3.6. Data handling

Each stress measure of *Quality of life status*, *Blood markers*, and *Urine markers* was binarized using the threshold values described in the reference studies. If threshold values were not reported in the cited references, binarization was performed based on the average value of the acquired data. The measured *Autonomic status* was used as numerical data.

2.4. Stress evaluation models

Separate evaluation models were created using various machine learning techniques to predict select stress outcomes in each of the 5 categories from the 3 different sources of facial data. Unlike the general machine learning approach where “the machine detects what the human can detect,” we aimed to establish machine learning technologies that “evaluate what the human does not detect.” Therefore, various models were exhaustively created using various machine learning techniques and objective variables based on facial data characteristics. The criteria for accuracy (using validation data) for establishing models were set at >0.7 based on the previous study, wherein the model evaluating the subjects’ political principles using facial data was developed with an accuracy of approximately 0.7.[24]

2.4.1. Models based on facial skin questionnaire data

Ten models of stress outcomes (Chalder Fatigue Scale, Mental Fatigue Scale, Physical Fatigue Scale, and Athens Insomnia Scale, isoprostane, 8-OHdG, vanillylmandelic acid, homovanillic acid, d-ROMs, Oxidative Stress Index) were created using the responses to 25 items of a subjective questionnaire for facial skin, sex, and age data. Principal component analysis was performed as a preprocessing step in the model creation process to verify the usefulness of dimensionality reduction (Fig. 1A). Regression models were created for each objective variable by combining the 6 types of regression analysis (multiple regression, logistic regression, ridge regression, least absolute shrinkage and selection operator regression, Random Forest, and support vector machine) and patterns of dimension compression (0–23), and 3 types of sex models (combined sex models and sex-separated models). Overall, 432 models were examined: 6 types of regression models × 24 patterns of dimension compression × 3 sex models. From the 432 models, we searched for the best evaluation model with the highest accuracy. Five cross-validations (learning 8: verification 2) were performed to evaluate the model, and the accuracy and F1 score (harmonic average of precision and recall) were calculated.

2.4.2. Models based on facial image data

Nine models of stress outcomes (Chalder Fatigue Scale, Pittsburgh Sleep Quality Index, Frustration score, isoprostane, 8-OHdG, vanillylmandelic acid, homovanillic acid, d-ROMs, and Oxidative Stress Index) were created using facial images (Fig. 1B). Evaluation models were developed for each objective variable by combining 4 types of machine learning models of neural network (ResNet, FixRes, HRNet, and DenseNet), 4 face image sites (whole face, cheeks, eyes, and mouth), and 2 types of sex-separated models. A total of 16 models were examined to determine the best evaluation model with the highest accuracy. Five cross-validations (learning 8: verification 2) were performed to evaluate the model, and the accuracy and F1 score (harmonic average of precision and recall) were calculated. As ResNet neural networks[25] demonstrated the highest accuracy, we subsequently focused on improving the accuracy in the ResNet model by hyperparameter tuning to optimize the settings of the machine learning algorithms.

While the machine learning models inherently identify and discriminate crucial image features during model creation, visualizing the specific facial areas employed in the established evaluation model is valuable for validating the machine learning model. Gradient-weighted class activation mapping (Grad-CAM) was used to visualize features from facial images using a heat map, with redder areas indicating stronger predictive model characteristics.[26]

2.4.3. Models based on facial video data

Four models of stress outcomes (heart rate, CVRR, LF/HF, and LF/HF rank) were created from facial video data (Fig. 1C) using approaches described previously.[27,28] Here, data on facial color change patterns were utilized. Facial color changes because of the movement of blood on the skin. Therefore, by analyzing the change pattern of facial color, the heart rate and its fluctuation pattern can be calculated. In addition, as the autonomic nervous system controls the fluctuation pattern of the heart rate, the state of the autonomic nervous system can be calculated from the heart rate fluctuation pattern. Each image in the video was separated into frames (30 fps). Subsequently, the central part of the face was detected using face detection technology (face landmark detection),[29] and the changes in the color component (x = green/[red + green + blue]) were calculated. Further, the data were Fourier transformed (Welch's method), and the mode frequency of the color component was detected as the heart rate. After noise elimination using a bandpass filter, spline interpolation converted the data into equal time interval data (R–R interval). CVRR was calculated using the mean (μ) and standard deviation (σ) of the R–R interval, with the following formula: CVRR = $\sigma/\mu \times 100$ (%). Moreover, the "R–R interval" was Fourier transformed (Welch's method) to analyze the power spectrum and calculate low-frequency (0.04–0.15 Hz) and high-frequency (0.15–0.4 Hz) bands in heart rate variability. LF/HF, the ratio of low- and high-frequency bands, was calculated.

3. Results

3.1. Participants

A total of 2343 participants (age: 36.89 ± 9.04 years, 47.4% female) were enrolled in the study. Skin questionnaires were completed by 1411 (for the Chalder Fatigue Scale and Athens Insomnia Scale) to 1892 (for Mental and Physical Fatigue Scales) participants, and facial images (for the Chalder Fatigue Scale, Pittsburgh Sleep Quality Index, Frustration score, blood markers, and urine markers) and videos (for heart rate, CVRR, LF/HF, and LF/HF rank) were obtained from 395 and 56 participants, respectively.

3.1.1. Models based on facial skin questionnaire data

Table 2 shows the details and accuracy of the stress state evaluation models using facial skin questionnaire data, with accuracy >0.7. Both the combined sex models and the sex-separated models for the Chalder Fatigue Scale, Mental Fatigue Scale, and Physical Fatigue Scale had accuracy >0.7. The accuracy of the male sex-separated evaluation model for the Athens Insomnia Scale was >0.7. Conversely, a reliable model could not be constructed for blood and urine stress markers.

3.1.2. Models based on facial image data

Table 3 demonstrates the details and accuracy of the stress state evaluation models using facial image data. Some predictions were most accurate using whole-face images, whereas others were most accurate using images of specific portions of the face. All models for the Pittsburgh Sleep Quality Index using whole-face images, Frustration score

Table 2 Evaluation models with the highest accuracy for predicting stress outcomes using Facial Skin Questionnaire data.

	Methods	Details	Sex	n	Model	PCA	Accuracy	F1 score
Stress scale test	Questionnaire	Chalder Fatigue Scale	All	1411	SVM	–	0.744*	0.676
			Female	654	Linear	1	0.781*	0.679
			Male	757	Logistic	1	0.782*	0.703
		Mental Fatigue Scale	All	1871	Linear	–	0.783*	0.749
			Female	875	Logistic	1	0.742*	0.700
			Male	996	Lasso	1	0.804*	0.730
		Physical Fatigue Scale	All	1871	Linear	–	0.777*	0.742
			Female	875	Linear	2	0.789*	0.725
			Male	996	Lasso	1	0.818*	0.742
		Athens Insomnia Scale	All	1411	Linear	–	0.668	0.648
			Female	654	Random Forest	–	0.679	0.668
			Male	757	Lasso	1	0.701*	0.669
Physiological test	Urine test	Isoprostane	Reliable models could not be constructed					
		8-OHdG						
		Vanillylmandelic acid						
		Homovanillic acid						
	Blood test	d-ROM						
		Oxidative Stress Index						

*Models with accuracy >0.7.

Table 3 Evaluation models with the highest accuracy for predicting stress outcomes using facial image data.

	Methods	Details	Area	Sex	n	Model	Accuracy	F1 score
Stress scale test	Questionnaire	Chalder Fatigue Scale	Mouth	Female	196	ResNet	0.753*	0.644
				Male	199	ResNet	0.695	0.621
		Pittsburgh Sleep Quality Index	Whole face	Female	196	ResNet	0.703*	0.690
				Male	199	ResNet	0.703*	0.675
		Frustration score	Mouth	Female	196	ResNet	0.737*	0.684
				Male	199	ResNet	0.703*	0.682
Physiological test	Urine test	Isoprostane	Mouth	Female	196	ResNet	0.684	0.674
				Male	199	ResNet	0.726*	0.698
		8-OHdG	Eye	Female	196	ResNet	0.711*	0.696
				Male	199	ResNet	0.653	0.641
		Vanillylmandelic acid	Eye	Female	196	ResNet	0.726*	0.725
				Male	199	ResNet	0.637	0.627
		Homovanillic acid	Mouth	Female	196	ResNet	0.705*	0.665
				Male	199	ResNet	0.689	0.669
	Blood test	d-ROM	Mouth	Female	196	ResNet	0.826*	0.659
				Male	199	ResNet	0.732*	0.703
		Oxidative Stress Index	Cheek	Female	196	ResNet	0.879*	0.686
				Male	199	ResNet	0.716*	0.709

*Models with accuracy >0.7.

and d-ROMs with mouth area images, and Oxidative Stress Index using cheek area images had accuracy >0.7 in both males and females. Models for the Chalder Fatigue Scale using mouth area images, 8-OHdG and vanillylmandelic acid using eye area images, and homovanillic acid using mouth area images had accuracy >0.7 in females, whereas models for isoprostane using mouth area images had accuracy >0.7 in males. Figure 2 shows the results of the facial location images acquired using Grad-CAM. It can be confirmed that the model is constructed using the facial locations shown in Table 3.

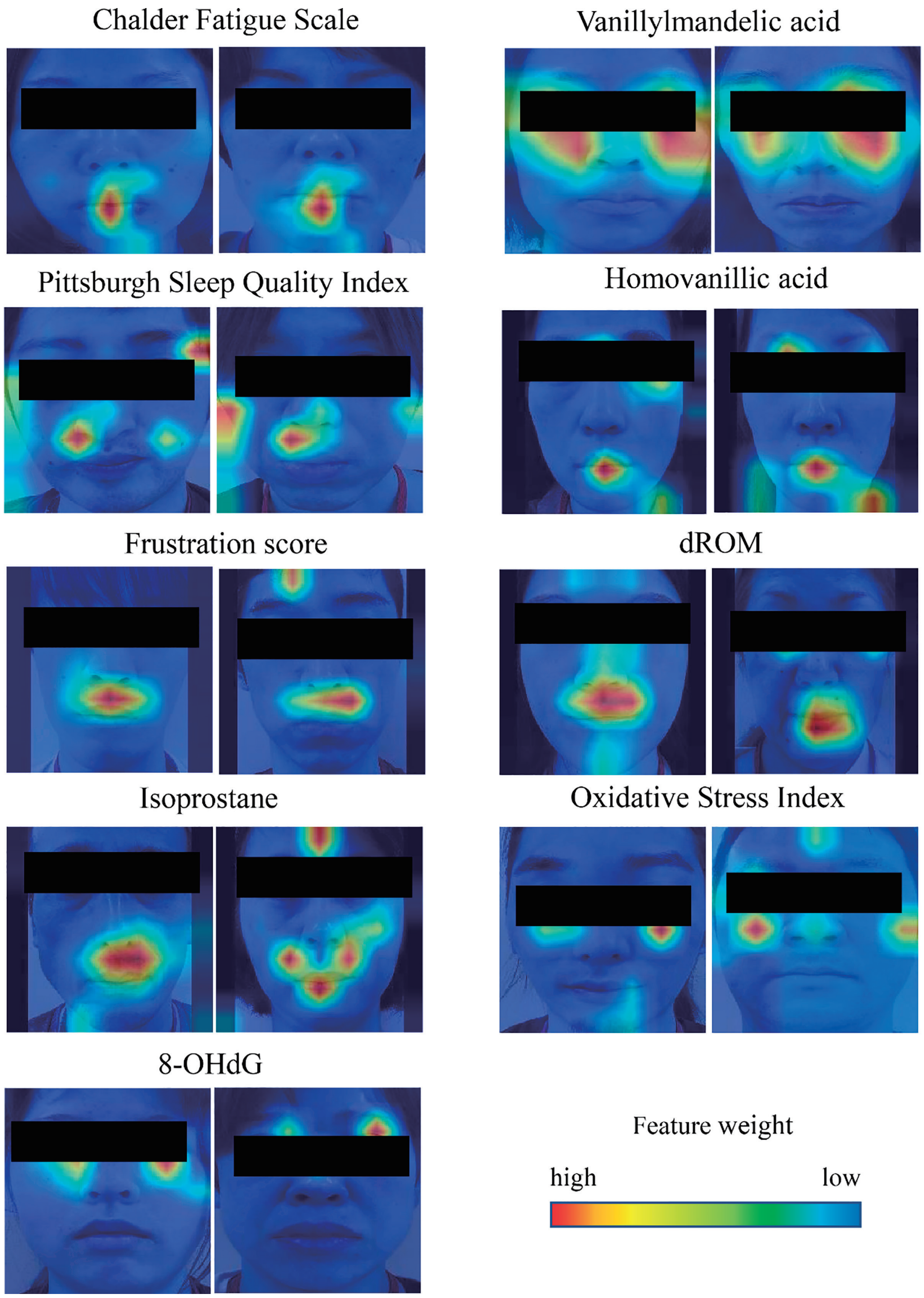

Fig. 2 Grad-Cam-based visualization, highlighting the specific facial areas employed in the established evaluation models. Redder areas in the heat map indicate stronger predictive model characteristics. The Chalder Fatigue Scale, Frustration score, Isoprostane, Homovanillic acid, and d-ROM estimation models were established mainly using images of the mouth area. The 8-OHdG and vanillylmandelic acid models were established using images of the eye area. The model of the Pittsburgh Sleep Quality Index was established using images of the entire face, and the Oxidative Stress Index was established using images of the cheek area.

3.1.3. Models based on facial video data

Table 4 presents the evaluation accuracy of the stress state evaluation models using facial video data. All 4 models for the dynamic stress states, reflected by autonomic nervous system-based biomarkers—heart rate, CVRR, LF/HF, and LF/HF rank—had a correlation coefficient or accuracy >0.7.

Table 4 Evaluation models with the highest accuracy (>0.7) for predicting stress outcomes using facial video data.

	Details	n	Model	Correlation coefficient or Accuracy
Physiological test	Heart Rate	56	Fourier transform	r = 0.988
	CVRR	56	Fourier transform	r = 0.755
	LF/HF	56	Fourier transform	r = 0.722
	LF/HF Rank	56	Fourier transform	Accuracy = 0.875

4. Discussion

The objective of this study was to develop user-friendly technology utilizing deep learning methods to capture and analyze facial data, enabling accessible stress level estimation. While stress monitoring holds significance for individuals in modern society, accurately gauging stress levels proves challenging owing to diverse symptoms and dynamic fluctuations. Stress tends to manifest in the face and skin, suggesting the potential to develop a technology for assessing stress levels based on facial data. We hypothesized this potential through a reverse analysis of facial and skin characteristics. Facial data were extracted from a subjective 25-item facial skin questionnaire, facial images, and videos obtained using a smartphone and used to build evaluation models for various stress outcomes that included stress measured using subjective questionnaires (for fatigue, sleep, and frustration) and using various blood, urine, and autonomic markers. Multiple models were created in an exhaustive manner using various machine learning techniques, and the models with the highest accuracy were chosen.

This approach yielded several models with accuracy >0.7 from the various sources of data. The models using facial image data emerged as the most accurate for predicting various static stress outcomes derived from questionnaires or from blood/urine biomarkers. These models accurately predicted stress states, as measured by the Pittsburgh Sleep Quality Index, Frustration score, blood d-ROM levels, and Oxidative Stress Index in both males and females, and by the Chalder Fatigue Scale, urine 8-OHdG, vanillylmandelic acid, homovanillic acid levels in females, and urine isoprostane levels in males, respectively. Some predictions were most accurate using whole-face images (Pittsburgh Sleep Quality Index), whereas others were most accurate using images of specific portions of the face, for example, mouth (Chalder Fatigue Scale, Frustration score, isoprostane, homovanillic acid, and d-ROMs), eye (8-OHdG and vanillylmandelic acid), or cheek (Oxidative Stress Index). Due to the well-known correlation between subjective stress markers (e.g., fatigue or insomnia) and oxidative stress biomarkers,[16,30–33] we were able to reasonably estimate stress using facial data in our study. Moreover, the results indicating different facial sites correlated with different biomarkers are intriguing. Various biomarkers and inner conditions manifest specific characteristics in distinct facial areas. For example, increased bilirubin affects eye color,[34] while systemic lupus erythematosus causes symmetrical eczema on the cheeks (butterfly rash).[35] Melasma, linked to female hormones, often appears on the cheeks,[36] and lip color changes are observed in anemic individuals. Considering these examples, our study results may relate to areas where (1) biomarker-related color changes are easily noticeable, (2) skin alterations are likely to occur from external factors (such as ultraviolet light) in addition to biomarker effects, (3) secondary changes (such as immune reactions) are triggered by biomarkers, and (4) blood color changes are likely to occur. Detailed analysis of biomarker pathways on the skin is necessary to validate these possibilities, providing crucial insights into what aspects of the face artificial intelligence evaluates and how. This constitutes an important avenue for future research. However, our current study aimed to construct a highly accurate model for estimating stress markers, which we successfully achieved. Besides its accuracy in predicting various stress states, the ease and simplicity of capturing images with camera-equipped devices, such as smartphones, tablets, and personal computers, underscores the user-friendly advantage of our image-based analysis model, making it the preferred option for large-scale stress assessments.

Conversely, "dynamic stress states," reflected by autonomic nervous system-based biomarkers such as the heart rate, CVRR, and LF/HF, were accurately predicted by facial video data. Since dynamic states cannot be assessed using "static" facial images, these models proved valuable. While models based on facial questionnaires could be constructed for subjective stress markers like the Chalder Fatigue Scale, Mental Fatigue Scale, Physical Fatigue Scale, and Athens Insomnia Scale, they could not be constructed for blood and urine stress markers. This may be attributed to the questionnaire's inability to capture detailed facial information obtainable from images. Improving the facial questionnaire content could address this limitation in the future. Nevertheless, even the current models remain useful, particularly in situations where photography is not feasible. Overall, these results highlight the advantages of each model for specific outcomes and scenarios.

In a prior investigation, we successfully predicted fatigue levels through the analysis of stratum corneum cells.[7] Extending this framework, we postulated that stress levels could be inferred from facial data. The technology developed in this study holds immense promise for broad adoption and practical utilization, as it can be effortlessly employed on a routine basis, noninvasively, and by anyone with the convenience of a smart device or personal computer. The ability to assess multiple stress states comprehensively through facial skin analysis without the need for collecting biological samples is particularly advantageous in that it allows for easy stress monitoring in daily life, as well as in the workplace, where stress levels are typically high.

Proactive recognition of stress levels, prior to them causing disruptions in daily life, constitutes the crucial initial step in effective stress management strategies. Beyond its applicability in organizational health initiatives, when viewed from a personal standpoint, comprehending one's daily stress levels offers the benefit of enhancing self-care motivation and fostering a shift in self-awareness toward self-care. This holds substantial importance in driving behavioral changes toward self-care actions.

Another unique aspect of this study is the use of facial data. In today's society, analysis using facial data is conducted in various places. For example, skin analysis at cosmetics counters, personal authentication when entering a room to protect confidentiality, and contactless body temperature measurement have already been implemented. Combining our technology with these existing technologies could be an effective means to achieve well-being by estimating stress conditions without increasing the burden on the user. Consequently, this skin-based stress analysis is regarded as highly promising for social well-being.

However, the study has a few limitations. First, the stress evaluation models were created using only data from Japanese participants and may not be directly generalizable to other populations. Future studies on other heterogeneous populations are needed to adapt the models for other ethnicities. Second, the study evaluated separate models derived from the different domains (facial skin questionnaire, images, or videos) and did not combine data from the various sources. Models that use data from multiple domains may allow for a more accurate model and should be investigated in future studies. Lastly, this study only provided a proof-of-concept and did not demonstrate implementability or effectiveness on stress recovery. Studies aimed at demonstrating the application of the facial stress analysis together with a solution technology to promote stress recovery through multiple sensory (5-sense) experiences are currently ongoing.

5. Conclusion

In summary, this study introduced multiple machine learning-based prediction models for assessing both static and dynamic stress levels using facial information comprising images, videos, and questionnaires that can be easily captured and analyzed with a camera-equipped device. This facial skin-based stress analysis holds promise for diverse applications, ranging from organizational health management to individual well-being, for early and easy detection of stress. This study effectively bridges the gap between skin analysis technology and well-being, transforming the concept of skin from a mere beauty attribute to a tool for enhancing overall quality of life.

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Ethical Approval/Informed Consent: This study was approved by the Committee for the Protection of Human Subjects (CPHS) of POLA CHEMICAL INDUSTRIES, INC., Kanagawa, Japan (Approval # 2018G134, 2019G58, 2019G86, 2019G128, 2020F102, and 2020F77), and conducted in accordance with the Ethical Guidelines for Medical and Health Research Involving Human Subjects (Ministry of Education, Culture, Sports, Science and Technology and Ministry of Health, Labour and Welfare, 2014, revised in 2017) and the Declaration of Helsinki (revised in 2013). The participants received a sufficient briefing on the objective and content of the study and signed a written informed consent form.

Conflicts of Interest: TM and TK are employees of POLA CHEMICAL INDUSTRIES, INC., which funded this study.

Abbreviations: CVRR, coefficient of variation of R-R interval; d-ROM, derivatives of reactive oxygen metabolites; Grad-CAM, gradient-weighted class activation mapping; LF/HF, the ratio of low- and high-frequency bands in heart rate variability; 8-OHdG, 8-hydroxy-2'-deoxyguanosine; PCA, principal component analysis.

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