Acne Skin Detection System Using You Only Look Once (YOLOv8) Based on Artificial Intelligence

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ABSTRACT
Acne is one of the most common skin problems among teenagers and young adults, and early detection is essential to prevent progression and long-term skin damage. This study aims to develop a real-time acne detection system utilizing the YOLOv8 deep learning algorithm, integrated with a Raspberry Pi and webcam, and supported by Telegram-based notifications for user monitoring. The dataset comprises 4,092 annotated facial images representing three types of acne: papule, pustule, and nodule. Model training was conducted in Google Colab with appropriate hyperparameter adjustments. The evaluation results show that the model performs well in detecting papule and pustule acne types, with correct predictions of 258 and 222 samples, respectively, in the confusion matrix, although misclassification remains high for comedones and background classes. The Precision–Confidence Curve indicates that the model achieves a perfect precision score of 1.00 at a confidence threshold of 0.929, while the F1–Confidence Curve shows an optimal F1-score of 0.73 at a confidence level of 0.39, demonstrating the best balance between precision and recall. Real-time testing further confirms that the system can detect papules with high confidence (88%), but confidence levels for comedones (31%) and nodules (29%) remain low due to visual similarity and non-ideal lighting conditions. Overall, the results indicate that the YOLOv8-based system is capable of performing real-time acne detection with acceptable accuracy. However, further improvements in dataset diversity and annotation quality are required to enhance performance, particularly for comedone detection.

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1. INTRODUCTION

Acne is a common inflammatory skin disorder that affects millions of people worldwide and often leads to long-term skin damage if not detected and treated promptly. Early symptoms such as comedones, papules, and pustules are frequently overlooked because they develop gradually and require continuous monitoring to recognize their progression. Without proper monitoring, acne conditions may worsen and lead to scarring, psychological distress, and a decline in overall skin health. This highlights the need for an accurate and real-time monitoring system that can assist users in identifying acne conditions early [1].

Several AI-based approaches have been developed for detecting acne lesions. Previous studies have introduced various deep-learning models such as YOLOv7, AcneDGNet, and DLI-Net, which have demonstrated good performance in lesion identification. However, these models still exhibit limitations:

YOLOv7 requires high computational power and tends to struggle with small object detection; AcneDGNet relies on complex architectures that reduce real-time efficiency; and DLI-Net, although accurate, is not optimized for multi-class acne detection across varied lighting and skin tone conditions. These limitations indicate that current models still lack a balance between accuracy, robustness, and processing speed for real-world acne monitoring applications [2].

Meanwhile, the introduction section of many existing studies still focuses on describing model performance without explicitly addressing the persistent challenges: (1) inconsistent accuracy when detecting multiple acne types simultaneously, (2) reduced performance under non-ideal lighting or home-use environments, and (3) limited applicability for real-time personal monitoring. These gaps show that previous research has not yet provided a practical, lightweight, and highly accurate solution that users can apply directly for continuous skin-health observation [3].

To address these unresolved challenges, this study employs YOLOv8, the latest evolution of the YOLO family, which introduces improved feature extraction, faster inference time, and higher precision in detecting small objects. YOLOv8 is designed to overcome several weaknesses found in earlier models, making it a strong candidate for real-time detection of acne. Unlike previous approaches, this research focuses on applying YOLOv8 specifically to multi-class acne identification and evaluating its performance in conditions that closely resemble daily usage [4].

The objectives of this research are to: (1) develop an acne detection system based on YOLOv8 capable of identifying multiple acne types accurately, (2) evaluate its performance in terms of precision, recall, and real-time detection capability, and (3) demonstrate how the proposed model addresses the limitations found in previous studies regarding accuracy, robustness, and practical usability [5].

This study offers novelty by integrating YOLOv8 into acne detection with a structured evaluation of its performance compared to the limitations of earlier models. It presents a clearer connection between the identified research gap and the proposed solution, providing a refined approach to real-time skin monitoring using modern deep-learning methods [3].

2. RESEARCH METHOD

This study involved different types of facial skin and acne. The facial skin samples were divided into three categories: normal skin, oily skin, and dry skin. While acne was divided into four categories: blackheads, papules, pustules, and nodules. 4,092 facial samples were used in this study.

The YOLOv8 model was tested by running Python scripts on the Google Colab platform, where several hyperparameters such as batch size, learning rate, and the number of epochs were configured to optimize the training process. During development, Visual Studio Code (VS Code) was used to edit and refine the program scripts before they were integrated into Python-based or IoT-based applications. After integration, the program was executed through the Command Line Interface (CMD) to ensure proper functionality and system responsiveness [6]. The detection performance was observed on facial images with varying skin types, lighting conditions, and face orientations to evaluate the model's robustness in different environments. In real-time implementation, facial skin type and acne analysis data captured by the webcam were processed through the Raspberry Pi 4, which subsequently sent the detection results to the Telegram application for user monitoring and notification [7].

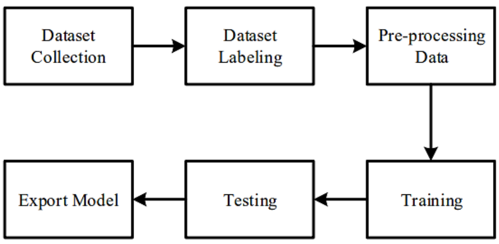


Figure 1. YOLO Block Diagram

In Figure 1 is a flow used in this research which is as follows. The first stage of this project involves collecting facial images that display various acne conditions. After the dataset is gathered, each image is annotated using bounding boxes to mark the precise location of acne lesions, allowing the YOLO algorithm to learn and recognize acne as an object during training. Before the model is trained, the dataset undergoes a preprocessing phase to adjust image formats and enhance overall quality, ensuring consistency and clarity within the training data [8]. The YOLOv8 model is then trained using the labeled and preprocessed images, enabling it to learn the visual characteristics of different acne types. Once the training process is completed, the model is evaluated using unseen test images to assess its generalization ability. If the test results meet the expected performance criteria, the model is exported and saved in a specific format, such as *.pt* for PyTorch-based YOLOv8, so it can be deployed for further use in the acne detection system [9].

2.1. Dataset

The datasets used for YOLOv8 object detection should reflect the application environment conditions such as object variations, lighting, and background. Several studies have shown that the quality and diversity of datasets are critical to improving the performance of YOLOv8.

SOD-YOLOv8, an improved model for detecting small objects in traffic scenes, was introduced in a study by Khalili and Smyth (2024) [10]. They emphasized that the YOLOv8 architecture can significantly enhance the accuracy of small object detection by incorporating a fourth detection layer and an Effective Multi-Scale Attention (EMA) module, particularly when the dataset comprises small, challenging-to-detect items.

The dataset used consists of over 4,092 facial images that have been annotated with the presence of acne. This dataset includes different types of acne (papule, pustule, nodule) and various skin colors with different lighting conditions. Public datasets such as ACNE04 and images from Roboflow were used, as well as manual annotation using Labeling [11].

2.2. Dataset Collection

This study only uses three types of datasets, namely papule, pustule, and nodule. Figure 2 illustrates the various types of acne.

Figure 2. Types of Acne

In this study, the dataset taken from the Roboflow website is in the form of acne images with 3 types (papule, pustule, nodule). These data will then be subjected to a training process later

2.3. Dataset Labeling

The process of dataset labeling in YOLOv8 object detection is a critical step that has a direct impact on the performance and accuracy of the model. Data labeling, also referred to as data labeling, is the process of annotating raw data, such as images or videos, with relevant information, such as the position and class of objects present in the data. This process allows the model to recognize patterns and make accurate predictions [12].

To teach the neural network model what to recognize, objects in the image are labeled. YOLO usually uses bounding boxes or polygons to mark objects such as pimples, blackheads, or skin inflammation. Their annotations are usually in the.txt format, which contains the class, position, and size of the object. However, a form of polygonal labeling commonly used with tools like LabelMe and Roboflow is seen in this image [13]. Figure 3 is an example of the data labeling process in Roboflow.

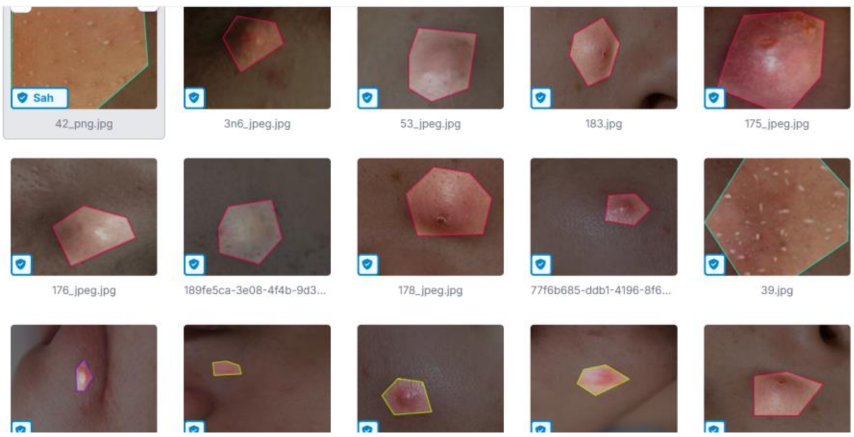


Figure 3. Example of data labeling in Roboflow

The data labeling process for the YOLO (You Only Look Once) based acne detection project is shown in Figure 3. Since the quality of annotations affects the detection accuracy, this labeling process is a very important early stage in the development of deep learning-based detection models. These images are slices of facial skin with different types of acne that have been labeled with polygon annotations.

Figure 3 shows the colorful polygons surrounding the acne area. These colors, which are derived from red, yellow, and green, may indicate different types of acne, such as Inflamed acne, also known as inflammatory acne, and Blackheads (black or white hair). Acne scars, also known as acne scar marks, are very important marks if the dataset is used for training multi-class classification models.

2.4. Model Development Using YOLOv8

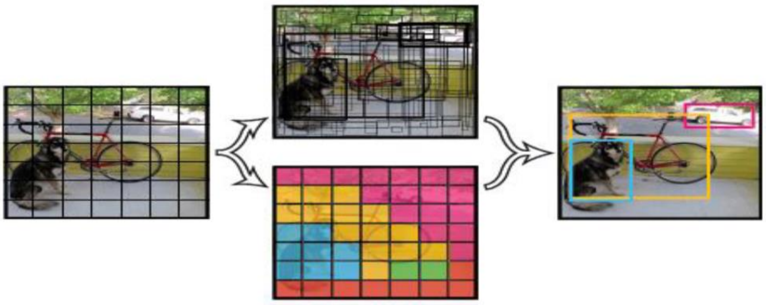


Figure 4. YOLO Algorithm Work Process [14]

YOLO algorithm work process can be seen in Figure 4. The development of the acne detection model in this study was carried out using the YOLOv8 architecture, which provides improvements in feature extraction, inference speed, and small-object recognition. The modeling process began with dataset preparation consisting of 4,092 acne images that had been annotated into three classes: papule, pustule, and nodule [15]. These annotated images were divided into training, validation, and testing sets to support a systematic model-building workflow. During model initialization, several hyperparameters were configured, including a batch size of 16, a learning rate of 0.001, an input size of 640×640 pixels, and a training duration of 100 epochs. These settings were selected based on preliminary trials to obtain stable convergence without overfitting [16].

Several experiments were conducted to optimize the performance of the YOLOv8 model. The first experiment tested different learning rates (0.0005, 0.001, and 0.002) to observe their effect on precision and recall. A learning rate of 0.001 produced the most stable training curve. The second experiment evaluated the impact of image resolution (416×416 vs. 640×640), where the 640×640 resolution yielded better detection of small acne lesions. A third experiment tested the use of data augmentation, including flipping, brightness adjustments, and rotation, which helped increase model robustness against lighting variations and face orientations. These experiments ensured that the final model configuration used in this study was the most optimal among the tested variants [17].

After the training experiments were completed, the model was evaluated using several standard performance metrics. The confusion matrix showed that the model achieved high correct classifications for papule (258 correctly predicted) and pustule (222 correctly predicted), although misclassifications still occurred, particularly for comedones and background classes. The Precision–Confidence Curve demonstrated that the model reached a perfect precision score of 1.00 at a confidence threshold of 0.929, indicating strong reliability at high confidence levels. Meanwhile, the F1–Confidence Curve showed an optimal F1-score of 0.73 at a confidence level of 0.39, representing the best balance between precision and recall. These results validate that the trained model performs well across multiple acne types [18].

To ensure practical usability, the trained YOLOv8 model was deployed in a real-time testing environment using Raspberry Pi 4 with a connected webcam. Real-time evaluation revealed that the model could detect papules with high confidence (88%), while confidence levels for comedones (31%) and nodules (29%) were lower, primarily due to similarity in color tone and low contrast. The successful integration with Telegram further demonstrated that the detection system can operate continuously and provide instant feedback to users. This stage confirmed that the YOLOv8 model is not only accurate in experimental settings but also functional in real-time scenarios, fulfilling the objective of developing a practical acne detection solution.

3. RESULT AND ANALYSIS

Here are the findings of the acne detection model's performance evaluation based on the computed metrics and visualizations, such as the confusion matrix and evaluation curve. Interpreting the model's performance for each acne class and identifying flaws and areas for development were the goals of the analysis. It is anticipated that these findings will advance knowledge of the model's capacity to reliably and precisely identify various forms of acne. This is particularly true when using the model in the actual world.

3.1. Confusion Matrix

At this point, the model's efficacy and accuracy in categorizing the different forms of acne that the system has identified are assessed using a confusion matrix. This confusion matrix graph compares the true label (actual label) with the model-predicted label (predicted label) for three different categories: comedones, nodules, and papules. This graph allows us to directly see how well the model is able to recognize and differentiate each type of acne. It also allows us to determine the locations where the model has misclassified. Therefore, the confusion matrix is one of the important tools in the process of analyzing the performance of artificial intelligence-based models, especially for automated acne detection projects that use the YOLOv8 algorithm [19]. Figure 5 shows the evaluation result of the confusion matrix.

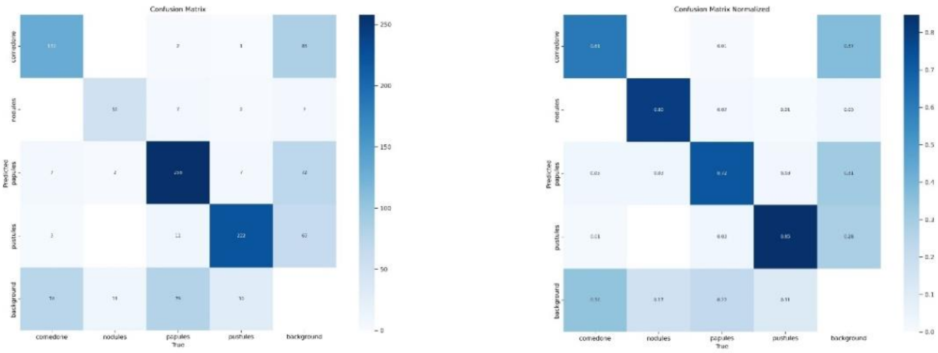


Figure 5. Confusion Matrix Evaluation Results

The effectiveness of the categorization model in identifying various forms of acne, such as nodules, papules, pustules, comedones, and background, is assessed in Figure 5. The results show that the model classifies well the papules and pustules acne types, with a high number of correct predictions, 258 and 222 respectively. However, the model failed to identify the pustules acne type, as indicated by the lower number of predictions. In addition, the background class can cause large errors as many comedones, papules, and pustules data are misclassified as background. For example, 85 comedones and 72 papules were considered as background [20].

3.2. Precision Confidence Curve

To support the performance evaluation of the created acne detection model, further analysis was done. The relationship between the accuracy of the projected outcomes and the model's degree of prediction confidence is displayed by the Confidence-Accuracy Curve graph. By looking at this curve, we can see how the performance of the model changes at various confidence thresholds, and we can figure out that as a result, this graph is very important to use as an aid in determining the right threshold for more accurate detection results. This is especially true when the model is applied to real environments or automated artificial intelligence-based systems [21]. Figure 6 is an image of the Precision Confidence Curve.

The acne detection model exhibits an increasing degree of precision in tandem with the level of confidence, as indicated by the Precision-Confidence Curve graph. The prediction is extremely accurate if only carried out at a high confidence threshold, as the model achieves the highest level of precision (1.00) with a confidence of almost 0.929 [22]. The model is still challenging to accurately categorize, as comedones are more precise, and pustules and papules are the most stable lesions. This graph helps identify the ideal confidence level to enhance the accuracy of model predictions.

3.3. F1-Confidence Curve

To support the performance evaluation of the generated acne detection model, visual analysis was carried out. The link between the model's confidence level in relation to the predictions and the F1-score value produced at different confidence levels is displayed in the F1-Confidence Curve graph. The F1-score, a statistic that combines precision and recall, is frequently used to assess classification models. With the help of this graph, we can determine the confidence point at which the model performs at its best. Additionally, we can comprehend the traits of each sort of acne that the model discovered, including comedone, papule, pustule, and nodule [23]. Figure 7 is an image of the F1 Confidence Curve.

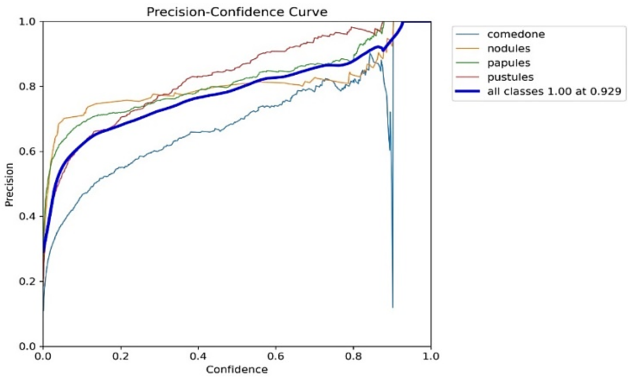


Figure 6. Precision Confidence Curve

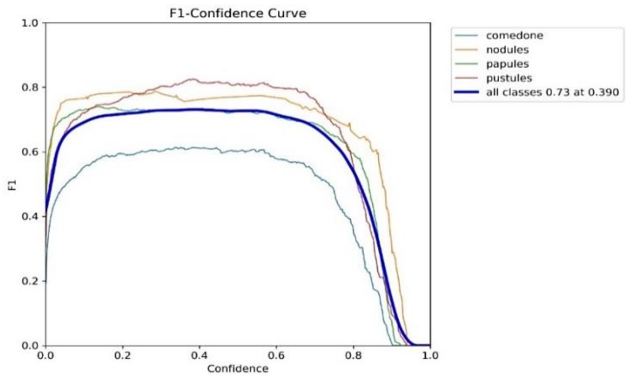


Figure 7. F1-Confidence Curve

The F1 Confidence Curve graph Figure 7 shows the F1-score for each acne class of comedones, nodules, papules, and pustules and the confidence level of the model. The thick blue line shows the combined results for each class, with the highest F1 value of 0.73 at 0.39 confidence, indicating that a confidence threshold of 0.39 is best for balancing precision and recall. Nodules and pustules show a greater level of activity than comedone, and suggest that the model is better suited for finding more visible types of acne. The drastic drop in F1 confidence indicates that the model becomes too selective and loses many accurate predictions [24].

3.4. Accuracy Testing

After the entire model training and validation process is completed, the next stage is testing the accuracy of the real-time acne detection system. Accuracy testing is done in real-time using a webcam camera that captures the user's face. Then, the trained YOLOv8 model is used on a Raspberry Pi to process the data, result the tes showed that models were able to detect papule-type acne with high accuracy (88%), but due to visual similarity and non-ideal lighting, they still detected comedones (31%) and nodules (29%). Despite this, the system was still able to provide the correct classification, which shows that the model is quite reliable despite its lack of confidence. Factors such as differences in skin tone, lighting, and face angle affect the detection ability, so further research should concentrate on adding representative data, developing methods, and optimizing the model to improve generalization to real situations [25]. Table 1 shows an example of system accuracy testing.

The Table 1 shows the results of testing the accuracy of real-time acne detection on three sample facial photos. The model analyzes each image to identify acne types such as papules, comedoes, and nodules, and then shows the accuracy (confidence) level of each prediction. The accuracy values found varied from 29% to 84%, but the model was still able to produce correct predictions according to the expected labels. This shows that the detection system can perform low-confidence classification.

Figure 8 shows the results of acne detection using the YOLO-based deep learning model. The model can identify and classify various forms of acne on a young man's face, including papules, pustules, comedones, and nodules, each accompanied by a corresponding confidence value (representing the model's confidence level). These results demonstrate that, although some labels are double-detected or overlapped, the model can accurately detect multiple lesions in a single image and distinguish between different types of acne. This indicates that the detection system has achieved a sufficient level of success, but Improvements can still be made in terms of classification, accuracy, and reduction of over-prediction (redundancy) [26].

Table 1. Sample Accuracy Testing

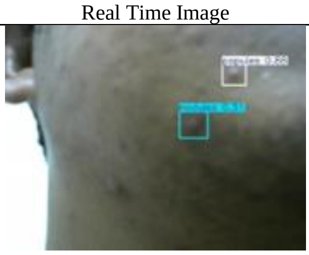
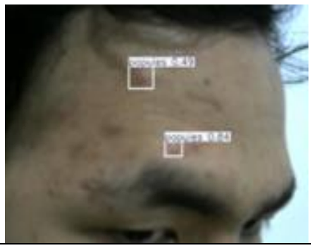
No	Real Time Image	Expected Results	Accuracy	Results
1		Papule	88%	True
2		Comedoes	31%	True
3		Nodule	29%	True

Figure 8. Real-Time Image Detection

3.5. Discussion

The accuracy results of this study show that YOLOv8 can detect papules and pustules with good performance, although the detection of comedones and nodules remains less optimal. This pattern is similar to findings in earlier studies, where small and low-contrast acne types were consistently difficult for detection models to classify accurately. These similarities indicate that the main challenge lies in the visual characteristics of the lesions rather than the specific algorithm used [27].

When compared with previous YOLO-based acne detection studies, the precision and F1-score results in this research show competitive performance. YOLOv8's ability to achieve perfect precision at higher confidence thresholds reflects the behavior reported in earlier YOLOv5 and YOLOv7 studies, where high confidence values were needed to maintain stability. However, the anchor-free structure of YOLOv8 allows for slightly better adaptability in varied lighting conditions than older YOLO versions [28].

Compared with hybrid or segmentation-supported models such as AcneDGNet or DLI-Net—which recorded higher accuracy due to richer feature extraction—YOLOv8 in this study performs lower for subtle lesions. However, YOLOv8 offers the advantage of faster inference and simpler deployment, making it more practical for real-time use. This contrasts with many earlier studies that focused solely on offline model evaluation on high-spec hardware [29].

Overall, the results of this study align with the general trends identified in previous literature, while also highlighting the added benefit of real-time implementation. Although improvements are still needed for small lesion types, the use of YOLOv8 on lightweight hardware like Raspberry Pi demonstrates its practical value for IoT-based acne detection systems. Future enhancements in dataset diversity and annotation quality may help bridge the remaining performance gaps [30].

4. CONCLUSION

This study developed a YOLOv8 algorithm-based acne detection system that can quickly identify various types of acne. The system enables automatic and effective monitoring of facial skin by utilizing a webcam, Raspberry Pi, cloud platform, and Telegram application. The dataset used enhances the model's generalization ability by including various types of acne and diverse lighting conditions.

Additionally, real-time testing demonstrates that the system can detect acne in various lighting conditions and across different skin types. Although there was little confidence in some predictions, the classification results still matched the actual labels. This demonstrates that the system can be utilized as a tool for self-monitoring users in daily life, particularly for teenagers and young adults who are prone to acne. According to the performance evaluation conducted using a confusion matrix, a precision-confidence curve, and an F1-confidence curve, the models demonstrate sufficient accuracy and precision in identifying papule and pustule acne types. Although it is difficult to accurately classify comedone and pustule types, the system can still provide relevant detection results with acceptable confidence levels in practical situations.

However, the system still struggles to accurately identify comedone acne types. The evaluation results indicate that comedones have a relatively high classification error. This may be due to the visual similarity between comedones and normal skin areas, as well as the absence of type-specific training data. Therefore, to enhance the model's performance in the future, dataset enrichment and improvement of annotation quality are necessary. Although the confidence value remains low, real-time testing of several samples indicates that the system can identify acne types with sufficient accuracy. Overall, the integration of YOLOv8 into this acne detection system proved to be effective and has many opportunities for further development in technology-based healthcare.

Overall, this YOLOv8-based acne detection algorithm has been proven to detect various types of acne with a decent level of accuracy. In the field of dermatology, the integration of Internet of Things and AI technologies offers a practical, low-cost, and widely accessible solution. The development of a multi-classification model that encompasses a broader range of acne types could be the focus of future research. In addition, this model can be applied to a more user-friendly mobile application.

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