 doi:10.20944/preprints202206.0384.v1

Article

Automatic Acne Object Detection and Acne Severity Grading Using Smartphone Images and Artificial Intelligence

Quan Thanh Huynh [1,+], Phuc Hoang Nguyen [1,2,+], Hieu Xuan Le [1], Lua Thi Ngo [1,2], Nhu-Thuy Trinh [1,2], Mai Thi-Thanh Tran [1,3], Hoan Tam Nguyen [1,3], Nga Thi Vu [1,4], Anh Tam Nguyen [1,5], Kazuma Suda [6], Kazuhiro Tsuji [7], Tsuyoshi Ishii [6], Trung Xuan Ngo [6,+], and Hoan Thanh Ngo [1,2,+]

1 Medical AI Co., Ltd., Ho Chi Minh City, Vietnam; hthquan28@gmail.com; lexuanhieu131297@gmail.com
2 School of Biomedical Engineering, International University, Vietnam National University-HCMC, Ho Chi Minh City, Vietnam; nhoangphuc.bme@gmail.com; ntlua@hcmiu.edu.vn; tnthuy@hcmiu.edu.vn,
3 University of Medicine and Pharmacy Clinic 1, Ho Chi Minh City, Vietnam; dungmaititi@yahoo.com; bstamhoan@gmail.com
4 People's Hospital 115, Ho Chi Minh City, Vietnam; vunga0501@gmail.com
5 School of Medicine, Vietnam National University-HCMC, Ho Chi Minh City, Vietnam; ntamanh@medvnu.edu.vn
6 Rohto Pharmaceutical Co., Ltd., Basic Research Division, Research Village Kyoto, 6-5-4 Kunimidai, Kizugawa, Kyoto 619-0216, Japan; suda@rohto.co.jp; ishii@rohto.co.jp
7 Rohto Pharmaceutical Co., Ltd., Regulatory Affairs Promotion Division, 1-8-1, Tatsumi-nishi, Ikuno-ku, Osaka 544-8666, Japan; ktsuji@rohto.co.jp
* Correspondence: ngoxuantrung@rohto.co.jp; nthoan@hcmiu.edu.vn
† These authors contributed equally to this work

Abstract: Skin image analysis using artificial intelligence (AI) has recently attracted significant research interest, particularly for analyzing skin images captured by mobile devices. Acne is one of the most common skin conditions with profound effects in severe cases. In this study, we developed an AI system called AcneDet for automatic acne object detection and acne severity grading using facial images captured by smartphones. AcneDet includes two models for conducting two tasks: (1) a Faster R-CNN-based deep learning model for the detection of acne lesion objects of four types including blackheads/whiteheads, papules/pustules, nodules/cysts, and acne scars; and (2) a LightGBM machine learning model for grading acne severity using the Investigator's Global Assessment (IGA) scale. The output of the Faster R-CNN model, i.e., the counts of each acne type, were used as input for the LightGBM model for acne severity grading. A dataset consisting of 1,572 labeled facial images captured by both iOS and Android smartphones was used for training. The results show that the Faster R-CNN model achieves a mAP of 0.54 for acne object detection. The mean accuracy of acne severity grading by the LightGBM model is 0.85. With this study, we hope to contribute to the development of artificial intelligent systems that are able to help acne patients understand more about their conditions and support doctors in acne diagnosis.

Keywords: Deep Learning; Smartphone Image; Acne Grading; Acne Object Detection

1. Introduction

Acne is one of the most common skin conditions [1], with acne prevalence reaching 9.38% among the entire world population [2]. Acne occurs owing to blockage or damage of the sebaceous glands and hair follicles. The most common areas affected are the face, chest, neck, shoulders, and back [3]. Acne lesions can be classified into two major types based on their non-inflammatory and inflammatory characteristics. Non-inflammatory lesions include blackheads and whiteheads. Inflammatory lesions include papules, pustules, nodules, and cysts [4]. Acne mainly occurs in adolescents at puberty, affecting 85% of adolescents, and can persist into adulthood [1]. Acne can cause a wide range of effects, from a physical appearance, e.g, scars, to a psychological effect, such as anxiety, poor self-image, lack of confidence, and other negative issues [5]. Improper treatment or delays can lead to damage to physical and mental health, which sometimes cannot be

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

restored. Approximately 20% of people affected by acne develop severe acne, which results in scarring [6]. In addition to its impact on individual patients, acne also has a significant impact on the economy. In the United States, the total treatment costs and loss of productivity related to acne have reached $3 billion [7]. According to the US Food and Drug Administration (FDA), the average cost per person for acne treatments over a 7-month period is $350 to $3,806 [8]. An accurate and timely diagnosis of acne is an important factor in the effective treatment of acne.

To receive a diagnosis, acne patients traditionally have had to visit a doctor's office, where the dermatologist would often observe the affected areas by the naked eye or through a dermatoscope. In combination with other types of information, dermatologists will give a diagnosis. This process is highly dependent on the expertise and experience of the dermatologist [9, 10]. In addition, owing to a lack of dermatologists in many areas of the world, many patients have to travel long distances or wait for a long time before they can see one. Recent advances in smartphone technology and its high penetration, with approximately 3.2 billion people around the world using smartphones [11], are opening doors for many smartphone-based solutions in healthcare [12]. One example is teledermatology, in which patients can receive consultations from a dermatologist at home through a smartphone without a visit to the doctor's office, thus saving the patient's time. Teledermatology can increase access to dermatological care for patients, particularly patients living in rural and remote areas. In addition, highly accurate, automatic skin image analysis algorithms can potentially help reduce the time and improve the accuracy of the diagnosis process. Developing and integrating these algorithms into dermatology and teledermatology is an active area of research.

Many skin image analysis algorithms have been developed, including algorithms for acne analysis [13, 14, 15]. However, owing to the complexity of skin lesions, traditional methods often do not achieve good results. The advent of deep learning techniques, particularly the convolutional neural network (CNN), has revolutionized the computer vision field in general and skin image analyses in particular. Many studies have recently been conducted for acne analysis using deep learning to improve the weaknesses of traditional methods. Case studies are presented below.

In 2018, Xiaolei Shen *et al.* [11] proposed a method to automatically diagnose facial acne based on a CNNs. The method was trained on a dataset containing 6,000 images (including 3,000 skin images and 3,000 non-skin images) to distinguish seven classes of acne lesions (blackheads, whiteheads, papules, pustules, modules, cysts, and normal skin). The results showed that the VGG16 neural network achieves the highest accuracy, ranging from 81.2% to 95% for the seven classes with class 3 (normal skin) and class 4 (pustule) being among the highest.

In 2019, Junayed *et al.* [16] used the AcneNet model based on a deep residual neural network to classify five classes of acne lesions (Closed Comedo, Cystic, Keloidalis, Open Comedo, and Pustular). A total of 1,800 images were divided equally between classes with 360 images for each class. The accuracy was over 94% with 99.44% accuracy for the Keloidalis class.

At the end of 2019, a new method for acne analysis using smartphone images based on deep learning was developed by Seite *et al.* [17]. The method can help determine the severity of grade acne based on the Global Evaluation Acne (GEA) scale and number of acne lesions. The method used a dataset collected from 1,072 patients using both iOS and Android phones when possible with a total of 5,972 images. The dataset was diverse in terms of skin color and race with skin images of Asians, Europeans, Africans, and Latinos. The method achieved a weighted average of the precision and recall of 84% for inflammatory lesions and 61% for non-inflammatory lesions.

In 2021, Yin Yang *et al.* [18] developed another acne assessment algorithm using deep learning in which a dataset comprising 5,871 clinical images of 1,957 patients collected using Fujifilm and Canon cameras was used. The method had three steps: preprocessing image data to remove interference from the eyes, nose, and mouth areas; classifying acne lesions using an Inception-V3 network; and finally, evaluating the model performance in patients with acne vulgaris. The results showed an average F1 score value of 0.8 for the deep learning model and Kappa coefficient (coefficient for evaluating the correlation between the deep learning model and the dermatologists) of 0.791. With the exception of one study [17], most of the above studies used non-smartphone images and focused on either the classification of acne lesion type or the severity grade of acne.

In this study, we developed an AI system called AcneDet based on deep learning and machine learning that can analyze facial smartphones images for two main purposes: (1) detecting acne lesion objects of four types: blackheads/whiteheads, papules/pustules, nodules/cysts, and acne scars; and (2) determining the severity grade of acne based on the IGA scale [19]. The data used in this study includes 1,572 images collected by both iOS and Android smartphones. The data were then labeled by four dermatologists and used for AI training.

2. Materials and Methods

2.1. Dataset

2.1.1. Data collection and labeling

Data were retreived from database of a mobile application called Skin Detective developed by our team that is available on both iOS and Android smartphones. User agreed with the app's terms and conditions before using the app. Only with user agreement, user's facial images were stored in the app's database for AI training. For each user that agreed to share facial images for AI training, three facial images taken at three different angles including, i.e., the front, left, and right angles, were stored. A total of de-indentified 1,572 images were included in this study. The images were labeled by four dermatologists (two juniors and two seniors). The dermatologists used LabelBox software to label images. There were two main labeling tasks. One was to draw rectangular bounding boxes to mark the location and type of acne lesions. Four types of acne were labeled, including blackheads/whiteheads, papules/pustules, nodulars/cysts, and acne scars. In this task, each image was first labeled using a junior dermatologist. A senior dermatologist will then review and correct the labeling if necessary. Another labeling task was to grade the acne severity for each image based on the results of the first labeling task. Acne severity was graded based on the IGA [19] scale: 0, clear; 1, almost clear; 2, mild; 3, moderate; and 4, severe. Similar to labeling task 1, the acne severity of each image was first graded by a junior dermatologist and then reviewed and corrected if necessary by a senior dermatologist.

2.1.2. Data Statistics

Table 1. Statistic of different types of acne

Type of acne	Number of acnes	Ratio (%)
Blackheads/Whiteheads	15686	37.47
Acne scars	23214	55.46
Papules/Pustules	2677	6.4
Nodular/Cyst lesions	282	0.67
Total	41859	100

A total of 41,859 acne lesions were labeled among 1572 images. Among them, acne scars are the most common with 23214 (55.46%) and nodular lesions are the least with 282 (0.67%). The number and percentage of each acne lesion type are detailed in Table 1.

In terms of acne severity, grade 1 is the most prevalent with 56.18%, and grade 4 the least with 2.16%. The distribution of acne severity grades is shown in Table 2.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

Table 2. Statistics of different acne severity grades based on the IGA scale

IGA scale acne severity grade	Number of images	Ratio (%)
0	211	13.42
1	883	56.18
2	361	22.96
3	83	5.28
4	34	2.16
Total	1572	100

Figure 1. From the original images, dermatologists labeled acne lesions (blackheads/whiteheads, papules/pustules, nodules/cysts, and acne scars) using bounding boxes and graded the acne severity using the IGA scale: grade 0, clear; grade 1, almost clear; grade 2, mild; grade 3, moderate; and grade 4, severe.

Figure 1 shows acne lesions that were labeled by dermatologists. The top row shows the original images of the patients captured by smartphones. The bottom row shows the corresponding images labeled by dermatologists. For each image, the dermatologists marked the locations of the acne lesions using bounding boxes and gave an acne severity grade using the IGA scale. Each acne lesion type has a distinct bounding box color: cyan for blackheads/whiteheads, pink for papules/pustules, red for nodules/cysts, and green for acne scars.

2.2. IGA scale

The IGA scale was recommended by the FDA to be a static, qualitative evaluation of the overall acne severity [19]. It has five levels ranging from grade 0 to grade 4 with grade 0 being clear; grade 1, almost clear; grade 2, mild; grade 3, moderate; and grade 4, severe (Table 3).

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

Table 3. Detailed description of the IGA scale [19]

Grade	Description
0	Clear skin with no inflammatory or noninflammatory lesions
1	Almost clear; rare non-inflammatory lesions with no more than one small inflammatory lesion
2	Mild severity; greater than Grade 1; some noninflammatory lesions with no more than a few inflammatory lesions (papules/pustules only, no nodular lesions)
3	Moderate severity; greater than Grade 2; up to many noninflammatory lesions and may have some inflammatory lesions, but no more than one small nodular lesion
4	Severe; greater than Grade 3; up to many noninflammatory lesions and many have some inflammatory lesions, but no more than a few nodular lesions

2.3. Methods

2.3.1. Overall model architecture

In terms of the overall architecture, the system includes two models for two different tasks:

1. Acne object detection model: determine the location and type of acne lesions.
2. Acne severity grading model: grade the overall acne severity of the input image using IGA scale.

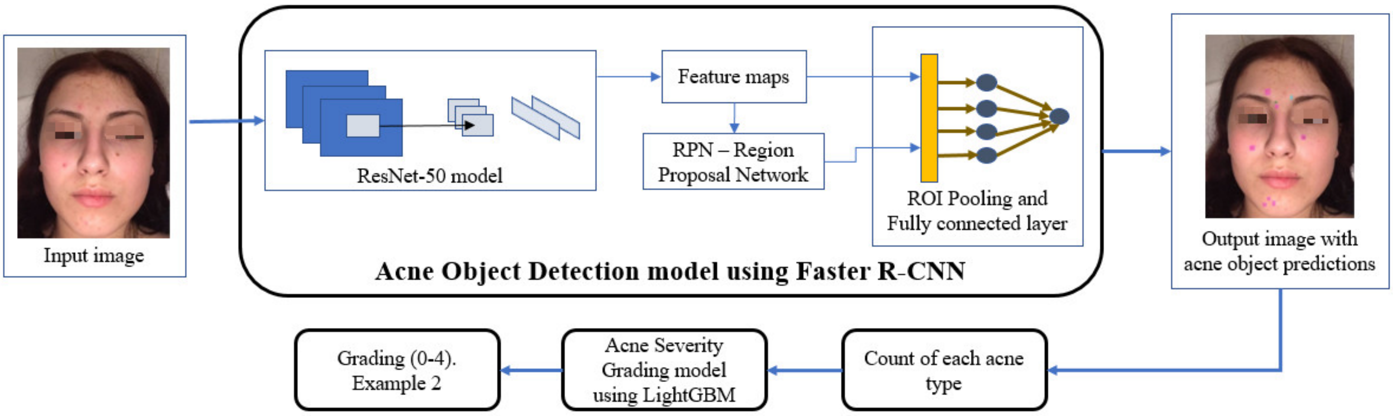

Figure 2. Pipeline of acne lesion object detection and acne severity grading system with two main steps: acne object detection and acne severity grading. The output of the acne object detection model was used as input to the acne severity grading model.

The architecture of the system is shown in Figure 2. The output of the acne object detection model, more specifically, the numbers of each acne type, was used as input for the acne severity grading model. In this way, our system mimics the acne severity grading process of dermatologists in which the number of blackheads/whiteheads, papules/pustules, nodules/cysts, and acne scar lesions were first estimated followed by applying the IGA scale rules shown in Table 3. As an advantage of this approach, the result is easy to interpret. Acne objects are detected and marked by bounding boxes. Different acne types have different bounding box colors. Acne severity is graded based on the numbers of each acne type. Therefore, the acne severity grade prediction output by

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

the system can be easily explained, thus avoiding the black box issue commonly found in CNN-based classifiers.

Acne object detection model

We chose the Faster R-CNN architecture [20] with the ResNet50 backbone to build our acne object detection model. The model was trained for 13,000 epochs on an NVIDIA GTX 2080 with a training time of 2 weeks. A Faster R-CNN is one of the state-of-art object detection architectures.

Acne severity grading model

We built our acne severity grading model based on the LightGBM algorithm [21], a tree-based machine learning algorithm. The model input, i.e., the numbers of each acne type, comes from output of the acne object detection model. LightGBM is a fast, high-performance machine learning model that has performed well on various machine learning competitions.

2.3.2. Training model

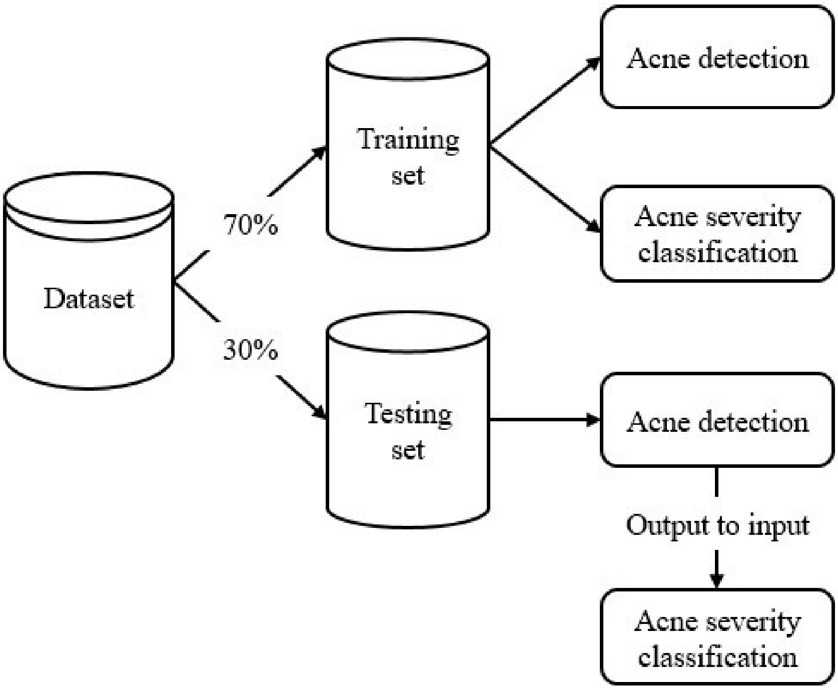

Figure 3. Data were divided into a ratio of 70:30 for training and testing.

We divided the dataset into two sets, as shown in Figure 3: a training set and a testing set with a ratio of 70:30. During the training phase, because information on acne objects, counts, and severity grades are all available, both models were trained in a parallel fashion on the training data until convergence. However, during the testing phase, the output of the acne object detection model was used as the input for the Acne severity grading model. The acne severity grading model in turn outputs the acne severity grade based on the IGA scale.

Evaluation metrics

We measured the model performance using two main metrics: the mean Average Precision (mAP) for the Acne object detection model and the area under the receiver operating characteristic (ROC) curve - (AUC) for the Acne severity grading model.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

3. Results

3.1. Acne object detection

Table 4. Mean Average Precision of object detection of four acne types

Type of Acne	mAP
Blackheads/Whiteheads	0.4
Acne scars	0.44
Papule/Pustule lesions	0.64
Nodular/Cyst lesions	0.68
Average mAP of four types	**0.54**

To evaluate the performance of the Acne object detection model in detecting acne objects, we used the mean Average Precision (mAP). Figure 4 details the precision-recall curve for each acne type. We achieved an average mAP of 0.54 for all four acne types (Table 4). As shown, mAP for nodule/cyst lesions was the highest at 0.68 and blackhead/whitehead lesions were the lowest at 0.4.

3.2. Acne severity grading

To evaluate the performance of the Acne severity grading model, we used the AUC. The ROC curve and AUC of each acne severity grade of 0-4 in the IGA scale are shown in Figure 5. A normalized confusion matrix and non-normalized confusion matrix of the Acne severity grading model are shown in Figure 6.

In addition to the AUC, we also calculated the accuracy, precision, recall, and F1 (Table 5). The average accuracy for five grades was 0.85. Figure 7 shows some examples of input images, the ground truth labeled by dermatologists, and the prediction by our AcneDet system. The system outputs two main predictions: (1) the location and type of acne objects in the image, and (2) the acne severity grade of the image. The accuracy in detecting acne objects and the grading of acne severity both contribute to the overall performance of AcneDet.

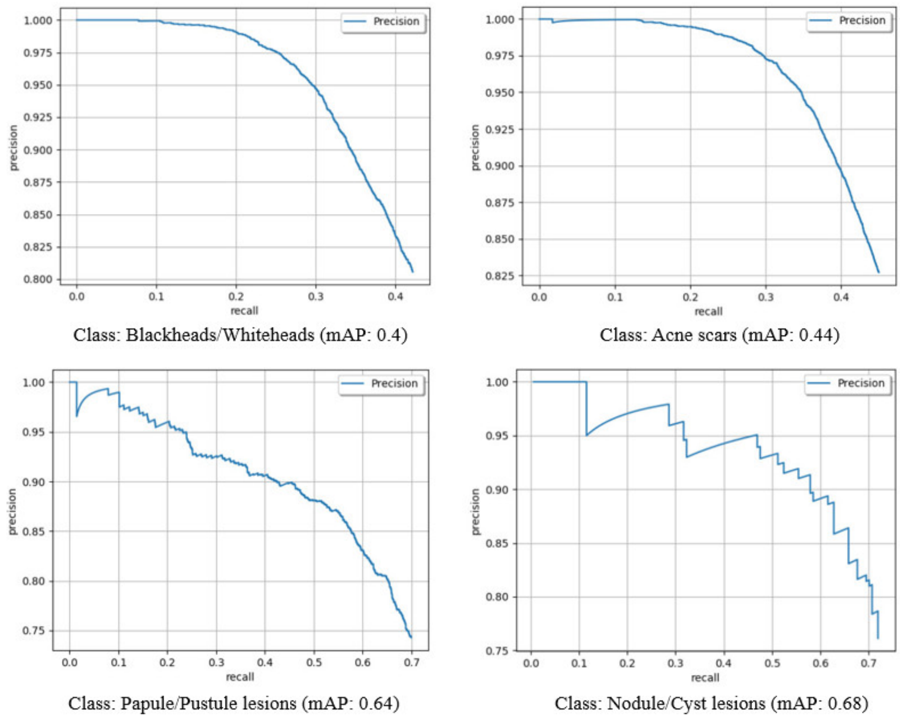

Figure 4. Precision-recall curve of object detection of four acne types.

 doi:10.20944/preprints202206.0384.v1

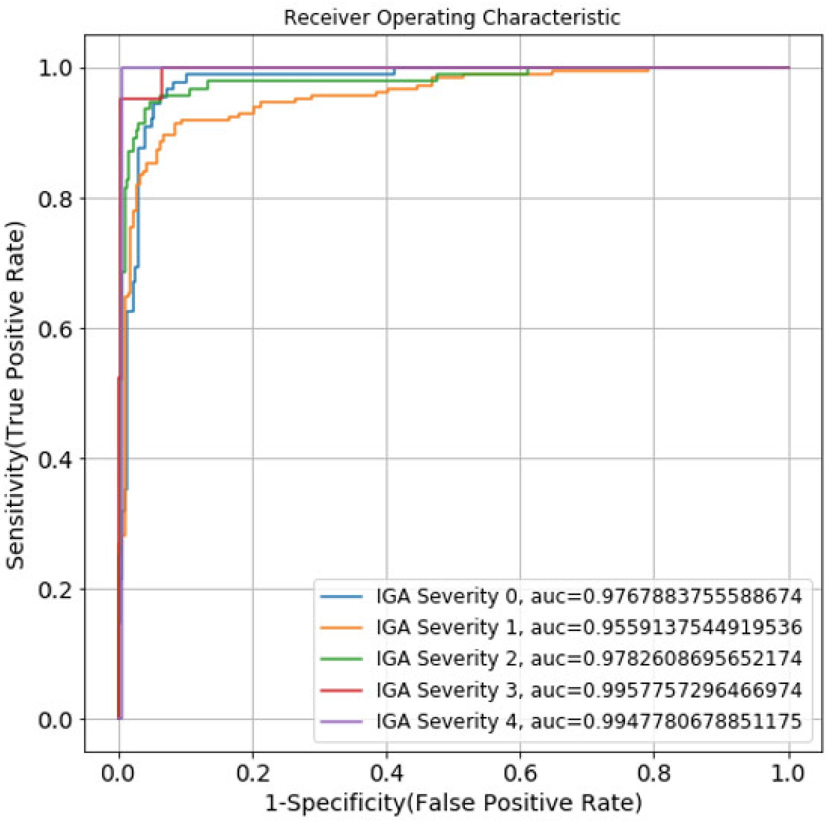

Figure 5. ROC-AUC diagram of the Acne severity grading model

Table 5. Precision, recall, F1 score and accuracy of acne grading model

Grade of IGA scale	Precision	Recall	F1
0	0.77	0.63	0.70
1	0.92	0.90	0.91
2	0.72	0.77	0.75
3	0.60	0.61	0.60
4	0.65	0.87	0.74
Accuracy		0.85	

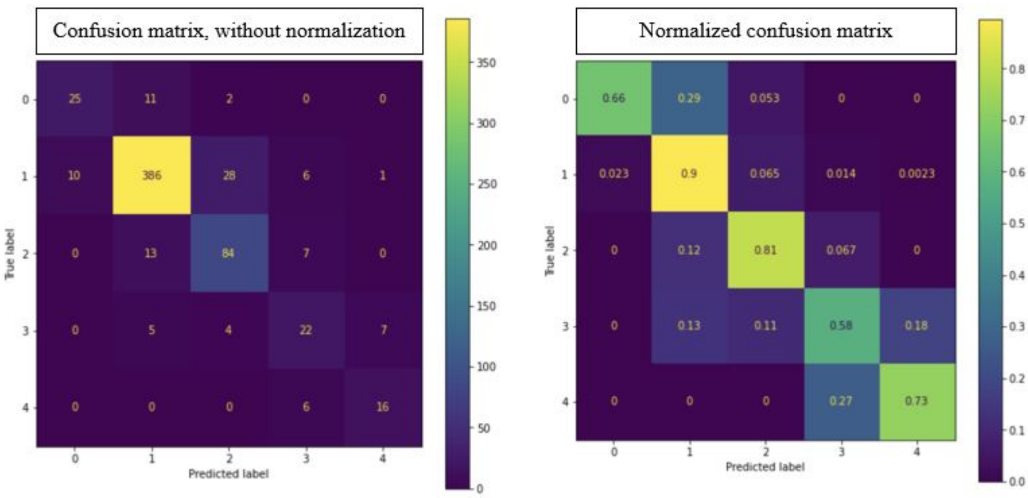

Figure 6. Confusion matrix with and without normalization on test set

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

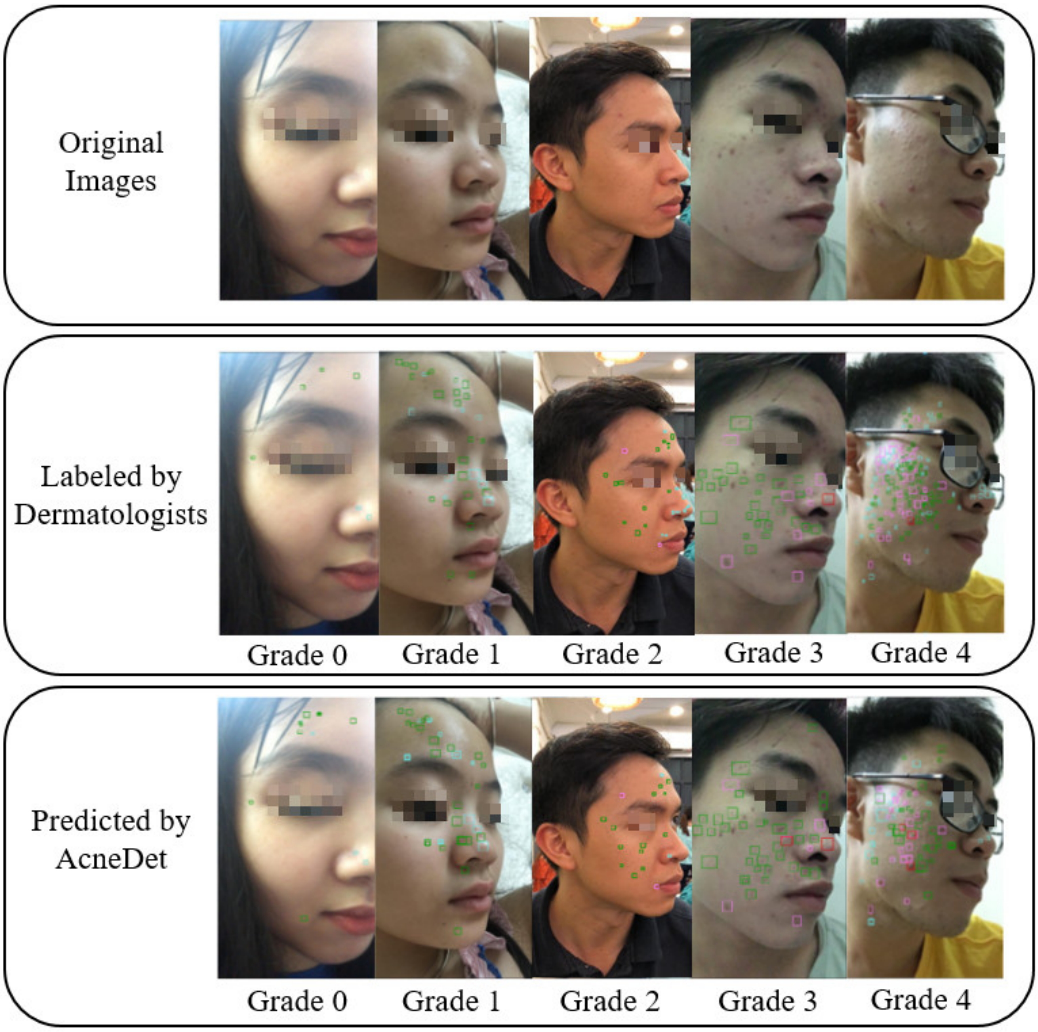

Figure 7. Comparison of predictions by AcneDet with ground truths labeled by dermatologists.

4. Discussion

We believe that skin image analysis algorithms will play an important role in future dermatology where dermatologists will likely be supported by AI systems during the diagnosis and treatment processes. Patients will also benefit from information provided by highly accurate skin image analysis algorithms. Acne is one of the most common skin conditions, affecting 9.38% of the world population, and can cause serious effects, including psychological effects and the quality of life. In this study, we developed an AI system called AcneDet that can automatically detect acne lesion objects and grade acne severity with a high level of accuracy.

Table 6. Compare the mAP in detecting acne objects obtained in our study and in previous studies.

Authors	Acne Types	Number of acnes	Model	mAP
Kuladech *et al.* [10]	Type I, Type III, Postinflammatory erythema, Postinflammatory hyperpigmentation	15917	Faster R-CNN, R-FCN	Faster R-CNN: 0.233 R-FCN: 0.283
Kyungseo Min *et al.* [22]	General Acne (not classification)	18983	ACNet	0.205
Proposed method	Blackheads/Whiteheads, Papules/Pustules, Nodules/Cysts, and Acne scars	41859	Faster R-CNN	**0.540**

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 28 June 2022 doi:10.20944/preprints202206.0384.v1

For the acne lesion object detection task, we used a Faster R-CNN architecture to build our model trained on a dataset of 41859 acne objects. The Faster R-CNN performed reasonably well with an average mAP for all four acne types of 0.54. This mAP is higher than the previous results of Kuladech *et al.* [10] and Kyungseo Min *et al.* [22]. Kuladech's study trained an R-FCN model on a dataset of 15,917 acne images and achieved mAP of only 0.283. In addition, Kyungseo Min's study trained a ACNet model that was composed of three main components, composite feature refinement, dynamic context enhancement, and mask-aware multi-attention on the ACNE04 dataset with 18,983 acne images. They achieved an mAP of only 0.205. Moreover, the study did not differentiate acne type. A comparison between our approach and the aforementioned methods is shown in Table 6.

It is noteworthy that our AI system was trained on a dataset with a larger number of acne objects. Regarding the acne types, the number of acne types in our study is the same as in Kuladech's study, i.e., four, and is higher than in Kyungseo Min's study. Our high mAP in acne object detection in combination with our two models and two stages approach results in a high accuracy of our acne severity grading. Note that, although the number of nodule/cyst lesions in our dataset is extremely small (only 0.67% of the total number of acne lesions), our model was able to detect nodule/cyst lesions with an mAP of 0.68. This can be explained by the fact that nodule/cyst lesions often have an extremely distinct color (usually red) and a substantially larger size. Thus, our model can learn to recognize them better. By contrast, whereas the number of acne scars accounts for 55.46% of the total number of acne objects, the mAP was only 0.44. We attribute this to the fact that most of the acne scars are small with a color not much different from the surrounding. Therefore, although the training examples of acne scars are abundant, the model had a hard time learning to recognize them. We believe the same cause applies to blackhead/whitehead lesions, which accounts for 37.47% of the total number of acne objects but has the lowest mAP of 0.4.

Table 7. Comparison of accuracy in grading acne severity obtained through our study and in previous research.

Authors	Acne severity scale	Number of images	Model	Accuracy
Sophie Seite *et al.* [17]	GEA scale	5972		0.68
Ziying Vanessa *et al.* [23]	IGA scale	472	Developed based on DenseNet, Inception v4 and ResNet18	0.67
Yin Yang *et al.* [18]	Classified according to the Chinese guidelines for the management of acne vulgaris with 4 severity class	5871	Inception-v3	0.8
Proposed method	IGA scale	1572	LightGBM	**0.85**

To grade the acne severity of the acne, we used the output of the Acne object detection model, specifically the number of each acne type, as input for the LightGBM-based acne severity grading model. Using this approach, we achieved an average accuracy of 0.85 for all five grades. The accuracy of our acne severity grading model is compared with the accuracy of previous studies in Table 7. The results show that our model achieved a higher accuracy than that of previous studies. More specifically, in comparison to the 0.67 accuracy reported by Ziying Vanessa et al., who also used the IGA scale [23], our accuracy of 0.85 is significantly higher. There is a significant imbalance in our dataset with the number of grade 3 (moderate) and grade 4 (severe) images, which are quite small, at 83 (5.28%) and 34 (2.16%), respectively. This reflects the scarcity of these two grades within the population. Because these two grades can have serious effects on patients, accurately grading them is important. Our system achieved acceptable F1 scores for these two grades, with grades 3 and 4 having F1 scores of 0.60 and 0.74, respectively. In the future, we plan to collect more images of grades 3 and 4 to further improve their grading accuracy.

Notably, the images used in our study were collected through smartphones. Therefore, they are lower in quality and less clinically informative than images obtained through digital cameras or a dermatoscope, making their analysis more challenging. However, we were able to achieve an average mAP of 0.54 and an accuracy of 0.85, which are higher than those of previous studies, which is a good foundation for future studies. Given the high number of people with acne, the shortage of dermatologists, and the popularity of smartphones, an AI that can quickly and accurately analyze smartphone-captured facial images to inform users about their acne conditions would be extremely useful. Through this study, we hope to contribute to the development of accurate algorithms for analyzing the skin conditions of patients and supporting doctors in diagnosing diseases more quickly and accurately.

5. Conclusions

In this study, we developed an AI system called AcneDet for acne object detection and acne severity grading using facial images captured by smartphones. The AcneDet system consists of two models for two different tasks: an acne object detection model using Faster R-CNN-based deep learning and an acne severity grading model based on LightGBM machine learning. Four types of acne could be detected: blackheads/whiteheads, papules/pustules, nodules/cysts, and acne scars. The test results show that the acne object detection model achieved an average mAP of 0.54. The output of the acne object detection model was used as input for the acne severity grading model, which achieved an accuracy of 0.85. In the future, we plan to collect more data to improve the mAP and accuracy of the system. We also plan to apply semi-supervised and unsupervised learning techniques to reduce the labeling workload.

Author Contributions: Q.T.H, P.H.N, H.X.L, L.T.N, and H.T.N designed and developed AI. M.T.T.T, H.T.N, N.T.V, and A.T.N labeled data. T.X.N, K.S, K.T, and T.I provided expertise on acne and acne analysis. T.N.T provided expertise on skin conditions and skin care. Q.T.H, P.H.N, and H.T.N wrote the manuscript. All authors participated in reviewing and editing the manuscript.

Funding: This research received no external funding

Institutional Review Board Statement: Not applicable

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are not publicly available due to privacy issues.

Acknowledgments: The authors thank Truong Dinh Tuan for reading the manuscript and providing valuable feedback. Special thanks to International University, VNU-HCMC, and University of Medicine and Pharmacy Clinic 1, Ho Chi Minh City and School of Medicine, VNU-HCMC, for their support.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bernardis E, Shou H, Barbieri JS, McMahon PJ, Perman MJ, Rola LA, Streicher JL, Treat JR, Castelo-Soccio L, Yan AC. Development and Initial Validation of a Multidimensional Acne Global Grading System Integrating Primary Lesions and Secondary Changes. JAMA Dermatol. 2020 Mar 1;156(3):296-302. doi: 10.1001/jamadermatol.2019.4668. PMID: 31995147; PMCID: PMC6990806.
2. Vos, Theo et al. "Years lived with disability (YLDs) for 1160 sequelae of 289 diseases and injuries 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010." Lancet (London, England) vol. 380,9859 (2012): 2163-96. doi:10.1016/S0140-6736(12)61729-2.

3. E. Malgina and M. -A. Kurochkina, "Development of the Mobile Application for Assessing Facial Acne Severity from Photos," 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus), 2021, pp. 1790-1793, doi: 10.1109/ElConRus51938.2021.9396382.
4. Andrea L Zaenglein, Arun L Pathy, Bethanee J Schlosser, Ali Alikhan, Hilary E Baldwin, Diane S Berson, Whitney P Bowe, Emmy M Graber, Julie C Harper, Sewon Kang, et al. 2016. Guidelines of care for the management of acne vulgaris. Journal of the American Academy of Dermatology 74, 5 (2016), 945–973.
5. T.B. Zhang, Y.P. Bai, Progress in the treatment of acne vulgaris, Chinese Journal of Dermatovenereology of Integrated Traditional and Western Medicine 18(2) (2019) 180-182.
6. Sutaria AH, Masood S, Schlessinger J. Acne Vulgaris. [Updated 2020 Aug 8]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2021 Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK459173/.
7. Bhate K, Williams HC. Epidemiology of acne vulgaris. Br J Dermatol. 2013 Mar;168(3):474-85. doi: 10.1111/bjd.12149. PMID: 23210645.
8. Tassavor, Michael, and Michael J Payette. "Estimated cost efficacy of U.S. Food and Drug Administration-approved treatments for acne." Dermatologic therapy vol. 32,1 (2019): e12765. doi:10.1111/dth.12765.
9. Shen, X., Zhang, J., Yan, C. et al. An Automatic Diagnosis Method of Facial Acne Vulgaris Based on Convolutional Neural Network. Sci Rep 8, 5839 (2018). https://doi.org/10.1038/s41598-018-24204-6.
10. Kuladech Rashatapruckpa, Chavalit Chuangchaichatchavarn et al. 2020. Acne Detection with Deep Neural Networks. In 2020 2nd International Conference on Image Processing and Machine Vision (IPMV 2020). Association for Computing Machinery, New York, NY, USA, 53–56. DOI: https://doi.org/10.1145/3421558.3421566.
11. Gu, T. Newzoo's global mobile market report: Insights into the world's 3.2 billion smartphone users, the devices they use & the mobile games they play (2019). Availabel at: https://newzoo.com/insights/articles/newzoos-global-mobile-market-report-insights-into-the-worlds-3-2-billion-smartphone-users-the-devices-they-use-the-mobile-games-they-play/. Last accessed 06 June 2021.
12. Gordon WJ, Landman A, Zhang H, Bates DW. Beyond validation: getting health apps into clinical practice. NPJ Digit Med. 2020 Feb 3;3:14. doi: 10.1038/s41746-019-0212-z. PMID: 32047860; PMCID: PMC6997363.
13. N. Alamdari, K. Tavakolian, M. Alhashim and R. Fazel-Rezai, "Detection and classification of acne lesions in acne patients: A mobile application," 2016 IEEE International Conference on Electro Information Technology (EIT), 2016, pp. 0739-0743, doi: 10.1109/EIT.2016.7535331.
14. G. Maroni, M. Ermidoro, F. Previdi and G. Bigini, "Automated detection, extraction and counting of acne lesions for automatic evaluation and tracking of acne severity," 2017 IEEE Symposium Series on Computational Intelligence (SSCI), 2017, pp. 1-6, doi: 10.1109/SSCI.2017.8280925.
15. E. Malgina and M. -A. Kurochkina, "Development of the Mobile Application for Assessing Facial Acne Severity from Photos," 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus), 2021, pp. 1790-1793, doi: 10.1109/ElConRus51938.2021.9396382.
16. Junayed, Masum Shah et al. "AcneNet - A Deep CNN Based Classification Approach for Acne Classes." 2019 12th International Conference on Information & Communication Technology and System (ICTS) (2019): 203-208.
17. Seité, Sophie et al. "Development and accuracy of an artificial intelligence algorithm for acne grading from smartphone photographs." Experimental dermatology vol. 28,11 (2019): 1252-1257. doi:10.1111/exd.14022
18. Yang, Y., Guo, L., Wu, Q. et al. Construction and Evaluation of a Deep Learning Model for Assessing Acne Vulgaris Using Clinical Images. Dermatol Ther (Heidelb) (2021). https://doi.org/10.1007/s13555-021-00541-9.
19. Research, C. for D. E. and. Acne vulgaris: establishing effectiveness of drugs intended for treatment. U.S. Food and Drug Administration. Available at: https://www.fda.gov/regulatory-information/search-fda-guidance-documents/acne-vulgaris-establishing-effectiveness-drugs-intended-treatment. Accessed July 30 2021
20. Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster r-cnn:Towards real-time object detection with region proposal networks. In Advances.
21. Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. 2017. LightGBM: a highly efficient gradient boosting decision tree. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 3149–3157.
22. Min, Kyungseo, Gun-Hee Lee, and Seong-Whan Lee. "ACNet: Mask-Aware Attention with Dynamic Context Enhancement for Robust Acne Detection." arXiv preprint arXiv:2105.14891 (2021).
23. Lim, Ziying Vanessa et al. "Automated grading of acne vulgaris by deep learning with convolutional neural networks." Skin research and technology : official journal of International Society for Bioengineering and the Skin (ISBS) [and] International Society for Digital Imaging of Skin (ISDIS) [and] International Society for Skin Imaging (ISSI) vol. 26,2 (2020): 187-192. doi:10.1111/srt.12794