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Research Article

# Normal is Not Normal in Skin Status: Analysis from 1072 Korean Participants

[a]Junseo Lee, [b]Joshua Nam, [c]Seungmi Choi, [d]Jaeyun Im and [*e]Bob Nam

[a]Trinity Pawling School, USA; [b]Gyeonggi Suwon International School, South Korea; [c]Cornerstone Collegiate Academy of Seoul, South Korea; [d]US International School, South Korea; [*e]Seoul Innovations Research Institute, South Korea
*Corresponding Author Email: bobyep25@gmail.com

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**Abstract**

Male chins and foreheads are more elastic than those of females. However, female participants show relatively better facial skin conditions in moisture level, wrinkle level, number of spots, and number of pores, which may be partly explained by a higher rate of self-diagnosis among females. The proportion of dry and normal skin types increases with age. One of the key observations of our study is that normal is not normal: normal skin type does not lie between oily and dry skin types. No noticeable advantage is present in the normal skin type, compared with the dry and oily skin types. Another significant observation is that the dry skin type has a higher moisture level than the oily and normal types among our 1072 Korean participants. This counterintuitive discrepancy between dryness and moisture levels warrants further investigation. In the PCA Biplot, age shows a near-perfect negative association with elasticity, while it is positively correlated with wrinkles. With measurement data, the skin-age concept constructed from Gradient Boost Regression's predicted values has two limitations: insufficient explanatory power and systematic overestimation of younger participants and underestimation of older participants. In skin type classification, Support Vector Machine (SVM) outperforms other methods, which is reasonable given that our metadata are not strongly hierarchical or spatial. Specifically, 3-type skin classifications show slightly lower accuracy but higher precision, recall, and F1 scores than 6-type classifications. Our SVM classification using only measurement data achieved a test set accuracy of 72.6%, which outperforms the validation accuracy rate of 44.5% by a deep-learning model using RexNet150. These results can be compared with the average accuracy of 77.6% reported by a previous deep learning model using ResNet50 trained on the same datasets to classify various skin statuses, such as wrinkles, pigmentation, and pores.

**Keywords:** Skin Types, RexNet150, ANOVA, PCA, Gradient Boost Regression, SVM Classification.

## 1. Introduction

Facial skin type classification and skin characteristics have shifted from handcrafted feature pipelines to CNN-based end-to-end classification, with increasing attention to skin-type labels (e.g., dry, oily, and normal) and to measurable facial skin attributes and their relationships [1].Facial skin type classification has become an active area of application in computer vision in dermatology and cosmetic science, as skin type is visually observable yet influenced by complex biophysical and environmental factors. Early and recent studies alike frame the task as a supervised classification problem in which facial images are used to assign users to categories such as dry, oily, or normal skin, often with downstream value for skincare recommendation systems.[1] More recent work

[1]https://www.nyckel.com/pretrained-classifiers/skin-types-identifier/

has shifted toward deep learning, especially convolutional neural networks, because CNNs can learn discriminative representations directly from facial images without extensive manual feature engineering [1].

A growing body of research reports that deep learning models can classify skin type with promising accuracy. For example, a CNN-based study on human skin type classification demonstrated that image-processing and deep learning methods can effectively separate skin types, supporting the feasibility of automated facial skin assessment [1]. Other model-development papers report using transfer learning architectures such as EfficientNet or ResNet to improve performance when training data are limited, which is common in cosmetic and dermatologic datasets.[2]

These studies suggest that model choice, data quality, and class balance strongly affect whether skin-type classification is robust enough for practical use.[3] In our study, we evaluated machine learning-based classification performance for 6 skin type classes in the original data and 3 in the transformed data, without merging the 125,424 image datasets, followed by deep learning skin type classification using a subset of the image datasets with RexNet150.

Another important theme, which was the target of our study, is the analysis of facial skin characteristics rather than only categorical skin type. Skin status is often represented by variables such as moisture, sebum, elasticity, pores, pigmentation, and wrinkle-related measures, which together describe facial skin condition more comprehensively than a single label [2].

Studies in healthy populations have found that these skin parameters are correlated with one another and with biological factors such as age and sex, suggesting that skin characteristics are multidimensional rather than independent [3]. This is especially relevant for studies that use statistical methods or multivariate learning because the same facial skin image may simultaneously reflect texture, hydration, oiliness, and aging-related changes [2]. In our research, we positioned various skin features in a single frame to enhance a more synthetic perspective.

Sex and ethnicity also matter in facial skin analysis. Reviews comparing male and female skin report systematic differences in barrier function, sebum production, and aging patterns, suggesting that models trained on mixed-sex datasets should account for potential shifts in distribution [4]. In Korean samples, age- and sex-related differences in visible skin aging have also been documented, and Korean facial skin studies have shown meaningful links between clinical skin measures and biological variables [5]. These findings support the inclusion of sex-stratified analysis or sex as a covariate in machine learning studies of facial skin type and skin condition [4]. In our subsequent investigations, we conducted numerous statistical tests to examine gender-related differences in skin features.

The field is also beginning to incorporate richer data sources and more complete pipelines. Recent studies and datasets include large facial image collections for skin analysis, and some systems combine skin-type classification with skin-disease detection within a single architecture.[3] This reflects a broader trend toward personalized skincare applications, where the objective is not only to classify skin type but also to infer facial skin characteristics that can guide diagnosis or product recommendation.[4] However, many studies still face common limitations, such as relatively small datasets, inconsistent ground-truth labeling, and limited generalizability across lighting conditions, skin tones, and imaging devices[2]. In our work, we aim to expand the range of personalized skincare applications by tracking changes in skin features as participants age, which can serve as a proxy for panel data that are not readily available.

Overall, the literature supports the use of machine learning and deep learning for facial skin type classification, but it also shows that the problem is inherently multivariate and context-sensitive [1]. Stronger studies tend to combine image-based classification with statistical analysis of skin characteristics, sex-related effects, and latent feature structure, which improve interpretability and clinical relevance [4].

In this study, we aim to examine the statistical relationships among skin features using Korean skin condition measurement data collected from 1072 participants in 2024, paying special attention to the gender effect and the heterogeneity across three main skin types: dry, normal, and oily.

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[2]https://github.com/skinnie-project/Machine-Learning
[3]https://www.kaggle.com/datasets/killa92/facial-skin-analysis-and-type-classification
[4]https://github.com/vinit714/A-Recommendation-system-for-Facial-Skin-Care-using-Machine-Learning-Models

## 2. Literature Review

Skin status is shaped by a combination of intrinsic factors, including sex, age, and skin type, as well as extrinsic factors such as ultraviolet exposure and lifestyle. Prior dermatologic and cosmetic research has shown that male and female skin can differ in structural and biophysical characteristics, with women often displaying higher wrinkle burden after adjustment for age and other covariates in Korean samples [5].

Reviews comparing male and female skin also note systematic differences in sebum production, barrier function, and aging patterns, indicating that sex should be treated as a key grouping variable in skin status studies [4]. Higher sebum levels are found in male subjects across different facial regions, except the forehead, where female subjects have higher sebum levels [6]. It has been demonstrated that sebum content in men was relatively stable on the cheeks and increased slightly on the forehead with age. In contrast, in women, it progressively decreased over their lifetimes [7]. In a study of [8], sebum content on the forehead was higher in men aged 13 to 70 years than in age-matched women. It is reported that skin pH is lower (i.e., more acidic) in men [6], but a study of [9] showed that skin pH was not correlated with sex. In the study of [7], skin pH was highest in the cheeks in both sexes.

As the skin ages, structural changes occur, and its functional characteristics change [10]. In modern society, interest in skincare and anti-aging is increasing, and efforts are being made to identify the causes of skin aging [11]. Several studies have reported an association between the skin microbiome and skin aging [12,13]. It is known that changes in individual skin conditions accompany alterations in the skin microbiome and physiology, and that phylogenetic diversity diminishes with age [13].

Research on Korean populations is especially relevant because ethnic and regional differences can influence skin phenotypes and aging patterns. In healthy Koreans, facial skin microbiome composition differed by sex and age. Microbiome taxa were correlated with moisture-related parameters and trans epidermal water loss, suggesting that visible and measurable skin status is linked to underlying biological variation [3]. Another Korean study reported distinct skin-type distributions in women using Baumann skin typing, reinforcing the idea that skin-type classification captures meaningful variation in skin characteristics rather than mere cosmetic preference [14].

The relationship between skin type and biophysical measures such as moisture, elasticity, and wrinkle formation has also been studied in cosmetic science. Dry skin is often associated with reduced hydration and impaired barrier function, which can contribute to roughness and the appearance of wrinkles [15]. In contrast, oily skin tends to be characterized by higher sebum output and different surface properties [4]. Because normal, dry, and oily skin types reflect different physiological states, ANOVA-based comparisons are appropriate for testing whether these groups differ in hydration, elasticity, and wrinkle indices [16]. Studies that compare skin features across clinically meaningful categories consistently support the value of group-wise statistical testing over reliance on overall averages [16].

Multivariate methods have increasingly been used in skin research because skin variables are intercorrelated. PCA is useful when several outcomes, such as moisture, elasticity, wrinkle depth, and other skin metrics, move together and may reflect shared underlying dimensions of skin condition [16]. In skin microbiome and skin-feature studies, PCA and related dimension-reduction methods have been used to identify latent structure in the data and to show that sebum-related variables and moisture-related variables often cluster together [2]. This makes PCA a strong analytical choice for this paper because it helps explain how different skin-status indicators relate to one another rather than treating each outcome in isolation [2].

Taken together, the literature supports our analytic strategy. Sex-based comparisons are justified because Korean and broader dermatologic studies show meaningful male-female differences in skin characteristics [2]. Group comparisons across dry, oily, and normal skin types are also well grouped because skin-type categories are associated with distinct hydration and barrier profiles [14]. Finally, PCA is appropriate for revealing the underlying structure among moisture, elasticity, and wrinkle variables, which is consistent with prior work using component-based approaches in skin science [16].

Our study can be positioned as extending earlier Korean skin research in three ways. First, the size of our sample (1072 participants) is larger than in many prior Korean skin studies, thereby strengthening the generalizability of sex- and skin-type comparisons [3]. Second, our use of ANOVA allows direct testing of differences among the clinically intuitive skin-type groups: dry, oily, and normal [14]. Third, our PCA adds a system-level view by examining whether hydration, elasticity, and wrinkles load onto common latent skin-status dimensions [15]. Most importantly, our study can complement the earlier deep learning model that uses the same image dataset obtained from the 1072 participants specified below.

**3. Data Preprocessing**

The following table shows the distributions of gender, age, camera angles, and facial position for 125,424 images collected from 1072 Korean participants and constructed in 2023 by KAILOSLAB Co., Ltd., IEC Korea, Dankook University Industry-Academic Cooperation Foundation, which are publicly available at a platform governed by the National Information Society Agency of Korea[5][17]. This dataset is called the Korean skin condition measurement dataset [17].

Skin appearance can vary significantly depending on the environment in which the image is captured (e.g., lighting, humidity, temperature) [17]. Such variations hinder AI models' ability to assess skin condition accurately from images. Therefore, facial images are captured in a controlled environment to ensure that AI models can learn under consistent conditions, unaffected by location or weather; the procedure is as follows [17].

1) All subjects wash their faces to remove any foreign substances before imaging [17].

2) Subjects wait for 15 minutes in a temperature- and humidity-controlled room to ensure accurate skin condition measurements, free from the influence of external environmental factors such as weather [17].

3) In a photography studio equipped with lighting, a high-resolution digital camera, and a custom-made ear-positioning device, the subject's face is aligned using a laser pointer parallel to the mouth to ensure consistent positioning across all subjects [17].

4) The camera angle is precisely adjusted using a custom-made rail system to capture images in the following sequence: frontal view, top, bottom, and 15° and 30° angles to both the left and right [17].

5) Images are also captured using a smartphone and a smart pad in the temperature- and humidity-controlled room, following the sequence of frontal, left, and right views [17].

Precise skin measurement devices are primarily used to assess moisture, elasticity, wrinkles, pigmentation, and pores. The specific devices employed—PRIMOS Lite (moisture), Cutometer MPA580 (wrinkles), and VISIA Complexion Analysis (pigmentation/pores)—are recognized worldwide as standard equipment by skin researchers [17]. Since the measurement ranges for these parameters vary, the values were normalized and mapped to the range 0-1 [17]. Five dermatologists evaluate the skin condition across eight distinct areas: the forehead, glabella, both eye areas, both cheeks, lips, and chin. The diagnostic categories include wrinkles (0–8), pigmentation (0–5), pores (0–5), lip dryness (0–4), and jawline sagging (0–6), with ratings assigned as integer values. A two-stage verification process is conducted to ensure the accuracy of the diagnostic results [17].

1) Primary Verification: Five dermatologists perform expert diagnostic labeling.

2) Secondary Verification: If a discrepancy arises between the diagnostic grade assigned by one expert and those assigned by at least two others, the final diagnostic grade is determined through an internal review meeting [17].

Of the 1,300 facial images collected, 1,200 were used for model training, and the remaining 100 were for performance evaluation [17]. Regarding performance evaluation, the average accuracy against expert diagnoses was 75% for wrinkles, 74.07% for pigmentation, 72.22% for pores, 77.78% for jawline sagging, and 88.89% for lip dryness; the MAE (Mean Absolute Error) values against precision measurement equipment were 0.0706 for wrinkles, 0.053 for elasticity, 0.0617 for moisture, and 0.0791 for pores [17].

To compare with the deep learning-based study of [17], our study focuses on statistical analyses of measurement datasets. Summary statistics for part of the measurement data are given in Table 2, which summarizes the meta dataset from 1072 Korean participants. A total of 83 features, including moisture level, elasticity, and wrinkles across various facial positions, are investigated.

[5]https://www.aihub.or.kr

**Table 1.** The components of image dataset.

| Feature | Sub category | Number | Rate (%) |
|---|---|---|---|
| Gender | Male | 62,478 | 49.81 |
| | Female | 62,946 | 50.19 |
| | Sum | 125,424 | 100.00 |
| Age | 10~19 | 12,402 | 9.89 |
| | 20~29 | 22,815 | 18.19 |
| | 30~39 | 22,815 | 18.19 |
| | 40~49 | 22,932 | 18.28 |
| | 50~59 | 22,698 | 18.10 |
| | 60~69 | 21,762 | 17.35 |
| | Sum | 125,424 | 100.00 |
| Camera angle | Digital camera front | 9,648 | 7.69 |
| | Digital camera left 15° | 9,648 | 7.69 |
| | Digital camera left 30° | 9,648 | 7.69 |
| | Digital camera right 15° | 9,648 | 7.69 |
| | Digital camera right 30° | 9,648 | 7.69 |
| | Digital camera up | 9,648 | 7.69 |
| | Digital camera down | 9,648 | 7.69 |
| | Smart pad front | 9,648 | 7.69 |
| | Smart pad left | 9,648 | 7.69 |
| | Smart pad right | 9,648 | 7.69 |
| | Smart phone front | 9,648 | 7.69 |
| | Smart phone left | 9,648 | 7.69 |
| | Smart phone right | 9,648 | 7.69 |
| | Sum | 13,936 | 100.00 |
| Face position | Whole | 13,936 | 11.11 |
| | Forehead | 13,936 | 11.11 |
| | Brow area | 13,936 | 11.11 |
| | Eye area (left) | 13,936 | 11.11 |
| | Eye area (right) | 13,936 | 11.11 |
| | Cheek (left) | 13,936 | 11.11 |
| | Cheek (right) | 13,936 | 11.11 |
| | Lip | 13,936 | 11.11 |
| | Chin | 13,936 | 11.11 |
| | Sum | 125,424 | 100.00 |

**Table 2.** Part of summary statistics.

| | moisture_foreheard | moisture_right_cheek | moisture_left_cheek | moisture_chin | elasticity_chin_R0 | elasticity_chin_R1 | elasticity_chin_R2 | elasticity_chin_R3 |
|---|---|---|---|---|---|---|---|---|
| count | 1072.000000 | 1072.000000 | 1072.000000 | 1072.000000 | 1072.000000 | 1072.000000 | 1072.000000 | 1072.000000 |
| mean | 60.387220 | 62.294095 | 62.727687 | 61.282659 | 0.234429 | 0.094282 | 0.583949 | 0.269822 |
| std | 9.763583 | 10.431054 | 10.336209 | 10.833118 | 0.060072 | 0.024794 | 0.106798 | 0.061007 |
| min | 24.670000 | 27.330000 | 22.330000 | 20.330000 | 0.100000 | 0.030000 | 0.220000 | 0.130000 |
| 25% | 54.247500 | 55.670000 | 56.330000 | 54.330000 | 0.190000 | 0.080000 | 0.510000 | 0.230000 |
| 50% | 60.670000 | 62.670000 | 62.670000 | 62.330000 | 0.230000 | 0.090000 | 0.580000 | 0.262000 |
| 75% | 66.752500 | 69.415000 | 70.000000 | 68.670000 | 0.270000 | 0.110000 | 0.651475 | 0.306250 |
| max | 94.330000 | 95.670000 | 98.670000 | 94.670000 | 0.498000 | 0.229000 | 0.890000 | 0.543000 |

8 rows × 83 columns

Figure 1 below demonstrates the skin type distribution, segmented by gender, where 1 indicates female. A clear tendency is that the proportion of females is higher in the dry type and lower in the oily type, which will be quantified in the later analysis. Since the original raw data contain only one participant of the "Extreme Dry" type, this participant serves as an outlier, casting doubt on the legitimacy of the 6-skin type classification and necessitating a new classification into 3 subgroups: dry, normal, and oily.

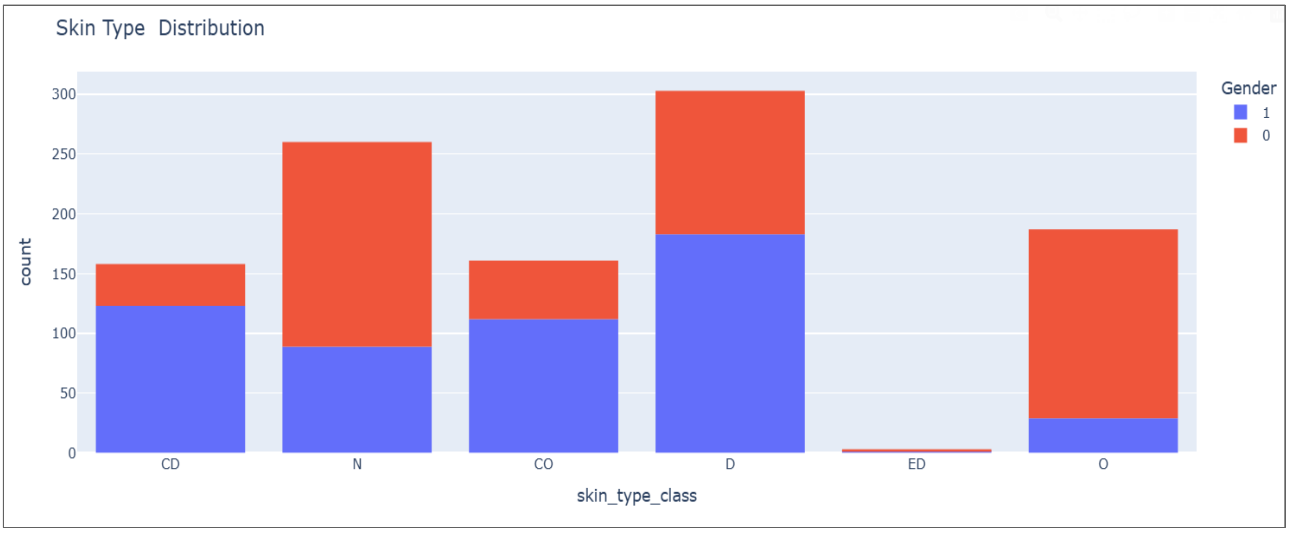


**Figure 1.** Skin type distribution (6 classes, CD: Combination dry, N: Normal, CO: Combination oily, D: Dry, ED: Extreme dry, O: Oily, 0 = Male, 1 = Female).

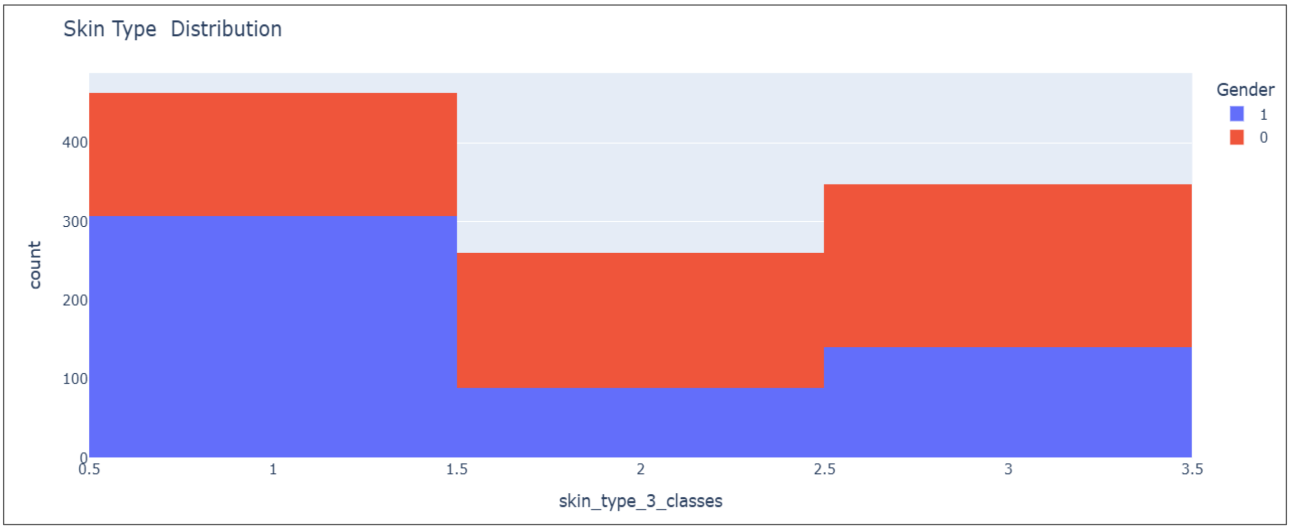


**Figure 2.** Skin type distribution (3-types, Class 1: Dry, Class 2: Normal, Class 3: Oily, 0 = Male, 1 = Female).

Under the 3-subgroup classification, combination dry, dry, and extreme dry types are combined into a dry type with numeric value 1, and combination oily and oily types are combined into an oily type with numeric value 3, reaffirming the clear gender-wise difference in skin type.

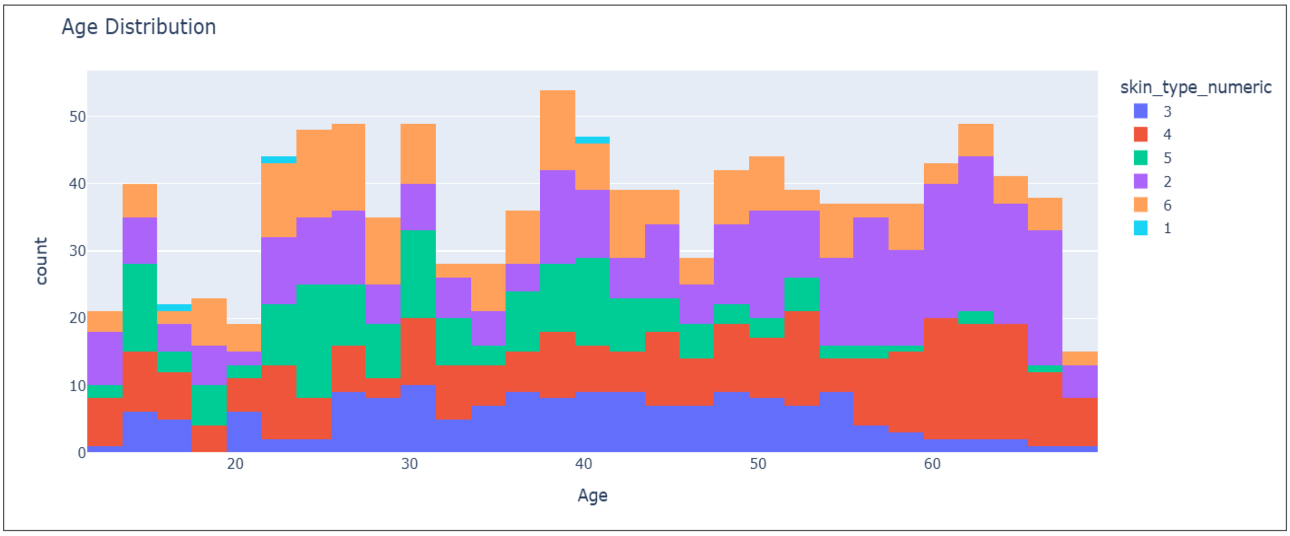


**Figure 3.** Age distribution (6-types, CD: Combination dry, N: Normal, CO: Combination oily, D: Dry, ED: Extreme dry, O: Oily).


**Figure 4.** Age distribution (3-types, Class 1: Dry, Class 2: Normal, Class 3: Oily).

Figures 3 and 4 show age distributions segmented by 6 and 3 skin types, respectively. As age increases, the relative proportion of dry and neutral skin types also increases, suggesting that participants' skin types evolve over time.

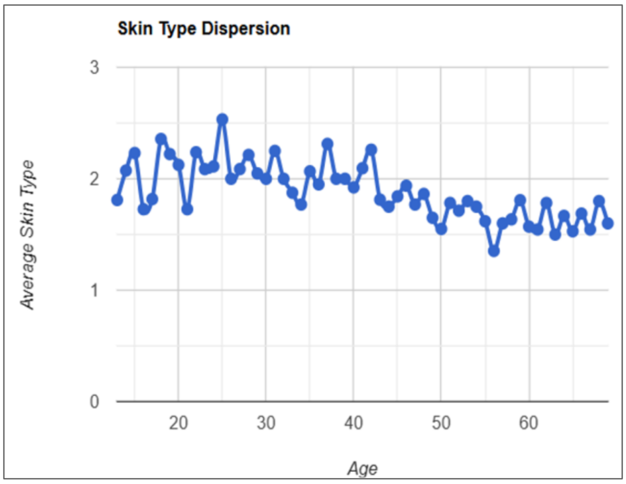


**Figure 5.** Average skin type versus age.

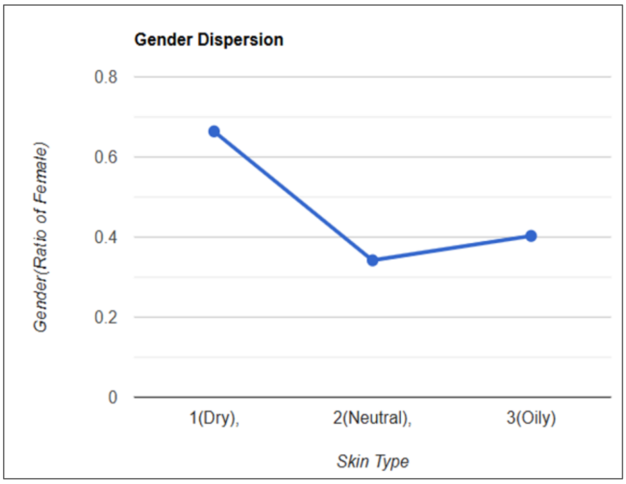


**Figure 6.** Ratio of female versus skin type.

To pin down the age effect more clearly, Figure 5 is constructed with the vertical axis showing average skin type and the horizontal axis showing age, based on an ANOVA. As participants' age increases, the average age across 3 skin types (1=Dry, 2=Normal, 3=Oily) increases and then decreases, resembling a periodic trigonometric function that diverges and then converges to the horizontal axis at 2. This figure may serve as an alternative statistical pattern when reliable panel data are unavailable. Likewise, Figure 6 more clearly demonstrates the difference in gender proportions across skin types observed in the previous segmented bar charts. The proportion of females is highest in the dry type and lowest in the neutral type. For the normal group, the proportion of females is only about 0.35. These observations from the raw data will be clarified through several statistical analyses.

## 4. Data Analysis I: Independent Samples t-Test

Table 3 summarizes the results of the independent-samples t-test. Since standard error inequalities are commonly observed across tests, the Welch method is adopted. All tests are significant, demonstrating the clear difference in gender-wise skin status.

Regarding moisture levels, female participants show higher levels than male participants across all facial positions. However, it is interesting that male participants show greater elasticity in the chin and forehead regions and less in the cheek regions. More wrinkles, spots, and pores are detected in male participants. As expected, self-diagnosis of facial skin problems is higher among female participants. In general, females exhibit a preferable facial skin condition, partly due to self-diagnosis.

**Table 3.** Output table of independent sample t tests.

| | Alternative | t (Welch) | df | p |
|---|---|---|---|---|
| Moisture forehead | $H_a : \mu_{Male} < \mu_{Female}$ | -14.250 | 1067.246 | < 0.001 |
| Moisture left cheek | $H_a : \mu_{Male} < \mu_{Female}$ | -17.209 | 1067.699 | < 0.001 |
| Moisture right cheek | $H_a : \mu_{Male} < \mu_{Female}$ | -17.574 | 1069.833 | < 0.001 |
| Moisture chin | $H_a : \mu_{Male} < \mu_{Female}$ | -16.142 | 1060.960 | < 0.001 |
| Elasticity chin | $H_a : \mu_{Male} > \mu_{Female}$ | 5.166 | 1068.916 | < 0.001 |
| Elasticity left cheek | $H_a : \mu_{Male} < \mu_{Female}$ | -1.847 | 1068.482 | 0.032 |
| Elasticity right cheek | $H_a : \mu_{Male} < \mu_{Female}$ | -2.887 | 1066.759 | 0.002 |
| Elasticity forehead | $H_a : \mu_{Male} > \mu_{Female}$ | 9.703 | 1052.528 | < 0.001 |
| Wrinkle left eye | $H_a : \mu_{Male} > \mu_{Female}$ | 20.098 | 963.998 | < 0.001 |
| Wrinkle right eye | $H_a : \mu_{Male} > \mu_{Female}$ | 19.068 | 1017.652 | < 0.001 |
| Number spot front | $H_a : \mu_{Male} > \mu_{Female}$ | 16.209 | 1044.376 | < 0.001 |
| Number pore left cheek | $H_a : \mu_{Male} > \mu_{Female}$ | 17.993 | 1016.596 | < 0.001 |
| Number pore right cheek | $H_a : \mu_{Male} > \mu_{Female}$ | 17.776 | 1034.073 | < 0.001 |
| Self-diagnosis | $H_a : \mu_{Male} < \mu_{Female}$ | -2.651 | 1065.873 | 0.004 |

## 5. Data Analysis II: ANOVA

To identify differences across 3 skin types, ANOVA tests are conducted for various independent variables, including moisture, elasticity, wrinkles, number of spots, number of pores, and age. The output tables of each ANOVA test are added in the appendix. All tests are significant, suggesting clear differences among the 3 skin status types in various features. Most importantly, the relative rankings of 3 skin types for each feature are summarized in Table 4.

**Table 4.** ANOVA-based rankings of skin characteristics depending on 3 types.

| | First | Second | Third |
|---|---|---|---|
| Moisture forehead | 1 (Dry) | 2 (Neutral) | 3 (Oily) |
| Moisture left cheek | 1 | 2 | 3 |
| Moisture right cheek | 1 | 2 | 3 |
| Moisture chin | 1 | 2 | 3 |
| Elasticity chin | 3 | 2 | 1 |
| Elasticity left cheek | 3 | 2 | 1 |
| Elasticity right cheek | 3 | 2 | 1 |
| Elasticity forehead | 3 | 2 | 1 |
| Wrinkle left eye (smallest is 1st) | 1 | 3 | 2 |
| Wrinkle right eye (smallest is 1st) | 1 | 3 | 2 |
| Number spot front (smallest is 1st) | 1 | 3 | 2 |
| Number pore left cheek (smallest is 1st) | 1 | 2 | 3 |
| Number pore right cheek (smallest is 1st) | 1 | 2 | 3 |
| Age (smallest is 1st) | 3 | 1 | 2 |
| Legend: 1: Dry, 2: Neutral, 3: Oily. | | | |

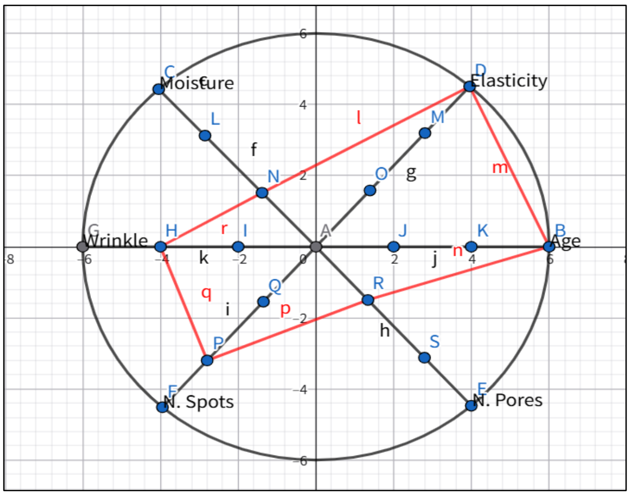


**Figure 7.** Diagram for oily skin.

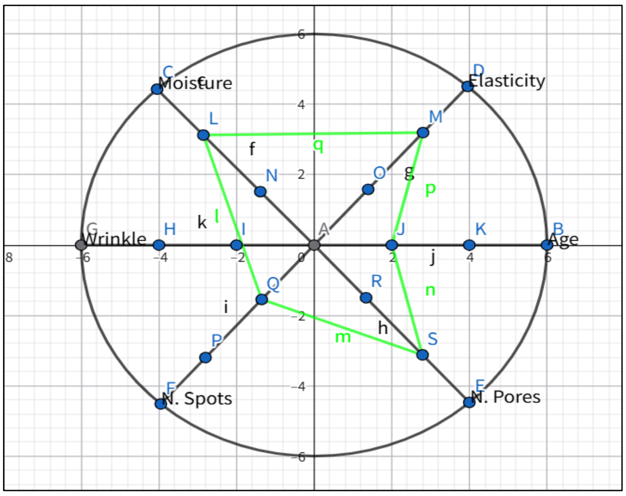


**Figure 8.** Diagram for normal skin.

For oily skin types, elasticity is highest while moisture is lowest. For wrinkle level and number of spots, oily skin type ranks second highest, while it shows the greatest number of pores. Relatively younger participants are classified as having oily skin. In the normal skin type, elasticity, moisture level, and pore count are the second highest, while wrinkle level is the worst among the three groups. Normal skin type exhibits the highest number of spots. A medium level of age corresponds to a normal skin type.

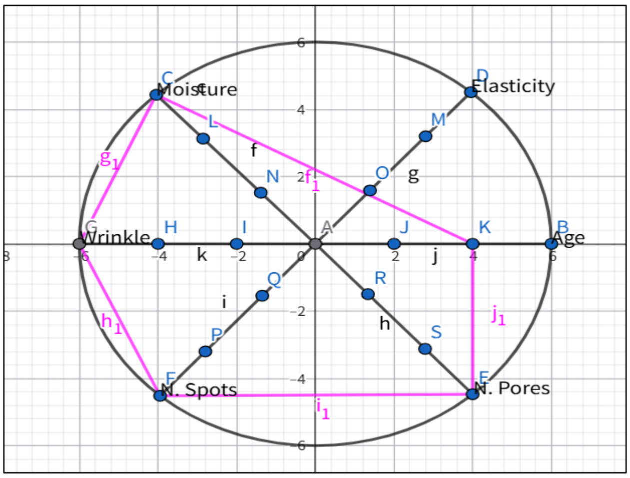


**Figure 9.** Diagram for dry skin.

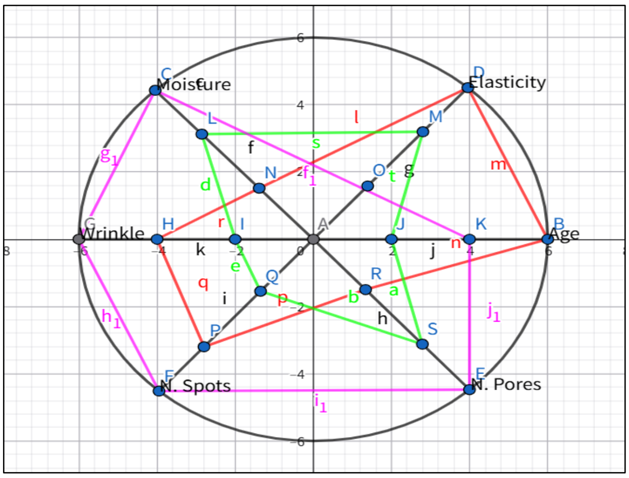


**Figure 10.** Diagram for all 3 skin types.

(Purple: Dry, Green: Normal, Red: Oily).

Dry skin types exhibit the lowest wrinkle and highest moisture levels, the fewest pores and spots, and the lowest elasticity. Our dataset shows that dry skin types have the highest moisture levels, which is inconsistent with previous studies and even counterintuitive. One possible explanation is that skin type is typically assessed visually, while moisture level is measured with an instrument such as a craniometer. That is, the dry skin group can be cosmetically dry but not physiologically dehydrated. In addition, from a behavioral standpoint, participants who are classified as dry skin type can use more moisturizers, occlusives, and humidifiers. This discrepancy needs more investigation. Younger participants relatively dominate this oily skin type.

Figure 10 shows the combined figure of 3 skin types. At a medium age level, the dry skin type exhibits many desirable characteristics, except for elasticity. On the other hand, oily skin type has an advantage in terms of elasticity. As people age, the proportion of normal skin types tends to increase, leading to more wrinkles and spots. Therefore, 'normal' is not normal in the traditional sense, which is the main assertion of our study. A normal skin type has relatively good moisture and elasticity levels, but it has more wrinkles and facial spots. The statistical finding that Dry skin type is correlated with the highest moisture level does not align with other literature findings, and the reason for this discrepancy warrants further investigation. By comparing 5 features simultaneously, excluding age, we can assert that the dry skin type has many relatively desirable characteristics.

### 6. Data Analysis III: PCA (Principal Component Analysis)

Since the original dataset has 83 features, the visibility of their graphical display is quite limited. Therefore, among 14 elasticity chin measurements, only one, elasticity chin R0, is selected. Likewise, 83 features are condensed into 17 variables, including 4 moisture features, 4 elasticity features, 2 wrinkle measures, the number of spots, the number of pores, age, gender, self-diagnosis, and skin type class.

Dimensions: Several findings from the below PCA Biplots are:

1) As expected, self-diagnosis does not have a significant effect.
2) Wrinkle measurements are negatively correlated with both moisture measures and elasticity measures.
3) Gender is positively correlated with moisture measures.
4) Age is positively correlated with wrinkles, the number of spots, and the number of pores.
5) Clustering of elasticity measures is not clear.
6) The relative impacts of skin types on elasticity are different in facial positions: Forehead is strongest, and cheek is weakest.
7) The most dominant hidden factor governs wrinkle, moisture, number of spots, number of pores, age, and gender.
8) The second most hidden factor governs elasticity and skin type.

9) Elasticity measures have almost perfect negative correlation, both of which are important features in the second principal component.

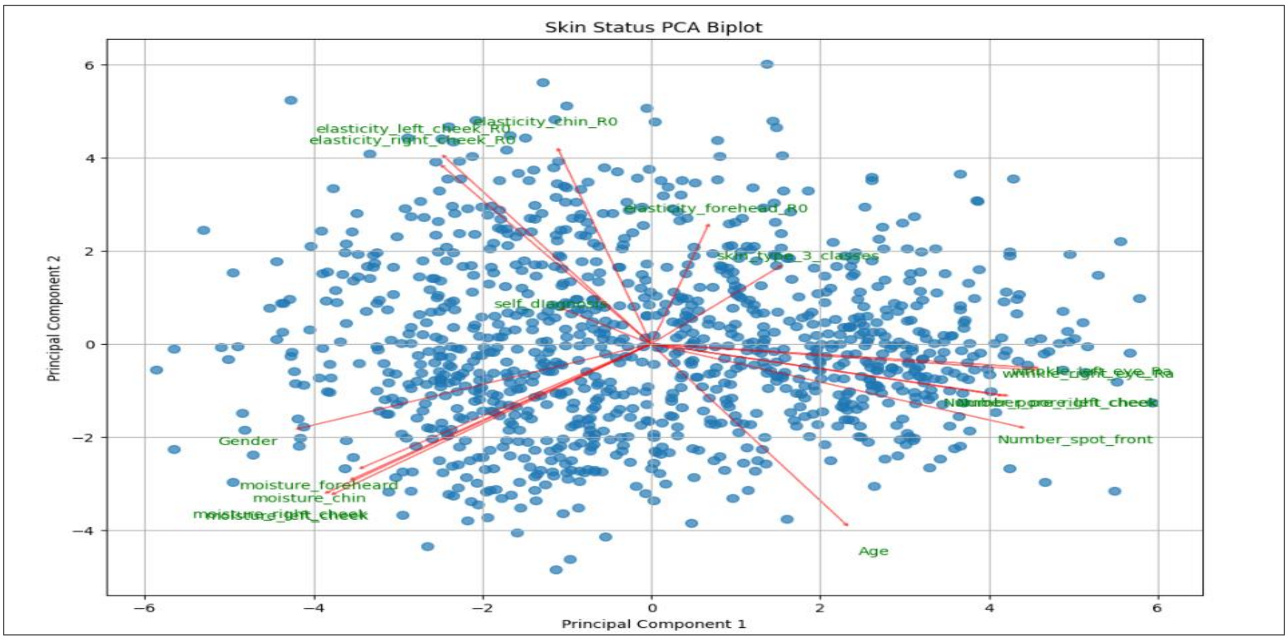


**Figure 11.** PCA biplot of simplified dataset.

## 7. Data Analysis IV: Gradient Boost Regression and Skin-Age Concept

To assess the feasibility of the skin-age concept adopted by many companies, such as Revieve, Beiersdorf, L'Oréal Group, Shiseido, OneSkin, and Olive Young, Gradient Boost Regression is used to predict age using 82 additional features (Table 5).

**Table 5.** Output of gradient boost regression.

| | **Value** |
|---|---|
| MSE | 93.49 |
| MSE (scaled) | 0.417 |
| RMSE | 9.669 |
| MAE/MAD | 7.633 |
| MAPE | 21.51% |
| $R^2$ | 0.625 |

From the output table above, the RMSE is higher than the MAE, suggesting the presence of large outliers. From the MAPE of 21.51%, predictions are, on average, off by about one-fifth of the true value. Most of all, for younger participants, predictions overestimate true values, whereas for elderly participants, underestimates are observed, as shown in the following plot.

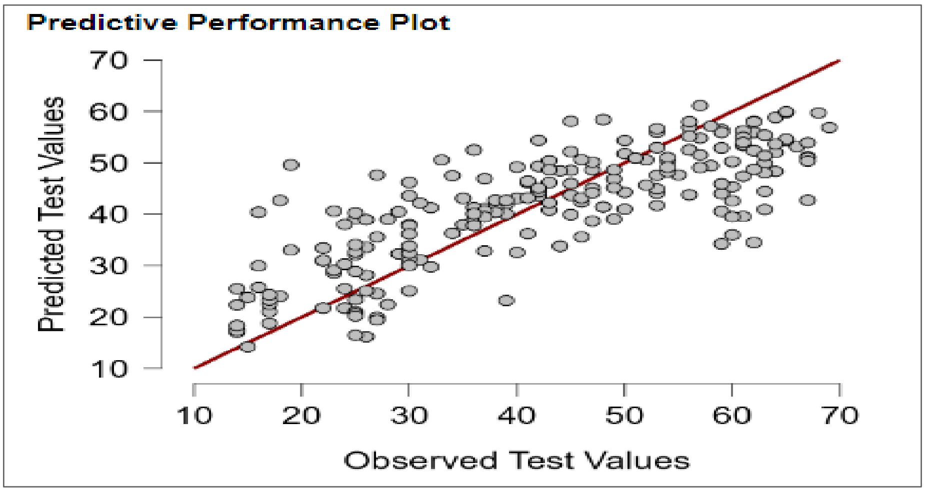


**Figure 12.** Perceived performance plot of gradient boost regression.

**Table 6.** Top 10 feature importance of gradient boost regression.

| Variables | Relative influence | Mean dropout loss |
|---|---|---|
| Number of spots, front | 25.092 | 11.084 |
| Elasticity, left cheek (R8) | 20.670 | 9.308 |
| Skin type | 6.478 | 9.258 |
| Elasticity chin (R6) | 6.083 | 8.800 |
| Elasticity, left cheek (Q2) | 4.705 | 8.632 |
| Elasticity, right cheek (R2) | 4.628 | 8.547 |
| Elasticity, left cheek (Q1) | 4.460 | 8.603 |
| Wrinkle, right eye (Rv) | 3.141 | 8.596 |
| Elasticity, left cheek (R6) | 2.747 | 8.493 |
| Elasticity, forehead (R7) | 2.612 | 8.507 |

For predicting age, the number of front spots and left cheek elasticity are the two most dominating features. From age predictions, the predicted values can serve as a concept similar to the skin-age of Olive Young. However, there are two limitations for this purpose. The first is that $R^2$ is only 0.625, which is insufficient for reliable predictions.

The second one is that regression-based predictions systematically overestimate youngsters and underestimate elders. These two limitations in using the predicted age value as a proxy for skin-age concepts can be reduced by merging metadata with image data. However, the skin-age concepts of many companies are known to measure visible and biological signs of skin conditions, which do not necessarily align with the predicted natural age.

## 8. Data Analysis V: ML Classification Comparison

Without merging measurement data with image data, the performance of machine learning-based classification is quite limited. With 6 subgroups in skin classification, the test set accuracy ranges from 0.712 to 0.790, and the precision, recall, and F1 scores are quite low. When 3 subgroups are used, the accuracy ranges from 0.598 to 0.726 with improved precision, recall, and F1 scores. Considering all outcomes in Tables 7 and 8, Support Vector Machine Classification exhibits the highest performance.

**Table 7.** Performance measures of 6-type classification.

| | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Boosting | 0.790 | 0.367 | 0.369 | 0.366 |
| Support vector machine classification | 0.757 | 0.386 | 0.393 | 0.385 |
| Neural network classification | 0.712 | 0.263 | 0.280 | 0.245 |
| K-nearest neighbors classification | 0.720 | 0.298 | 0.299 | 0.294 |
| Linear discriminant classification | 0.787 | 0.362 | 0.360 | 0.356 |
| Naïve bayes classification | 0.773 | 0.419 | 0.318 | 0.291 |
| Decision tree classification | 0.725 | 0.216 | 0.313 | 0.252 |
| Random forest classification | 0.742 | 0.361 | 0.355 | 0.352 |

**Table 8.** Performance measures of 3-type classification.

| | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Boosting | 0.651 | 0.453 | 0.477 | 0.458 |
| Support vector machine classification | 0.726 | 0.552 | 0.589 | 0.554 |
| Neural network classification | 0.673 | 0.487 | 0.509 | 0.490 |
| K-nearest neighbors classification | 0.598 | 0.396 | 0.299 | 0.294 |
| Linear discriminant classification | 0.679 | 0.522 | 0.519 | 0.512 |
| Naïve bayes classification | 0.667 | 0.502 | 0.500 | 0.500 |
| Decision tree classification | 0.673 | 0.488 | 0.509 | 0.494 |
| Random forest classification | 0.636 | 0.439 | 0.453 | 0.445 |

To compare machine learning-based skin type classification with measurement data, a deep learning model based on RexNet150 is used. With 1072 front image datasets, some of which are shown in Figure 13, the RexNet150 model with an epoch size of 50, batch sizes of 32 and 16, and a patience level of 5 resulted in a train set accuracy of 95% and a validation accuracy of around 45.5%.


**Figure 13.** Part of 1072 input image data.

The performance plots are shown in Figures 14-16. One possible cause of the lower validation accuracy compared with the 95% accuracy in the train set is that only 1072 front images from the full 125,424 dataset are used, leading to overfitting.

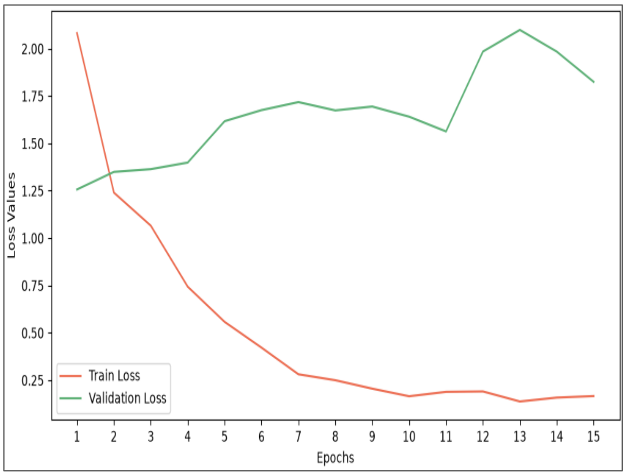


**Figure 14.** Plot of loss function.

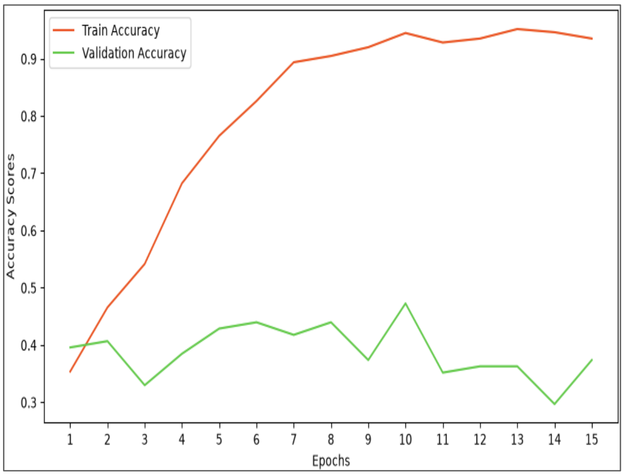


**Figure 15.** Plot of accuracy.

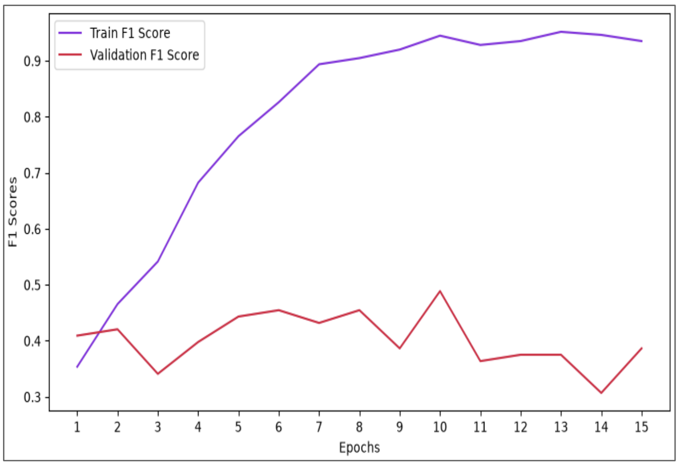


**Figure 16.** Plot of F1 score.

## 9. Conclusion

The low validation accuracy of deep learning models constrains our study. Within this limitation, differences in facial skin characteristics are examined by gender, skin type, and age. Except for the fact that male chins and foreheads are more elastic than those of females, female participants show relatively better skin conditions in moisture level, wrinkle level, number of spots, and number of pores. As age increases, the proportion of dry and normal skin types also increases. The key claim of our study is that normal is not normal: normal skin type does not lie between oily and dry skin types. No significant advantage is present in the normal skin type.

Moreover, in the PCA Biplot, age shows a near-perfect negative correlation with elasticity and a positive correlation with wrinkles. With the measurement data, the skin-age concept approximated by the Gradient Boost Regression predictions has two limitations: insufficient explanatory power and systematic overestimation of younger participants and underestimation of older participants. Although the performance measure is not satisfactory due to the intrinsic limitation of measurement data that are not merged with image data, Support Vector Machine classification outperforms other methods.

Compared with 6-type classifications, 3-type classifications lose a little accuracy but gain precision, recall, and F1 scores. Both classifications achieved accuracy rates of around 72.6%, which outperformed the deep learning-based skin type classification using RexNet150. These outcomes can be compared with the average accuracy of 77.6% from a deep learning-based model trained on the same image datasets. Figuring out the causes of low validation rates in deep learning classification and improving them to enhance application credibility are our ongoing areas of study.

## APPENDIX

**Table 9.** Output table of ANOVA: Moisture forehead.

| **Moisture forehead** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 3298.266 | 2 | 1649.133 | 17.862 | <0.001 | 0.031 |
| | Residuals | 98602.959 | 1068 | 92.325 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 62.334 | 10.087 | 0.468 | 0.162 | |
| | 2 (Neutral) | 260 | 59.456 | 9.429 | 0.585 | 0.159 | |
| | 3 (Oily) | 347 | 58.441 | 9.070 | 0.487 | 0.155 | |

**Table 10.** Output table of ANOVA: Moisture right cheek.

| **Moisture right cheek** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 4351.275 | 2 | 2175.637 | 20.718 | <0.001 | 0.036 |
| | Residuals | 112151.971 | 1068 | 105.011 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 64.470 | 10.485 | 0.487 | 0.163 | |
| | 2 (Neutral) | 260 | 61.626 | 9.833 | 0.610 | 0.160 | |
| | 3 (Oily) | 347 | 59.870 | 10.230 | 0.549 | 0.171 | |

**Table 11.** Output table of ANOVA: Moisture left cheek.

| **Moisture left cheek** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 3755.781 | 2 | 1877.890 | 18.132 | <0.001 | 0.031 |
| | Residuals | 110609.031 | 1068 | 103.567 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 64.749 | 10.298 | 0.478 | 0.159 | |
| | 2 (Neutral) | 260 | 62.095 | 9.711 | 0.602 | 0.156 | |
| | 3 (Oily) | 347 | 60.478 | 10.353 | 0.556 | 0.171 | |

**Table 12.** Output table of ANOVA: Moisture chin.

| **Moisture chin** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 3593.570 | 2 | 1796.785 | 15.721 | <0.001 | 0.027 |
| | Residuals | 122062.455 | 1068 | 114.291 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 63.233 | 10.844 | 0.503 | 0.171 | |
| | 2 (Neutral) | 260 | 60.789 | 10.220 | 0.634 | 0.168 | |
| | 3 (Oily) | 347 | 59.028 | 10.828 | 0.581 | 0.183 | |

**Table 13.** Output table of ANOVA: Elasticity chin.

| **Elasticity chin** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | **$\omega^2$** |
|---|---|---|---|---|---|---|---|
| | Skin-type | 0.037 | 2 | 0.018 | 5.155 | 0.006 | 0.008 |
| | Residuals | 3.824 | 1068 | 0.004 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 0.228 | 0.058 | 0.003 | 0.256 | |
| | 2 (Neutral) | 260 | 0.239 | 0.060 | 0.004 | 0.251 | |
| | 3 (Oily) | 347 | 0.240 | 0.062 | 0.003 | 0.258 | |

**Table 14.** Output table of ANOVA: Elasticity left cheek.

| **Elasticity left cheek** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | **$\omega^2$** |
|---|---|---|---|---|---|---|---|
| | Skin-type | 0.021 | 2 | 0.011 | 3.355 | 0.035 | 0.004 |
| | Residuals | 3.359 | 1068 | 0.003 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 0.249 | 0.053 | 0.002 | 0.214 | |
| | 2 (Neutral) | 260 | 0.255 | 0.057 | 0.004 | 0.223 | |
| | 3 (Oily) | 347 | 0.260 | 0.059 | 0.003 | 0.227 | |

**Table 15.** Output table of ANOVA: Elasticity right cheek.

| **Elasticity right cheek** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | **$\omega^2$** |
|---|---|---|---|---|---|---|---|
| | Skin-type | 0.017 | 2 | 0.009 | 2.812 | 0.061 | 0.003 |
| | Residuals | 3.307 | 1068 | 0.003 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 0.250 | 0.052 | 0.002 | 0.209 | |
| | 2 (Neutral) | 260 | 0.256 | 0.057 | 0.004 | 0.224 | |
| | 3 (Oily) | 347 | 0.260 | 0.059 | 0.003 | 0.226 | |

**Table 16.** Output table of ANOVA: Elasticity forehead.

| **Elasticity forehead** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | **$\omega^2$** |
|---|---|---|---|---|---|---|---|
| | Skin-type | 0.057 | 2 | 0.028 | 7.616 | <0.001 | 0.012 |
| | Residuals | 3.995 | 1068 | 0.004 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 0.240 | 0.061 | 0.003 | 0.255 | |
| | 2 (Neutral) | 260 | 0.254 | 0.060 | 0.004 | 0.234 | |
| | 3 (Oily) | 347 | 0.255 | 0.062 | 0.003 | 0.244 | |

**Table 17.** Output table of ANOVA: Wrinkle left eye.

| **Wrinkle left eye** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | **$\omega^2$** |
|---|---|---|---|---|---|---|---|
| | Skin-type | 1243.138 | 2 | 621.569 | 18.664 | <0.001 | 0.032 |
| | Residuals | 35567.977 | 1068 | 33.303 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 20.720 | 5.677 | 0.264 | 0.274 | |
| | 2 (Neutral) | 260 | 23.108 | 5.916 | 0.367 | 0.256 | |
| | 3 (Oily) | 347 | 22.696 | 5.786 | 0.311 | 0.255 | |

**Table 18.** Output table of ANOVA: Wrinkle right eye.

| **Wrinkle right eye** | **Cases** | **Sum of squares** | **df** | **Mean square** | **F** | **P** | **$\omega^2$** |
|---|---|---|---|---|---|---|---|
| | Skin-type | 1115.412 | 2 | 557.706 | 18.996 | <0.001 | 0.033 |
| | Residuals | 31355.713 | 1068 | 29.359 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 20.569 | 5.381 | 0.250 | 0.262 | |
| | 2 (Neutral) | 260 | 22.870 | 5.665 | 0.351 | 0.248 | |
| | 3 (Oily) | 347 | 22.392 | 5.278 | 0.283 | 0.236 | |

**Table 19.** Output table of ANOVA: Number of spot front.

| Number of spot front | Cases | Sum of squares | df | Mean square | F | P | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 92992.426 | 2 | 46496.213 | 11.594 | <0.001 | 0.019 |
| | Residuals | $4.283 \cdot 10^6$ | 1068 | 4010.271 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 148.685 | 60.765 | 2.821 | 0.409 | |
| | 2 (Neutral) | 260 | 169.342 | 66.590 | 4.130 | 0.393 | |
| | 3 (Oily) | 347 | 165.764 | 64.175 | 3.445 | 0.387 | |

**Table 20.** Output table of ANOVA: Number of pores in the right cheek.

| Number of pores right cheek | Cases | Sum of squares | df | Mean square | F | P | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | $1.270 \cdot 10^7$ | 2 | $6.350 \cdot 10^6$ | 31.147 | <0.001 | 0.053 |
| | Residuals | $2.177 \cdot 10^8$ | 1068 | 203863.725 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 812.748 | 436.502 | 20.264 | 0.537 | |
| | 2 (Neutral) | 260 | 979.031 | 492.220 | 30.526 | 0.503 | |
| | 3 (Oily) | 347 | 1058.199 | 439.254 | 23.580 | 0.145 | |

**Table 21.** Output table of ANOVA: Number of pores in the left cheek.

| Number of pores left cheek | Cases | Sum of squares | df | Mean square | F | P | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | $1.231 \cdot 10^7$ | 2 | $6.153 \cdot 10^6$ | 33.395 | <0.001 | 0.057 |
| | Residuals | $1.968 \cdot 10^8$ | 1068 | 184241.477 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 763.358 | 404.688 | 18.787 | 0.530 | |
| | 2 (Neutral) | 260 | 928.808 | 471.068 | 29.214 | 0.507 | |
| | 3 (Oily) | 347 | 1004.473 | 428.298 | 22.992 | 0.426 | |

**Table 22.** Output table of ANOVA: Age.

| Age | Cases | Sum of squares | df | Mean square | F | P | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 16792.875 | 2 | 8396.437 | 35.526 | <0.001 | 0.061 |
| | Residuals | 252415.379 | 1068 | 236.344 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 43.817 | 15.636 | 0.726 | 0.357 | |
| | 2 (Neutral) | 260 | 44.600 | 16.887 | 1.047 | 0.379 | |
| | 3 (Oily) | 347 | 35.663 | 13.774 | 0.738 | 0.385 | |

**Table 23.** Output table of ANOVA: Gender.

| Gender | Cases | Sum of squares | df | Mean square | F | P | $\omega^2$ |
|---|---|---|---|---|---|---|---|
| | Skin-type | 22.146 | 2 | 11.073 | 48.150 | <0.001 | 0.081 |
| | Residuals | 245.602 | 1068 | 0.230 | | | |
| | **Skin type** | **N** | **Mean** | **SD** | **SE** | **Coefficient of variation** | |
| | 1 (Dry) | 464 | 0.664 | 0.473 | 0.022 | 0.712 | |
| | 2 (Neutral) | 260 | 0.342 | 0.475 | 0.029 | 1.389 | |
| | 3 (Oily) | 347 | 0.403 | 0.491 | 0.026 | 1.218 | |

## Declarations

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