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Feasibility Study of Multilight Facial Imaging for Multiparameter Skin Assessment Using Lightweight Convolutional Neural Network

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Abstract

This study utilizes multi-light facial imaging to develop a lightweight Convolutional Neural Network (CNN) architecture based on MobileNetV2. The dataset consists of 211 participants, each with eight images captured under the following light modalities: white light, blue light, red light, brown light, UV light, Wu light, positive polarization, and negative polarization. Each respondent also has 13 parameters that quantitatively represent skin conditions, including sebum, pores, spots, wrinkles, acne, blackheads, dark circles, skin color, PL sensitivity, UV spots, pigment, UV acne, and collagen fibers. The eight image datasets were processed through resizing, pixel normalization, data augmentation, and target normalization. The MobileNetV2 model was designed to extract light modalities via feature fusion and perform quantitative predictions of skin parameters. Model evaluation was conducted using 5-fold cross-validation, parameter distribution analysis, prediction-actual correlation, regression, and Bland-Altman plots. The multi-light method approach has the potential to provide more visual information than standard RGB images. The performance of the sebum and dark circle parameters is relatively lower than that of other parameters. The uneven distribution of the dataset limits the performance of the lightweight CNN model. The low R^2 value indicates that the development of prediction models based on lightweight CNNs still faces challenges in feature extraction. Thus, this study provides an initial baseline for the development of skin analysis systems using a multi-light approach. This study also highlights the need for a well-balanced dataset with a large sample size in future research.

1. Introduction

Facial skin plays a crucial role in dermatology, particularly in the development of skincare treatments and cosmetics. The condition of facial skin is characterized by several parameters, such as sebum, wrinkles, pores, pigment, acne, and skin sensitivity. Consequently, these parameters can serve as evaluation criteria to determine personalized skincare regimens for each individual. Accurate assessment of these skin parameters can also aid in the early detection and monitoring of skin disorders.

The process of skin analysis assisted by dermatologists has visual limitations. The experience and subjectivity of dermatologists serve as the standard for manual skin analysis [1]. Developing technological innovations using specialized devices requires high costs to implement [2]. Additionally, dermatologist consultations are not inexpensive. Due to these limitations, the process for individuals to evaluate their skin condition becomes restricted and impractical. Therefore, the development of an automated skin analysis system is urgently needed to provide objective and consistent assessments.

Advances in artificial intelligence (AI) have driven rapid progress in digital-based skin analysis. Skin condition parameters such as acne, wrinkles, and skin lesions can be classified using deep learning methods, particularly Convolutional Neural Networks (CNNs). CNNs can automatically extract features from images, making them well-suited for complex image data [3]. However, most developments in facial skin analysis using AI are still based on RGB images under standard lighting [4]. Consequently, they cannot yet optimally represent all of the skin's optical characteristics. Human skin is divided into

two parts: the surface and the inner layers. In the inner layers of the skin, parameters such as UV spots, collagen, and skin sensitivity cannot be clearly observed using ordinary white light. This limits AI's ability to extract skin information.

Multi-light facial imaging is an approach designed to enhance the visualization of skin conditions using multiple types of light. Each type of light serves a distinct purpose in representing skin conditions. For example, UV light helps AI identify skin conditions such as pigment and spots caused by UV exposure [5]. Other types of light, such as polarized imaging, can help images focus more on the condition of pores, wrinkles, and collagen structure in the skin [6]. Therefore, the development of multi-light-based AI can enrich the information available for automated skin analysis.

Research in this field has progressed, utilizing AI for skin condition analysis. However, it remains focused on a single skin parameter and specific types of light. Current research is advancing in the use of AI for acne classification and the use of red light for the development of photobiomodulation devices [7–8]. Research on multi-input and multi-output systems using CNNs remains very limited, particularly those utilizing multi-light facial imaging. Therefore, a lightweight and efficient approach is needed to integrate skin condition information through multiple parameters from various light sources to numerically estimate facial skin parameters.

Given the urgency of the issues outlined above, the researchers propose a feasibility study framework for the multi-parameter analysis of facial skin conditions using multi-light facial imaging and a MobileNetV2-based CNN. Facial images captured under various lighting conditions are processed using a MobileNetV2-based multi-input CNN architecture to generate numerical outputs for 13 skin parameters. The researcher contributes to: (1) the development of a lightweight multi-input and multi-output CNN based on MobileNetV2 for image extraction, (2) the application of multi-light facial imaging for multi-parameter analysis of facial skin conditions, and (3) the evaluation of the feasibility of using multi-light imaging for automatic skin analysis based on MobileNetV2 CNN.

2. Methods

Image Acquisition

This study uses multi-light facial imaging to enrich the architectural information of the CNN. The types of light used include blue light, white light, red light, brown light, UV light, Wu light, negative polarization, and positive polarization. Each type of light affects the parameters individually, thereby enabling more accurate prediction of skin parameter values. Each respondent generated eight different types of images. The images were obtained by taking frontal shots using the VISIA Skin Analyzer to minimize variations in shooting angle, intensity, and other factors. An example of images from one respondent is shown in Fig. 1 below.

The effects of different light types on the 13 skin condition Parameters are shown in Table 1 below.

Table 1
The Relationship Between Light Modality and Skin Parameters

Light Modality	Skin Parameters
Brown Light	Pigment
Red Light	Sebum
White Light	Spots, skin color, wrinkles
Blue Light	Acne, blackheads
UV Light	UV spot, UV acne
Wu Light	Dark circle, skin color
Positive Polarization	Pores
Negative Polarization	Wrinkles, collagen fiber, PL sensitivity

This mapping serves as the foundation for the design of a multi-light facial imaging system. It is essential for calculating skin Parameters for the artificial intelligence system to be developed. This approach enables the CNN model to extract information and create targeted lighting for quantitative feature extraction and multi-Parameters skin prediction.

Multi-light is superior to RGB lighting in representing a broader range of facial skin conditions. Through multi-light, skin dermis Parameters such as pigment and UV-induced spots—which are not visible under white light—can be detected by AI [9]. Therefore, the multi-light facial imaging approach has the potential to enhance model design for comprehensively recognizing visual patterns of facial skin conditions.

Dataset and Skin Parameters

Each respondent's research dataset includes 8 multi-light facial images and 13 quantitative skin Parameters. The total dataset consists of 1,688 images from 211 respondents aged 16 to 60 years. Image data acquisition was performed using the VISIA Skin Analyzer to minimize positional variations in the visualized images shown in Fig. 1. The respondents' facial positions were adjusted to ensure clear image capture without external light interference or obstructions. Each Parameters and image was then processed via multi-output regression within a lightweight CNN model. The skin Parameters used in this study include sebum, pores, spots, wrinkles, acne, blackheads, dark circles, skin color, PL sensitivity, UV spots, pigment, UV acne, and collagen fibers. Through these Parameters, participants can assess both the surface condition of their skin and the condition of the dermis.

All face images are then processed during the preprocessing stage. Each image is resized to 96 x 96 pixels and normalized to ensure the stability of the training process using Eq. (1) with the min-max method as follows.

$$x_{normalization} = \frac{x - x_{min}}{x_{maz} - x_{min}}$$

1

Here, the variable x represents the pixel value. The image data is also augmented through random horizontal flipping, random vertical flipping, random brightness adjustments with a maximum factor, and random contrast adjustments within a specified range. A clipping function is applied to limit the pixel values. The augmentation process is applied only to the training data to ensure that the original image data remains objective in the model.

Dataset Distribution

Overall, the dataset consists of 1,688 facial images with reference values for several skin condition Parameters. These Parameters were obtained as numerical values to serve as references in designing the MobileNetV2 CNN model. The distribution of the respondents' Parameters is visualized in Fig. 2. The distributions of the values for each Parameters differ from one another. Some Parameters have a wide range of values.

Figure 2 shows that the respondents' sebum Parameters values are concentrated in the 60–90 range, indicating that tropical skin tends to have higher oil content than non-tropical skin. The dark circle Parameters, meanwhile, exhibits a high value at a single point within the 30–35 range. The respondents' skin color is predominantly in the 20–30 range. The higher the value, the darker the person's skin. The respondents' UV acne Parameters is dominant on the right side, with a range of 75–90. The blackheads Parameters has a more uniform value compared to the other Parameters. The PL sensitivity and wrinkles Parameters form a discrete pattern, indicating that they are rarely found in tropical skin. This is important because label distribution can affect the model's ability to learn random prediction patterns.

Training

Lightweight modeling generally consists of three stages: image acquisition, data preprocessing, and skin Parameters prediction. Each type of lightweight image is processed through a lightweight CNN to perform feature extraction and multi-output regression.

The CNN model architecture was developed based on MobileNetV2. MobileNetV2 was chosen for its visual feature extraction capabilities and computational efficiency. The architecture is designed with eight branches, each of which accepts 96×96×3 image dimensions using pretrained ImageNet for feature extraction, as visualized in Fig. 3. All layers are frozen except for the last 30 layers, which are left for the fine-tuning process. Feature extraction is summarized using Global Average Pooling. The image data is then processed through a dense layer, batch normalization, and dropout. A fully connected layer combines all features, resulting in an output of 13 skin Parameters via sigmoid activation.

Evaluation and Statisitcal Analysis

The model was trained using a k-fold cross-validation approach to test the stability of the model's performance across various datasets. The datasets in this study were divided into five parts in rotation, using different training and validation sets. The model was trained using a multi-output regression approach to quantitatively predict 13 skin Parameters. The loss was calculated using the Mean Absolute Error and the coefficient of determination R² in Equations (2) and (3).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_a - y_p\right|$$

2

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_a - y_p\right)^2}{\sum_{i=1}^{n}\left(y_a - \check{y_a}\right)^2}$$

3

Where y_a is the actual value and y_p is the predicted value. The MAE value is used to calculate the prediction error per skin Parameters. The larger the value, the further the predicted results deviate from the reference values. R² is calculated as the coefficient of determination. Thus, the correlation matrix and scatter plot can be used to examine the model's predicted output values and the actual Parameters values. Training-validation loss evaluation is performed to assess the stability of the process during training. Meanwhile, the Bland-Altman plot is used to evaluate the prediction results within the Limit of Agreement range via Eq. (4).

$$LoA = Bias \pm 1{,}96SD$$

4

SD stands for standard deviation. Using this formula, three boundary lines are obtained: the center line, the upper line, and the lower line. The center line is used to assess the bias of the prediction results, while the upper and lower lines serve as the upper and lower limits of agreement. The more prediction points that fall outside these limits, the less agreement the model has with the actual values from the VISIA Skin Analyzer.

3. Results

Dataset Characteristics

The distribution of the dataset in Fig. 2 is used to determine the range of values for each skin Parameters for regression modeling. This distribution significantly affects the stability of the training process and the model's ability to perform regression. The distributions of the acne, spots, and pores Parameters vary widely within the 0–100 range. However, the dark circle and skin color Parameters among respondents do not vary, so they are concentrated around a few values and form a discrete

graph. This variation in distribution has the potential to affect the model's ability to learn patterns in the lightweight CNN MobileNetV2.

Regression Performance Evaluation

The model was evaluated using MAE and R^2 to measure the discrepancy between the predicted results and the actual values. The MAE indicates the model's performance in predicting skin Parameters. The overall evaluation of the MobileNetV2 lightweight CNN regression model is presented in Table 2 below.

Table 2
Regression Values for Each Skin Parameter

Parameters	MAE	R^2	Parameters	MAE	R^2
Sebum	14,32	0,001	Skin Color	9,47	0,021
Pores	23,07	0,031	PL Sensitivity	25,59	0,014
Spots	13,45	0,142	UV Spot	11,91	0,039
Wrinkles	18,74	0,041	Pigment	9,18	0,103
Acne	15,46	0,032	UV Acne	22,2	0,078
Blackheads	24,09	0,037	Collagen Fiber	16,94	0,120
Dark Circle	13,83	0,003			

As shown in Table 2, some Parameters perform better than others. Spots, pigment, and collagen fibers are the highest-performing Parameters in the model because they are easy to learn and have a uniform distribution. In contrast, Parameters such as sebum and dark circles are the lowest-performing compared to the others. This indicates that the model's ability to recognize sebum and dark circles is very limited. This reduced performance is due to the model's difficulty in identifying oily areas on the face with complex skin textures.

Cross-Validation Evaluation

The stability of the lightweight CN MobileNet V2 model was evaluated using a 5-fold cross-validation approach. The dataset was divided into five sets for training and validation. Some Parameters showed fluctuating performance and tended to improve in Fold 5, as shown in Fig. 4 below.

The model's performance across folds shows a generally upward regression trend for all Parameters, particularly Collagen Fiber, UV Acne, Pigment, UV Spot, and Spots. These Parameters exhibit the best performance compared to the others. The regression value for sebum is nearly zero. This is because sebum is not visually observable or visible to the naked eye. Other Parameters, such as Pores, Skin Color, and Dark Circles, also tend to show regression values approaching zero.

The model's predictive ability is influenced by the composition of the training and validation data in each fold. This is due to the uneven distribution of Parameters data, making it difficult for the model to predict. These fluctuating regression values indicate that the model is highly sensitive to data partitioning. More complex image quality affects performance differences. Although Fold 5 tends to show a significant improvement in performance, the model's overall performance also takes into account folds 1 through the last.

Correlation Analysis of Skin Parameters

Correlation analysis was conducted using a linear relationship between actual and predicted values. A value of + 1 indicates a positive correlation between Parameters, while a value of -1 indicates a negative correlation. The closer the correlation approaches 0, the weaker the relationship between the Parameters. This correlation is visualized in the form of a correlation matrix in Fig. 5 below.

Figure 5 shows that some Parameters are interrelated. Consistently, the spot, pigment, collagen fiber, and UV acne Parameters exhibit a higher correlation between predicted and actual values than some of the other Parameters. The other Parameters are cross-correlated, indicating that the model has not yet optimally distinguished the characteristic capabilities of each Parameters.

Bland-Altman Analysis

The lightweight CNN model was also evaluated using a Bland-Altman plot to determine the degree of agreement between the actual values and the model's predicted results. The Bland-Altman analysis was used to examine the distribution of prediction errors within the limits specified in Eq. (4). The model's performance for each Parameters, based on the results of the Bland-Altman plot evaluation, is visualized in Fig. 6 below.

Most of the error distribution Parameters are evenly distributed. The Parameters for spots, acne, blackheads, UV acne, and collagen fibers form error distribution patterns that increase as the mean value rises. The prediction patterns are not constant across all Parameters values. The patterns for dark circles and skin color spread out in a diagonal line. This indicates that the model has a low ability to predict Parameters with random distribution patterns.

If the distribution pattern is above the mean, the model tends to overestimate. Conversely, if the distribution pattern is below the mean, the model tends to underestimate. Figure 6 also indicates that the model is random. The distribution patterns of the pores, sebum, UV spot, and pigment Parameters in Fig. 6 show error dispersion extending beyond the LoA limits. This indicates that the model produces predictions that are significantly different from the actual values. Overall, the Bland-Altman plot shows that the model does not yet have fully consistent predictive capabilities across all skin Parameters due to errors falling outside the LoA limits. Therefore, this multi-light CNN approach still requires further optimization to improve performance and reduce bias for certain Parameters.

Predicted and Actual Analysis

The scatter plot is presented as an evaluation tool to illustrate the relationship between predicted and actual values. Points on the scatter plot that lie close to the gradient line indicate that the relationship between predicted and actual values is linear. The scatter plot of the model is shown in Fig. 7. The R^2 values for the Parameters sebum, pores, spots, wrinkles, acne, blackheads, dark circles, skin color, PL sensitivity, UV spots, pigment, UV acne, and collagen fibers are, in order, 0.001; 0.031; 0.142; 0.041; 0.031; 0.036; 0.003; 0.021; 0.014; 0.039; 0.103; 0.079; 0.120. Thus, the best performance is consistently provided by the spot, collagen fiber, pigment, and UV acne Parameters.

As shown in Fig. 7, the predicted points on the scatter plot tend to cluster in a single area. This indicates that the model exhibits regression to the mean, which tends to predict values based on the overall average of the data. Model loss can be minimized, but not model sensitivity. Consequently, the R^2 value tends to be low, approaching zero. However, this low R^2 value does not indicate an error in model development. Rather, it reflects the limitations of the data. The development of multi-light facial imaging still faces challenges due to the complexity of the skin's biological characteristics. The presence of noise in the images and uneven distribution affect the evaluation of model performance.

4. Discussion

The multi-light facial imaging approach holds potential for the development of automated skin analysis systems based on lightweight CNNs. Multi-light imaging is used to enrich deep learning information compared to the use of RGB images. This study still has limitations regarding the relatively low regression performance for each Parameters. The relatively low R^2 values across several parameters, such as sebum and dark circles, highlight the significant challenge of predicting highly subtle visual features using a lightweight model without domain-specific attention mechanisms. Furthermore, the uneven distribution of the dataset across Parameters affects model performance. Additionally, the multi-light facial imaging approach, which still uses simple feature fusion, has not yet been able to optimize the relationship between the types of light used. This confirms that while multi-light imaging provides richer data, straightforward feature fusion requires more advanced temporal or spatial alignment in future iterations. Thus, this feasibility study indicates that the integration of multi-light imaging with lightweight CNNs still holds potential for the development of more accurate and efficient skin analysis systems

5. Conclusion

This feasibility study was designed using a multi-light facial imaging approach based on a lightweight CNN for automatic skin condition analysis. The lighting setup utilized eight types of illumination: white light, red light, blue light, brown light, UV light, Wu light, positive polarization, and negative polarization. This multi-light approach is used to obtain more complex and comprehensive skin information compared to using standard RGB alone.

The R^2 value obtained in this study is relatively low. This indicates that predicting skin parameters such as sebum and dark circles remains a challenge in the development of lightweight CNN with simple feature extraction. Limitations in data distribution, inter-subject variability, and image noise are among the factors contributing to the limited performance of lightweight CNN. Therefore, this study is best characterized as a preliminary feasibility and baseline study. Future research should involve larger datasets and a balanced distribution of variations. In addition, further development of preprocessing techniques, spatial attention, and multi-light fusion is essential for improving model accuracy.

Declarations

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Ethics Approval

This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Health Research Ethics Committee, Faculty of Nursing, Universitas Airlangga (Nomor: 4113-KEPK).

Consent to Participate

Informed consent was obtained from all individual participants included in the study.

Consent to Publish

The authors affirm that human research participants provided informed consent to publish the facial images in Fig. 1.

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Author Contribution

Detak Yan Pratama took the lead in research and manuscript preparation. Ghinasti Khansa Hamidah and Mohammad M. Afandi contributed to the preparation of the draft manuscript. Desiana Widityaning Sari and Myhammad Nazhif Haykal were responsible for data collection. Sefi Novendra Patrialova analyzed

the prediction results. Agus Muhamad Hatta directed and supervised the study. All authors reviewed and approved the final manuscript.

Data Availability

The datasets generated during and/or analysed during the current study are not publicly available due to privacy and ethical restrictions regarding human facial images, but are available from the corresponding author on reasonable request.

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Figures

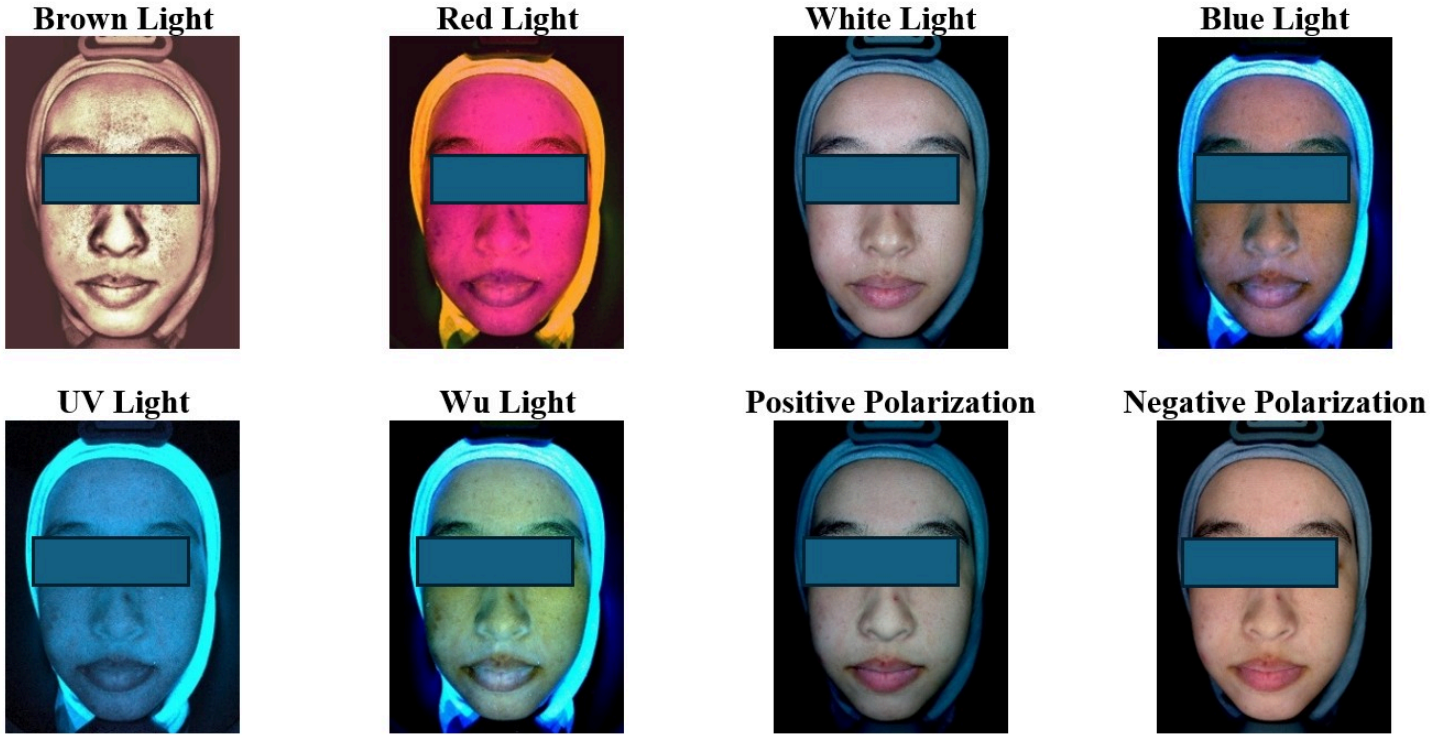


Figure 1

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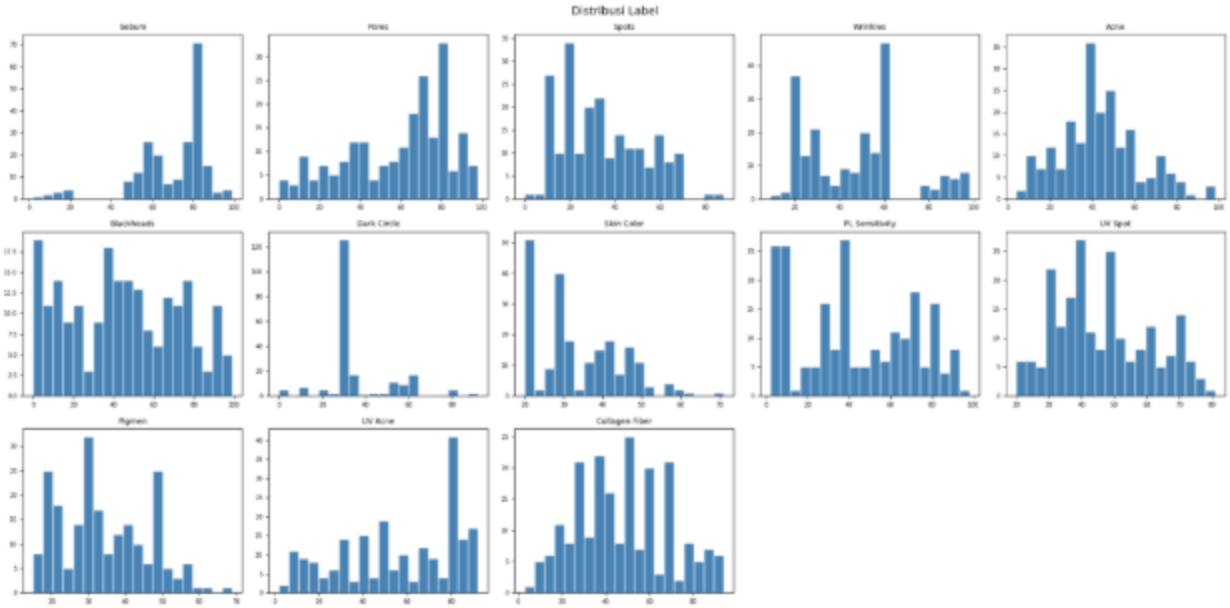


Figure 2

Dataset Distribution

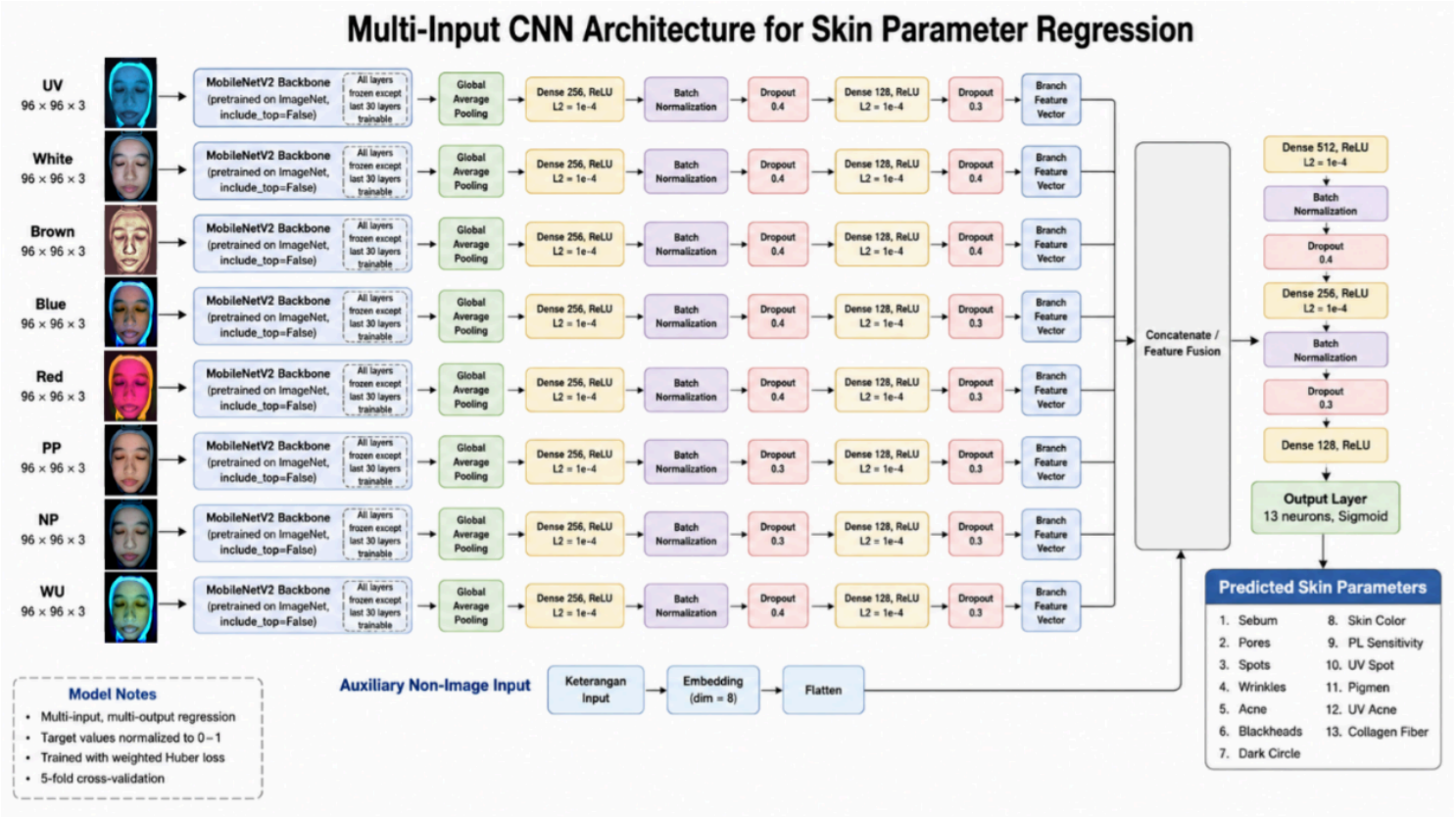


Figure 3

Lightweight CNN Architecture Diagram

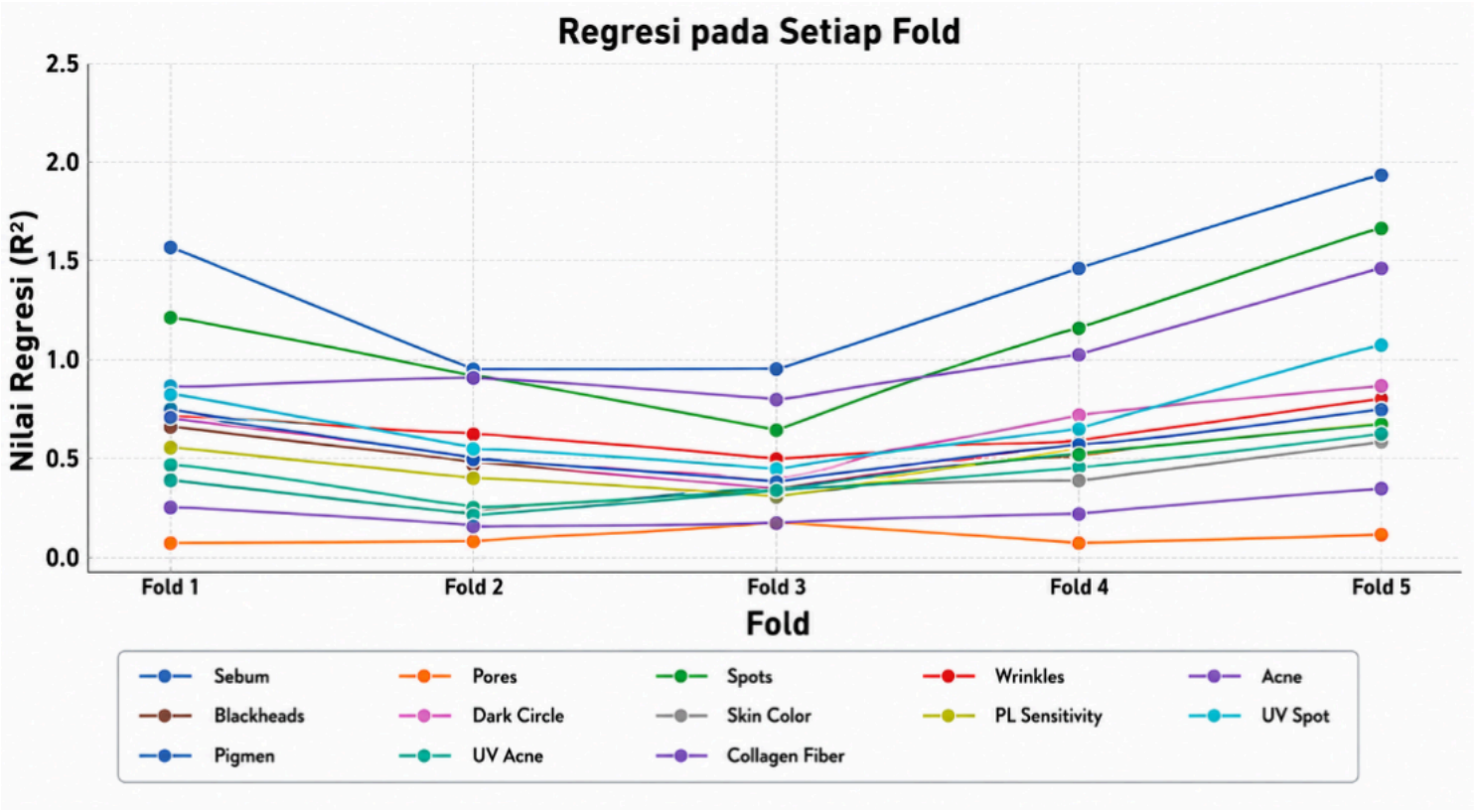


Figure 4

Performance of the Lightweight CNN for Each Fold

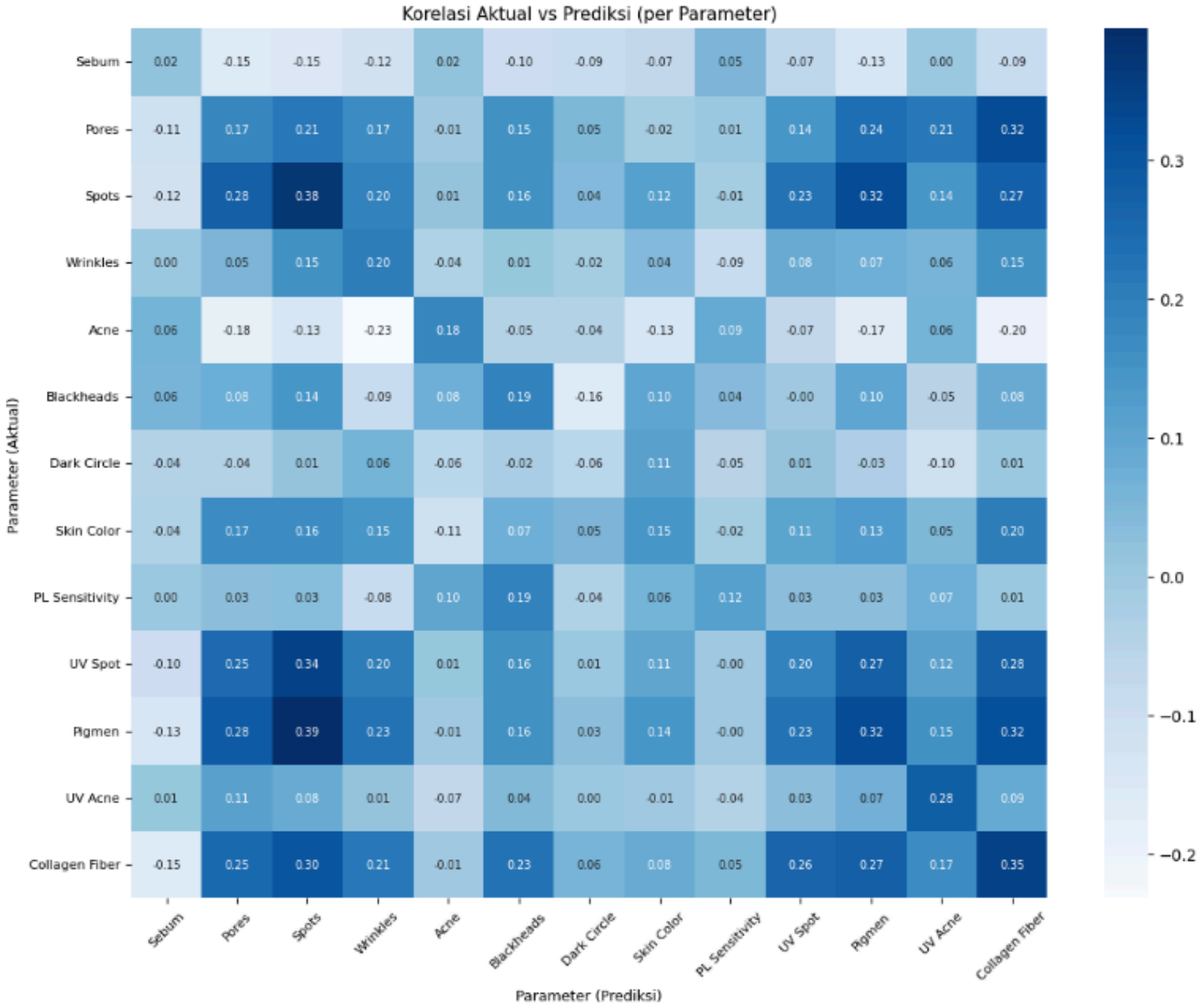


Figure 5

Matrix Correlation

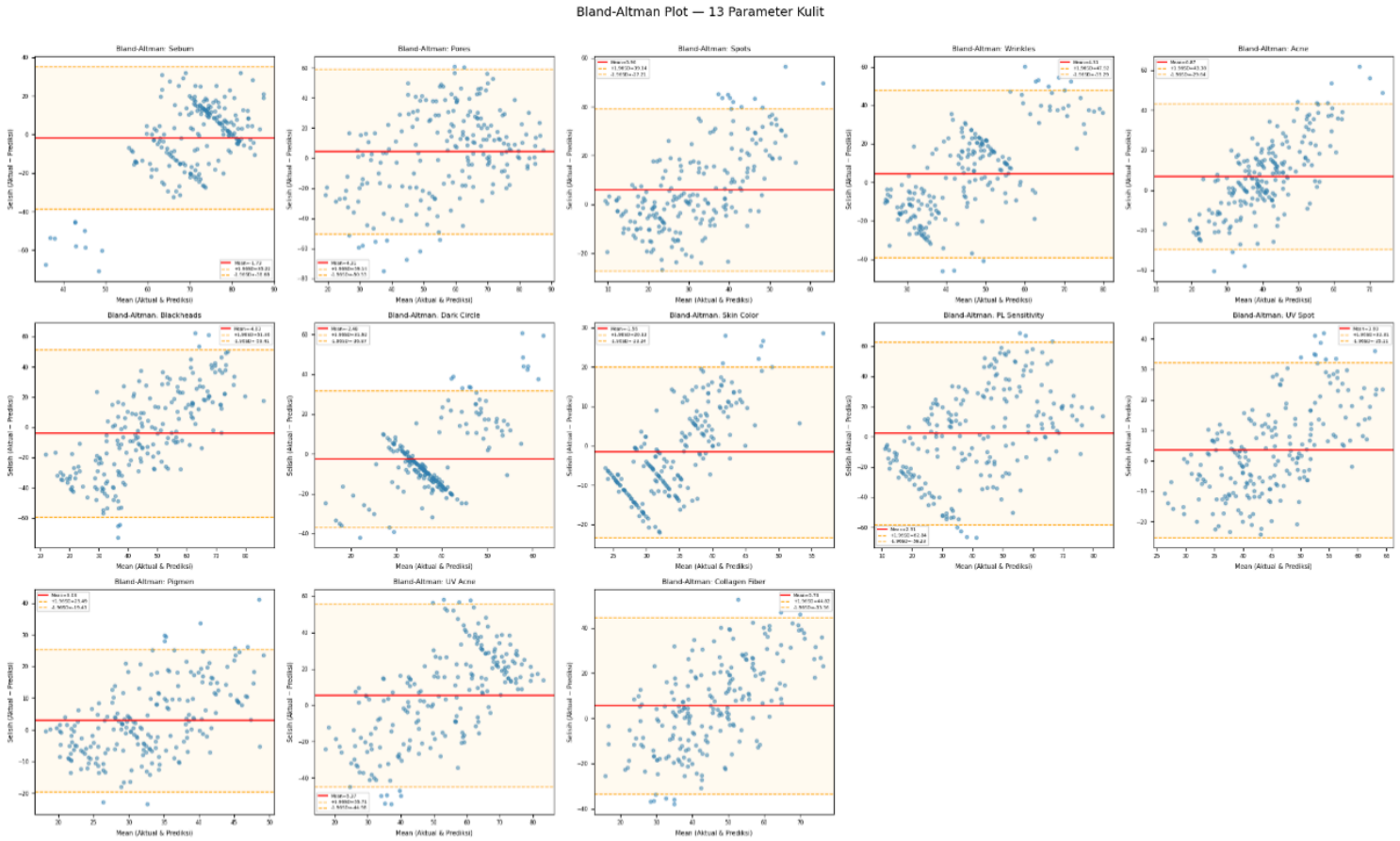


Figure 6

Bland-Altman Plot Analysis

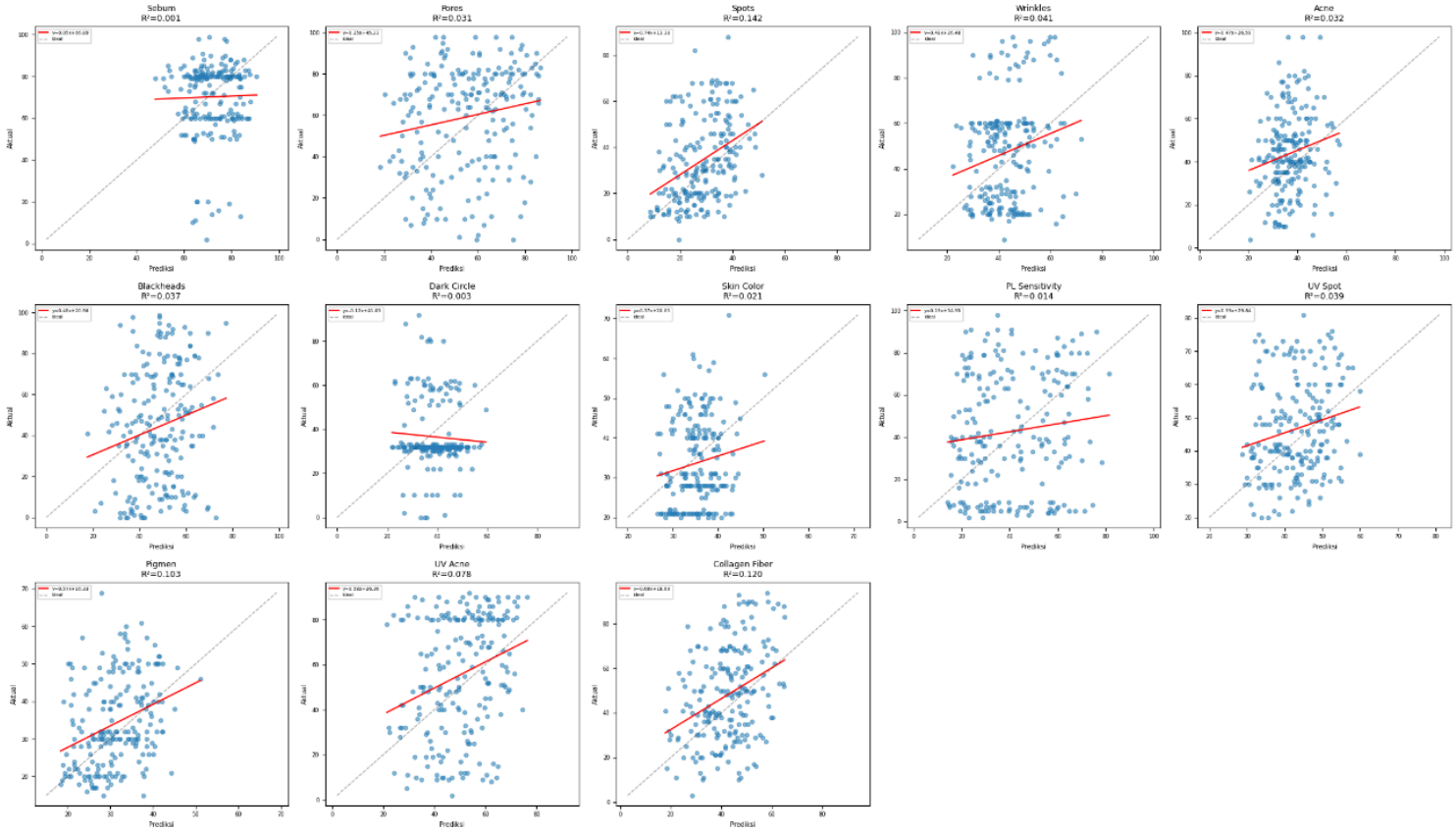


Figure 7

Scatter Plot