Skincare Recommendation System Based on Facial Skin Type with Real-Time Weather Integration

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***Abstract*— Skin conditions can be significantly affected by unpredictable weather changes, creating the need for a solution that can provide personalized skincare product recommendations. This study presents the development of an AI-based skincare recommendation system that integrates skin type classification using Convolutional Neural Networks (CNN) with real-time weather data via the OpenWeatherMap API. The system consists of three main components: a ResNet50-based Skin Analyzer, a Weather Analyzer using the Decision Tree algorithm, and a Product Recommendation module. The image dataset is sourced from two Kaggle datasets: "Dry, Oily, and Normal Skin Types" and "Acne Dataset." The total dataset consists of 2,885 images, divided into four classes: Acne (549 images), Dry (652 images), Normal (884 images), and Oily (800 images). The dataset exhibits diversity in skin types, allowing for a more valid evaluation of the CNN model. The training and testing process involved splitting the data into training and testing sets, with augmentation applied to the training data to enhance the feature diversity across classes. Evaluation results show an average validation accuracy of 90.94% ± 0.60% with consistent performance. This system aids users in identifying their skin type and suggests appropriate skincare products based on current weather conditions. It is expected to contribute to the advancement of AI-driven personalization in the skincare industry.**

Keywords*— *Weather, Skin Type Classification, ResNet50, Product Recommendation, Skincare

I. Introduction

In the ever-evolving digital era, artificial intelligence technology (Artificial Intelligence/AI) has been integrated into various aspects of life, including the beauty and skincare industries. AI can analyze large amounts of data and provide personalized recommendations more accurately [1]. One of the increasingly popular applications of AI is the recommendation system Skincare, which considers factors such as the individual preferences, the user's skin type, and environmental conditions, especially the weather Real-time. Environmental factors such as humidity, temperature, and UV exposure have a significant influence on skin health. For example, oily skin tends to be more prone to acne in hot and humid weather, while dry skin is more prone to irritation at low temperatures [2].

Based on surveys ZAP Beauty Index in 2023 and 2024, only about 5% of Indonesian women have a normal skin type. The rest experience various problems, such as dull skin (53.8%), panda eyes (33.3%), and signs of aging that are beginning to be felt by almost 30% of Gen Z women. Meanwhile, 99% of Indonesian men do not know their skin type, and although 56.6% understand the content of the product Skincare, only 4.1% understand it in depth [3]. The study indicates that there is still a significant number of users who struggle to select skincare products for their skin type and adjust to weather conditions.

Deep learning technology, especially regarding Convolutional Neural Network (CNN), holds a crucial role in improving skincare recommendation systems to be more adaptive. CNN can be used to analyze faces and classify them based on skin types, like oily, dry, and prone to acne. The data will then be combined with real-time weather information via API, used to give recommendations on products that are relevant to the user's skin condition and environment [4]. Information regarding skin types can be combined with real-time data that is obtained via API to give recommendations on skincare products according to the user's environment. A study in [5] considered using deep learning to analyze the content of cosmetics and skin condition, but it is void of the variable of environment, such as weather conditions [5]. Another study [6] focus mainly on product personalization on users and like the study in [5] did not consider the environmental conditions.

In everyday situations, weather conditions play an important role in a person's skin needs. Hot and humid weather often triggers increased oil production on the face, while cold temperatures can cause the skin to become dry and more prone to irritation [7]. Therefore, combining skin type classification technology with real-time weather data is a potential solution to provide more personalized and relevant skincare product recommendations. Not only that, the use of a camera to scan the face also allows skin condition analysis to be done instantly and practically, without the need for special tools or direct consultation with an expert [8].

In research conducted by [9], entitled “Deep learning-based skin care product recommendation: A focus on cosmetic ingredient analysis and facial skin conditions” focuses on analyzing cosmetic ingredients with deep learning and YOLOv4 to detect skin conditions. The results showed that the approach was able to identify the effectiveness of skincare products through ingredient analysis using deep learning, as well as provide personalized product recommendations based

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on the user's skin condition. However, the model still has limitations, especially in terms of the limited amount of valid data and the narrow scope of skin conditions, which affects the performance and generalization ability of the system [9]. Although Lee et al. proposed a robust integration of ingredient-based analysis and facial skin detection using U-Net and Transformer architectures, the system does not factor in external environmental variables such as real-time weather conditions, thereby limiting the contextual adaptability of the recommendations.

A study by [10] entitled “Designing a System to Recommend Skincare Products Using the NLP Method” proposes a Natural Language Processing (NLP)-based skincare product recommendation system that utilizes user reviews from the Female Daily platform. The system uses the cosine similarity method to measure product suitability with the user's skin type and successfully shows high accuracy in providing recommendations. This research is relevant because both aim to provide personalized skincare recommendations, although the approaches used are different [10]. While effective in measuring product suitability with user skin types, it lacks adaptability to real-time weather changes. Their approach leverages user-generated textual reviews, but the system solely depends on historical review content without accommodating dynamic factors like weather or instant skin conditions detected via image processing.

A study by [11] entitled “A Systematic Approach for Skin Disease Detection & Prediction by using CNN” developed an image classification-based skin disease diagnosis system using the Convolutional Neural Network (CNN) algorithm. The system receives input in the form of images of infected skin areas, then classifies them into certain types of skin diseases, such as melanoma, nevi, or other benign lesions. To improve accuracy, this research also uses data augmentation techniques because the dataset used is quite unbalanced. The results show that CNN has an accurate performance in recognizing various skin diseases from dermatoscopic images [11]. Although effective for medical diagnosis, it does not address cosmetic skincare recommendations or consider environmental adaptability.

Although several previous studies have explored AI-based skincare recommendations, facial skin classification, or cosmetic ingredient analysis, many of them ignore the influence of real-time environmental conditions, especially weather. This shows that most systems are still limited in terms of contextual awareness, despite the proven impact of environmental changes on skin health.

This research aims to design an artificial intelligence-based skincare recommendation system by combining skin type classification using CNN and current weather information to produce appropriate product suggestions. This research is based on the need for adaptive solutions in choosing skincare products, considering that weather changes can affect skin conditions and become a challenge for users in maintaining consistency in skincare routines. By applying machine learning and deep learning algorithms, this system is developed to help users choose appropriate skincare products based on a combination of skin type and current environmental conditions.

In terms of implementation, the developed system is expected to assist users in choosing skincare products more efficiently and in accordance with their actual conditions. In addition, the system also aims to educate users on the importance of adjusting skincare products to changing environmental conditions. The target audience of this research includes skincare product users who need technological assistance to improve skincare effectiveness, as well as researchers or application developers who are interested in integrating weather data into machine learning and deep learning-based models. Thus, this research is expected to contribute to the advancement of personalization technology in the beauty industry, which is increasingly sophisticated, adaptive, and data-driven.

Most previous studies only focused on either skin type classification or general skincare recommendations, and rarely considered changing weather conditions like temperature or humidity. This research fills that gap by combining facial skin analysis using CNN with real-time weather data, so the recommendations given can be more accurate and suitable for each user's current situation.

II. Research Methods

This research focuses on utilizing AI technology to provide personalized skincare product recommendations based on real-time weather conditions and the user's skin type. The results of this research are intended for individuals who care about skincare, especially those who experience problems such as oily, dry, and acne-prone skin. This research uses a quantitative approach by utilizing numerical and image data to train and evaluate CNN and Decision Tree models in a real-time weather-based skincare recommendation system.

The system works by utilizing the latest weather data through APIs and machine learning-based facial scans to detect the user's skin condition. The analysis results are used to recommend appropriate skincare products, such as moisturizer or sunscreen. This research aims to solve users' confusion in choosing skincare products and to adapt skincare to changing weather conditions.

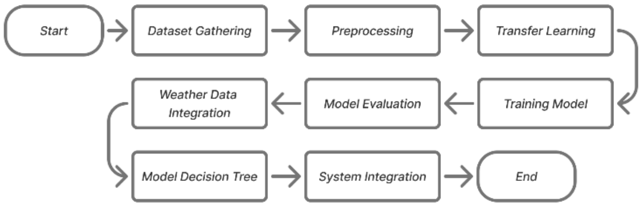

Fig. 1. Decision Tree-Based Recommendation Model

Figure 1 shows the workflow of the system developed in this study. The process begins with Dataset gathering and preprocessing to prepare facial image data. Furthermore, Transfer Learning and Training Models were carried out using CNN, followed by Model Evaluation to obtain the best skin type classification model. After that, the system integrates weather information at the Weather Data Integration stage, which is then combined with the Decision Tree model to

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generate skincare product recommendations. All stages end with System Integration to build a system that is ready to use.

Transfer learning is an approach that leverages pre-trained models to complete new tasks on different datasets, so the training process does not need to be done from scratch. In its implementation, adjustments are usually made at the end of the model to match the characteristics of the new data [12]. The CNN model itself generally consists of several layers that are in charge of extracting features from the image data.

A. *Dataset and Preprocessing*

The dataset used in this study comes from two different sources on the Kaggle platform, namely the "Dry, Oily, and Normal Skin Types" by Shakya Dissanayake [13] and "Acne Dataset" by Nayan Chaure [14]. The two datasets are then combined and classified into four skin types: Acne, Dry, Normal, and Oily. The dataset consists of four main classes, namely Acne, Dry, Normal, and Oily, with an unbalanced amount of data between classes. The total number of images used is 2,885, with the following distribution: Acne (549 images), Dry (652 images), Normal (884 images), and Oily (800 images). It should be noted that the datasets used do not include metadata such as age, gender, or ethnicity. As a result, this study does not analyze skin type classification performance across demographic groups. Future work is recommended to incorporate more diverse datasets to enhance generalizability.

The researcher decided to use the dataset in its original form without balancing (such as undersampling or oversampling), because based on the initial experiments, the balancing effort actually caused a significant decrease in model performance, with an accuracy of only about 50%–60% compared to the use of the original data which achieved an accuracy of more than 90%. Therefore, the data remains used in its original distribution to maintain the stability and accuracy of the model. The datasets are organized in a folder structure according to their respective classes and are loaded using ImageFolder from PyTorch. This process includes several stages:

a. Resize: All images in each dataset class are resized to 224x224 pixels to fit the required standard input of the CNN model.
b. ToTensor: The image is converted from the PIL Image format to the PyTorch tensor, with the pixel value scaled between 0 to 1.
c. Normalization: The image is normalized using the mean (mean) and standard deviation (std) values of the ImageNet dataset, which are:
   - Red: [0.485, 0.456, 0.406]
   - Std: [0.229, 0.224, 0.225]

B. *Skin Type Classification Model*

The architecture used is a ResNet50-based CNN. ResNet50 was chosen because it has a residual block structure that helps solve the problem of vanishing gradients during deep model training.

The model is trained using pre-processed facial data, with the configuration shown in Table 1:

- Loss Function: CrossEntropyLoss, because the classification is multi-class.
- Optimizer: AdamW, with an initial learning rate of 5e-5.
- Epochs: Models are trained for 20 epochs.
- Batch size: 32.

TABLE I. SKIN CLASSIFICATION MODEL CONFIGURATION

Yes	Component	Detail
1	*Loss Function*	*CrossEntropyLoss*
2	*Optimizer*	Adam
3	*Learning rate*	5e-5
4	*Epochs*	15
5	*Batch Size*	32

1. *ResNet50-Based CNN Model*

Convolutional Neural Network (CNN) is a type of artificial neural network architecture that is commonly used in image processing due to its ability to extract spatial features from images through a multi-stage learning process. CNN consists of several main layers, such as convolutional layers, activation layers (e.g., ReLU), pooling layers, and fully connected layers. The main advantage of CNN is its ability to recognize features in images well, even in conditions that are subject to position, scale, or distortion [15].

In the context of skin disease diagnosis, CNN is used to recognize certain visual patterns and characteristics in skin images, which allows the system to classify types of skin diseases with greater accuracy. CNN can learn to detect the distinctive features of skin diseases through the training process, so that it is able to distinguish diseases based on features that are difficult for the human eye to see [16].

The architecture used in the skin type classification model in this study is a ResNet50-based CNN. ResNet50 is a type of Deep Network residual learning-based that facilitates training by considering the Input layer as a reference. ResNet50 has 50 layers, where each block passes through three layers, including a 1x1 convolution layer [17]. In this study, ResNet50 was used as a Feature Extractor and a fine-tuned classification model on a facial dataset with skin type labels. The training process was carried out using Adam optimization and Loss Function of Cross-Entropy Loss.

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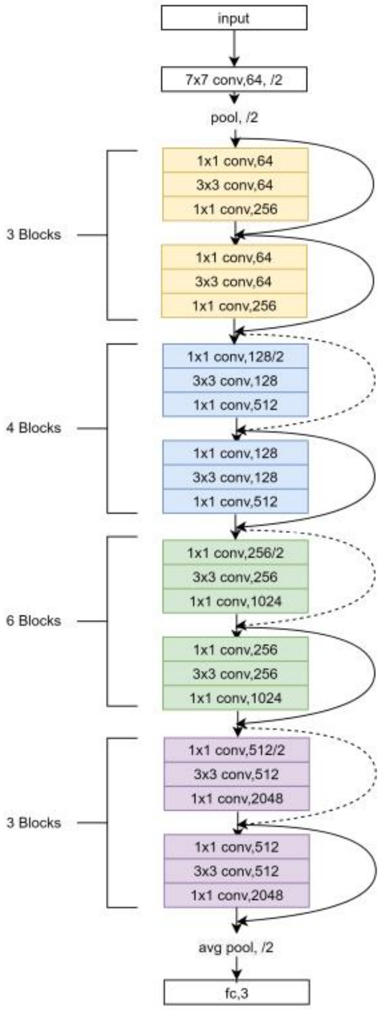

Fig. 2. ResNet50 Layer Architecture [18]

2. Tools and Frameworks

This study uses PyTorch as a Framework, a key element in model development for Deep Learning. PyTorch is one of the libraries in the Python programming language designed to support computing Deep Learning. Library. It is known for its flexibility in building models. Deep Learning uses intuitive and expressive Python syntax. This easy-to-use approach has made PyTorch popular among researchers since its inception, and over time, it has evolved to become one of the key tools in app development, Deep Learning Wide [19].

PyTorch also provides various modules that simplify the training process, such as torchvision. models for pretrained models (ResNet50), DataLoader for dataset management, and transforms for image augmentation and preprocessing. In addition to PyTorch, other tools and supports are:

- OpenCV: To detect faces in real-time via webcam before skin type classification.
- Torchvision: To load the dataset using ImageFolder and image transformation.
- Matplotlib and Seaborn: For visualization of accuracy, loss, and confusion matrix.
- Jupyter Notebook: As a model development and training environment.
- OpenWeatherMap API: To retrieve real-time weather data that will later be used in the recommendation system.

C. Weather and Its Effects on Skin

The weather has an important influence on skin health [7]. UV rays that are too strong will make the skin quickly damage and trigger diseases such as skin cancer [5]. Excessive sun exposure will make unprotected skin will be damaged, because human skin needs treatment that is appropriate to the skin problems it faces [20].

Exposure to sunlight and UV rays can cause the skin to appear dull, especially when sunscreen is not used. To address this, the application leverages real-time weather data to provide skincare recommendations that align with current weather conditions. By accessing weather information through an API, the system can tailor skincare advice based on factors such as UV intensity and humidity levels, helping users adjust their routines accordingly.

D. Face Detection

Before the skin type classification process is carried out, the initial stage is real-time detection of the user's face. This face detection serves to ensure that the input analyzed by the CNN model is an area of the face and not the background or other parts of the body. In this study, the MTCNN (Multi-task Cascaded Convolutional Networks) algorithm is used for real-time face detection and alignment prior to classification.

MTCNN is a method of face detection and alignment based on deep convolutional neural networks that performs joint face detection and facial landmark localization across three cascading stages of networks: P-Net, R-Net, and O-Net [21].

The rapid evolution of deep learning has significantly enhanced CNN-based face detection techniques. Early models like AlexNet, VGGNet, GoogLeNet, and ResNet have laid the groundwork for deep learning-driven improvements in image recognition and object detection [22].

Haar Cascade and MTCNN was two of the option choosen in this study, but considering that MTCNN has better robustness and accuracy compared to Haar Cascade, it was chosen as the ideal method, especially considering that under less ideal conditions such as partially covered faces, faces that are not directly facing the camera and low lighting, it could still detect faces while identying facial features thus making it very suitable for real-time applications that require accuracy and fast responds.

One of the primary reasons to use MTCNN is that it is robust for nonideal case. In tests, the system was able to accurately identify faces at all times, whether the user had light makeup or was in a low light environment. This is to improve the applicability of the system in daily life conditions and the reliability of the skincare recommendation process, which is proven with more operational angles use for recommendation and without the need for an ideal lighting or face directly facing the camera.

The MTCNN-based face detection system is created to be

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implemented in real-time and capable of detecting the face region accurately and processing it quickly. Performance measures of latency and frame rate will be outlined in greater depth in the Results section in Figure 7 though the decision to use MTCNN was based on its previously demonstrated real time performance. This is essential to enable the interactive characteristic of the skincare recommender system.

Once the skin type classification model has been trained and validated, it can be applied into a real-time face detector. In this setup, we used the MTCNN method to detect faces from the webcam directly. MTCNN was selected because of its higher accuracy and robustness than other methods (Haar Cascade,etc.), and in the uncertain lit conditions and face directions.

E. Skincare Product Recommendations

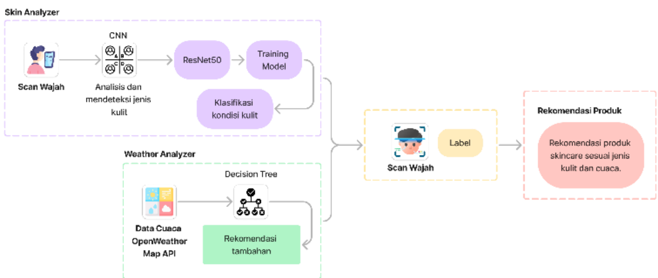

Fig. 3. Skincare Product Recommendation Framework

The proposed framework can be seen in Figure 3. The system consists of three main components, namely: Skin Analyzer, Weather Analyzer, and Product Recommendation Module. The Skin Analyzer component uses the ResNet50-based Convolutional Neural Network (CNN) model to classify the skin type of the user's facial image. The Weather Analyzer component utilizes the Decision Tree algorithm to generate additional recommendations based on weather data obtained in real-time through the OpenWeatherMap API. Furthermore, the results of skin type classification and weather information are then combined in the Product Recommendation Module, which will provide skincare product suggestions that best suit the user's needs based on current skin and weather conditions.

The service is configured to produce advice on the most suitable skincare product products to use for one’s skin condition and for current weather but does not include analysis of the particular products composition of ingredient. The whole procedure is kicked off from the Skin Analyzer, where a ResNet50 CNN model is applied to predict and classify the user skin type according to a pre-trained skin dataset. Meanwhile, the imposed weather data from the OpenWeatherMap API is also taken and using the Decision Tree approach and their corresponding weather-based suggestions are also suggested.

The results of this process are used to generate skincare product recommendations that cater to both the user's skin needs and the surrounding environmental conditions, which are then presented through the Product Recommendations module.

As seen in Figure 4 below, this system produces the final output in the form of personalized skincare product suggestions that consider skin classification and weather conditions. This integration enhances the relevance of product suggestions for individual users.

At this stage, the system also enables the user to provide the history of the product usage and allergies (optional) used to enhance the recommendations. This will become available in upcoming releases with more substantial user profiles and skin aspects.

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Tekan 'a' untuk mengambil gambar wajah...

Masukkan informasi tambahan:
Apakah kamu memiliki alergi pada bahan skincare tertentu? (Ya/Tidak): ya
Alergi terhadap bahan apa? (Contoh: Niacinamide, Parfum): glycerin
Apa nama produk skincare terakhir yang kamu gunakan? (kosongkan jika belum pernah):

--- REKOMENDASI SKINCARE ---
📍 Lokasi        : Bekasi
🌤 Cuaca         : Lembap (26.02°C, 83%)
🧬 Jenis Kulit   : Dry
🚫 Alergi        : Ya (glycerin)
📦 Riwayat Produk: Belum Pernah

🧴 Rekomendasi  : Produk basic tanpa iritan
💧 Bahan Aktif  : Squalane
🚫 Hindari      : glycerin, Produk trial-unknown
```

Fig. 4. Face Recognition System

III. Result and Discussion

In building a skin type classification model, the time required to do Training at Jupyter Notebook takes approximately 2 hours and 30 minutes using the components mentioned in Table 1. The following are the results obtained after doing Training to Accuracy and levels Loss.

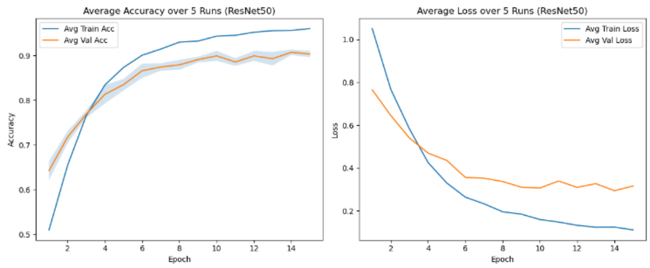

Fig. 5. Average Accuracy and Average Loss

The graph seen in Figure 5 shows the performance of the ResNet50 model during training and validation over 15 epochs, taken from an average of 5 experiments. The left chart depicts the average accuracy, while the right chart shows the average loss. It was seen that the training accuracy (Avg Train Acc) improved consistently and was quite stable close to 1.0, indicating that the model was able to learn well from the training data. The validation accuracy from the figure (Avg Val Acc) also improved rapidly at the beginning and then stabilized at around 91.00% ± 1.00%.

These results suggest that the model might be experiencing some overfitting. It continues to improve on training data, but performance on validation data does not increase further. However, when we look at other evaluation results like macro average accuracy, recall, and F1-score, as well as the confusion matrix, the model still performs well across all classes. So even if there are signs of overfitting, the model is still reliable and

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balanced in classifying skin types.

On the right chart, training losses (Avg Train Loss) dropped sharply to close to zero, while validation losses (Avg Val Loss) also decreased but tended to stagnate after the 8th epoch. This supports the earlier indication of possible overfitting, where the model continues to fit the training data very well while its performance on validation data remains unchanged. Even so, the overall performance remains stable and acceptable for the intended real-time skincare application.

This skin type classification model was trained 5 times using the same configuration for cross-validation purposes. This process aims to reduce the variance in training results and provide a more stable and accurate picture of model performance. From the five experiments, average performance metrics such as accuracy and loss were obtained, both in training and validation data.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{Number\ of\ Correct\ Predictions}}{\boldsymbol{Total\ Number\ of\ Data}} \times \mathbf{100}\%$$

The above formula is used to calculate the accuracy of each run, both on training and validation data. This average is then visualized in the previous graph, so that an analysis of the overall performance of the model can be carried out. The best results from each run were recorded for the validation accuracy (val accuracy), precision, recall, and F1-score metrics. Here are the results of the highest validation accuracy of each run, shown in Table 2:

TABLE II. VALIDATION ACCURACY SUMMARY

Yes	Run	Result
1	*Run 1*	90.81%
2	*Run 2*	91.37%
3	*Run 3*	90.47%
4	*Run 4*	90.36%
5	*Run 5*	91.70%

The average validation accuracy of the five runs was 90.94% with a standard deviation of 0.52%, calculated using the following average formula and standard deviation:

Average formula:

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

with:

$\bar{x}$ = average sample

n = total amount of data

x_i= the value of the i data

i= data index from 1 to n

Standard deviation formula:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

with:

s = standard deviation of the sample

n = total amount of data

x_i= the value of the i data

$\bar{x}$ = average sample

i = data index from 1 to n

This calculation aims to assess the consistency of model performance between runs. A low deviation value indicates that the model has a stable performance against training variations.

Furthermore, an evaluation was also carried out on macro classification metrics (macro average) to avoid bias against the majority class. The results of the macro evaluation of precision, recall, and F1-score from the five runs are shown in Table 3:

Table 3. Macro Evaluation Results

Run	Accuracy	Recall	F1 Score
1	90.99%	90.38%	90.66%
2	91.40%	90.65%	91.00%
3	90.17%	90.10%	90.11%
4	90.01%	90.31%	90.11%
5	91.42%	91.96%	91.64%

The average results of these metrics are:

- Accuracy: 90.80% ± 0.60%
- Recall: 90.68% ± 0.66%
- F1 Score: 90.70% ± 0.58%

The high average scores on these metrics indicate that the ResNet50 model is able to classify the entire class well, with a sufficient balance between the true positive rate (recall) and the prediction accuracy produced. This stable distribution of results reinforces the finding that the ResNet50 architecture can be used effectively in facial image-based skin type classification tasks, both to support skincare recommendation systems and as an initial component in dermatology-based facial recognition systems.

Figure 6 shows the confusion matrix from the best-performing model (Run 5) on the validation dataset. The matrix demonstrates strong classification performance across all four skin type categories: Acne, Dry, Normal, and Oily. The model correctly classified most samples, particularly in the Dry (302) and Normal (209) classes. A small number of misclassifications are observed, such as some Dry images being predicted as Acne (19) and Oily being confused with Dry or Normal (10 each). These confusions are understandable due to the visual similarity between certain skin types under specific lighting or image conditions.

This matrix complements the macro average metrics reported earlier, showing that the model not only achieves high

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overall accuracy but also maintains a balanced performance across all classes.

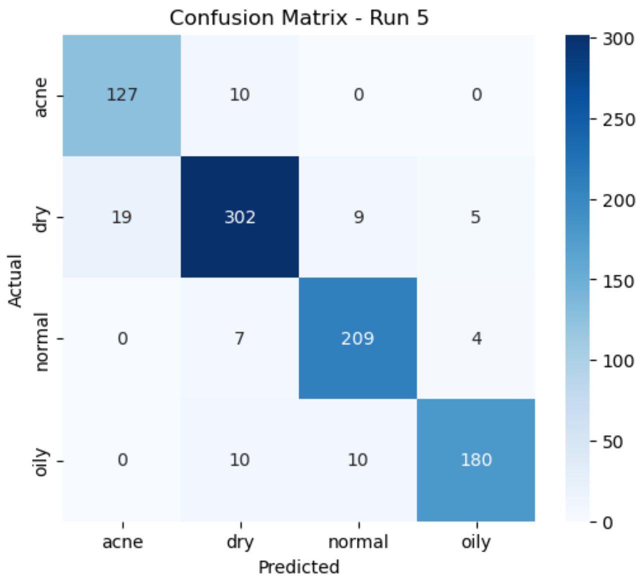

Fig. 6. Confusion Matrix of Skin Type Classification (Run 5)

These misclassifications, such as Dry being predicted as Acne or Oily being confused with Normal, are likely influenced by visual similarities between certain skin types, particularly under inconsistent lighting conditions or due to low-resolution image inputs from webcams. Such factors highlight the challenges of image-based classification in uncontrolled environments. Nonetheless, the model maintained high accuracy across all classes.

Compared to the study by Lee et al., which utilized U-Net and Transformer architectures for analyzing skin conditions, the ResNet50 model applied in this research demonstrated more stable performance, with an average validation accuracy of 91%, while offering significantly faster inference times. This reinforces its practicality for real-time skincare recommendation systems, where low latency and reliable output are critical.

To support real-time operation, the system processes facial input from a webcam feed. Once a face is detected using MTCNN, the region is cropped and resized to 224×224 pixels before being passed into the pre-trained ResNet50 model. The classification result is then combined with real-time weather data retrieved via the OpenWeatherMap API, categorized into Hot, Humid, or Cold based on temperature and humidity. These combined inputs form the basis for personalized skincare product recommendations, as illustrated in Figure 4.

To assess the responsiveness of the implemented real-time system, measurements were taken on the latency per frame and the frame rate (FPS) during webcam-based facial input. The evaluation demonstrated that the system processes each frame in approximately 62.29 milliseconds and maintains a frame rate of around 14.77 FPS, indicating its ability to operate efficiently in real-time with minimal delay.

In addition, the MTCNN-based face detection mechanism proved to be highly robust under various conditions, including suboptimal lighting and non-frontal facial positions such as tilted or partially obstructed views. This robustness enhances the system's practicality for everyday use without requiring controlled environments or precise user positioning (Figure 7).

```
Tekan 'a' untuk mengambil gambar wajah...

Real-Time Performance:
Rata-rata Latency per Frame: 62.29 ms
Frame per Second (FPS)     : 14.77

Masukkan informasi tambahan:
Apakah kamu memiliki alergi pada bahan skincare tertentu? (Ya/Tidak): ya
Alergi terhadap bahan apa? (Contoh: Niacinamide, Parfum): glycerin
Apa nama produk skincare terakhir yang kamu gunakan? (kosongkan jika belum pernah):

--- REKOMENDASI SKINCARE ---
Lokasi         : Bekasi
Cuaca          : Lembap (26.02°C, 83%)
Jenis Kulit    : Dry
Alergi         : Ya (glycerin)
Riwayat Produk: Belum Pernah

Rekomendasi   : Produk basic tanpa iritan
Bahan Aktif   : Squalane
Hindari       : glycerin, Produk trial-unknown
```

Figure 7. Real-time system output showing skin type detection and personalized skincare recommendation, including latency and FPS metrics.

IV. Conclusion

This research successfully developed an Artificial Intelligence-based skincare recommendation system that combines skin type classification with real-time weather data. The system meets the research objective by providing more personalized and context-aware skincare product recommendations, achieved through the integration of a ResNet50-based CNN for skin analysis and a Decision Tree algorithm for weather-based adjustment. The evaluation results show a high level of accuracy (90.94% ± 0.60%) and stable performance, supporting the system's effectiveness.

However, this study also has several limitations. First, the image dataset used, although diverse, is relatively limited in terms of ethnicity and lighting variations, which may affect the generalizability of the model in real-world conditions. Second, the weather categories used are simplified into three types (hot, humid, cold), which may not capture more nuanced climate variables. Future work may focus on expanding the dataset, integrating more detailed weather metrics.

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