ClearFace: Facial Acne Detection and Classification System Using YOLOv11 and EfficientNet-B0

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***Abstract*—Facial acne is a highly prevalent dermatological condition that significantly affects individuals' physical and psychological well-being. Although clinical diagnosis remains the gold standard, limited access to specialized care highlights the need for scalable, automated solutions. This study presents a deep learning-based system for the detection and classification of facial acne lesions, combining object detection and image classification techniques. The YOLOv11-m model was employed to localize lesions in facial images, followed by classification using an EfficientNet-B0 network. To train and evaluate the system, the Acne21 dataset was adapted to a two-stage pipeline: bounding boxes were used for detection, while cropped regions were labeled into six classes for classification. The system generates lesion counts and calculates the Investigator's Global Assessment (IGA) severity score based on clinical weights. Experimental results demonstrate the model's effectiveness in detecting and categorizing different lesion types, offering a promising tool for preliminary acne self-assessment in mobile health applications. This approach contributes to the advancement of accessible dermatological care through AI-driven technologies.**

I. Introduction

Acne, a chronic inflammatory skin disease that affects the pilosebaceous units, is characterized by seborrhea, comedones, papules, nodules, pimples, and scars [1], [2]. This condition affects up to 650 million people, including 85% of teenagers and young adults worldwide [3]. In addition to physical damage, acne has a significant impact on patients' psychological health, often resulting in low self-esteem, depression, anxiety, and even suicidal tendencies [4], [5].

Although common, access to clinical diagnosis is not always immediate, especially in regions with limited specialized professionals. The adoption of technology in healthcare practices shows significant potential, especially in the field of dermatology, where precision in skin visualization and analysis is crucial [6], [7]. The increase in skin diseases and the need for accessible and accurate diagnoses are driving innovations that overcome physical barriers and broaden access to information [8], [9].

Teledermatology has emerged as a significant solution, enabling remote consultations with dermatologists and making care more accessible [10]–[12]. Patients can send photos of their dermatological conditions for evaluation, reducing the need for face-to-face consultations and facilitating access to specialized care, especially in regions with more limited access to specialists [13], [14].

Deep neural networks (DNNs) are a class of machine learning algorithms inspired by the structure of the human brain. They consist of multiple layers of artificial neurons, which process and transform data at different levels of abstraction. The concept of deep neural networks dates back to the 1940s and 1950s, with the development of the first artificial neuron models. However, it is only in recent decades, with the increase in computing power and the development of efficient training algorithms, that DNNs have become widely used.

The applicability of deep neural networks is vast and covers a wide range of areas, including computer vision, natural language processing, speech recognition, bioinformatics, among others. One of the most significant milestones in the advancement of DNNs was the emergence of Convolutional Neural Networks (CNNs), especially in the area of computer vision. CNNs are highly effective at extracting features from images and have found wide application in tasks such as object recognition, image segmentation, medical image diagnosis, and beyond [15]. A recent example is the YOLOv11 model, which has been explored to improve diagnosis in medical images analysis, as discussed by [16], [17].

The use of artificial intelligence (AI) and computer vision (CV) techniques allows the implementation of algorithms that perform complex tasks, such as skin lesion characterization, which are essential to the success of this project. Robust diagnostic tools are of critical importance due to the significant impact of skin diseases on the quality of life of patients, who can suffer from low self-esteem and mental health problems. This technology seeks to accelerate diagnostic processes and mitigate these impacts [18], [19].

At the same time, advances in dermatological analysis have enabled detailed assessments of the skin, such as inflammation, texture, and blocked pores. These solutions facilitate dermatologists to make precise diagnoses and personalize treatments according to each patient's needs [8], [20], [21]. Recent studies show not only the feasibility of adopting new technologies in dermatology, but also their implementation, which has been well received by patients and healthcare professionals [22], [23].

In addition, the application of artificial intelligence to support the diagnosis and treatment of dermatological conditions reflects the continuous trajectory of innovation in the field [24]–[29]. These advances underscore the importance of researching and implementing AI-based solutions designed to provide more accurate diagnoses and significantly improve the clinical management of dermatological diseases [30]–[32].

In this context, the present project aimed to develop an artificial intelligence model, based on computer vision techniques, to classify the severity of facial acne. The proposal seeks to enable users to conduct a preliminary self-assessment of their skin condition using a mobile application. The main stages developed were:

- Theoretical survey on acne and the main methodologies for classifying its severity;
- Definition of the technologies and tools for use in the development of the solution;
- Training of the YOLOv11 model in acne detection and classification.
- Training of the YOLOv11 model for the detection and classification of acne lesions;
- Development of an API for integration between the mobile application and the AI model;
- Implementation of the mobile application for acne self-assessment.

The structure of this article is as follows: Section II presents the state of the art; Section III describes the methodology adopted; Section IV discusses the results obtained; and Section V presents the conclusions of this study.

II. State of Art

Recent advancements in artificial intelligence (AI) and computer vision have facilitated the automation of facial acne detection and classification systems, reducing dependence on subjective dermatologist assessments [33], [34]. Most approaches employ convolutional neural networks (CNNs), segmentation algorithms, and object detectors such as YOLO to localize lesions in facial images [35], [36]. Once localized, lesions can be classified and assigned a severity score, such as the Global Acne Grading System (GAGS) or the Investigator's Global Assessment (IGA) [37], [38]. Although accuracy has improved through public datasets, expert annotations, and data augmentation, research continues to explore attention and context-aware models to enhance robustness against variations in lighting, skin tone, and facial angle [39].

A. Detection

Common acne detection typically involves a clinical visual examination by a specialist, which can be costly and subject to variability. To address these challenges, automated detection methods using artificial intelligence (AI) have been proposed, helping to mitigate issues related to human error [34], [38]. In this context, Convolutional Neural Networks (CNNs) are the most commonly used architectures for detecting facial lesions, due to their ability to extract hierarchical patterns from images [37], [39].

The main models employing this technique include VGG16, ResNet, DenseNet, and InceptionV3, which have been used across various projects to fulfill this role [40]–[43].

Other models focused on object detection, such as YOLO (You Only Look Once) which is more general but less accurate in medical contexts—and SSD (Single Shot Multibox Detector) which tends to be more precise for medical applications but also slower are also frequently applied in the field, even though they were not originally designed specifically for facial lesion detection [44], [45]. Additionally, techniques such as semantic segmentation and transfer learning are commonly employed in the context of lesion detection [33], [39].

B. Classification

The classification of acne severity is often based on clinical examination, similarly to the detection process. However, while detection aims to identify the presence and location of acne lesions, classification focuses on determining the type and severity of those lesions. Both tasks traditionally depend on dermatologists' expertise and are subject to inter-observer variability and high operational costs [38].

To address these limitations, artificial intelligence (AI)-based models have been developed for the classification of facial acne severity. These models frequently leverage pre-trained convolutional neural networks (CNNs) or combine multiple deep learning and machine learning techniques to improve accuracy and generalization [34], [35], [37].

One notable example is AcneDet, which combines Faster R-CNN for lesion detection with LightGBM for severity classification. This model is capable of identifying up to four types of lesions and has achieved classification accuracy of up to 85 percent on benchmark datasets [34]. Similarly, the DLI-Net architecture, which integrates DeepLabV3 and InceptionV3, reached an accuracy of 97 percent [37], while an ensemble approach combining ResNet50 and YOLOv5 demonstrated high performance in both detection and classification tasks [35].

An alternative based on traditional machine learning is the use of a hybrid pipeline combining k-means clustering, Gray-Level Co-occurrence Matrix (GLCM) texture analysis, and a Random Forest classifier. Previous research has demonstrated that such approaches can achieve high accuracy in classifying different types of facial acne [46], [47]. These methods present a viable alternative to purely CNN-based architectures, particularly in scenarios with limited computational resources.

Despite the promising results, most models have been evaluated under controlled conditions and may not generalize well to real-world settings with diverse skin tones, lighting variations, or smartphone-quality images. Therefore, further research is needed to enhance robustness, interpretability, and clinical reliability [36], [39].

C. Metrics

To assess the performance of the proposed system for acne lesion detection and classification, we adopted three widely used metrics in the field of Computer Vision: Precision, Recall, and mean Average Precision (mAP). Precision indicates the proportion of correct predictions among all detections made, while recall measures the model's ability to identify all actual lesions present in an image. mAP, in turn, provides the average precision across different Intersection over Union (IoU) thresholds, reflecting the overall performance of the model across all classes.

These metrics are standard in renowned benchmarks such as PASCAL VOC [48] and MS COCO [49], and have also been adopted in recent studies on dermatological detection, such as Zhang et al. [50]. By employing them, we aim to ensure a robust and consistent evaluation of the automated acne detection system, as well as enable direct and reliable comparisons with existing approaches in the literature.

III. Methodology

The study focused on building an automated system for identifying facial acne by combining object detection and image classification techniques. The proposed approach was designed as a two-stage pipeline: (i) a detection model to localize acne lesions in facial images, and (ii) a classification model to categorize each lesion into clinically relevant categories (blackheads, whiteheads, papules, pustules, nodules, and cysts), following recent frameworks in dermatology research [50]. The overall operating pipeline of the system is illustrated in Figure 1.

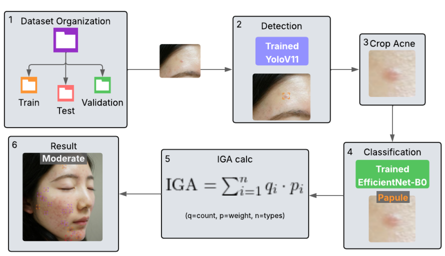

Figure 1. Operating pipeline of the proposed system

A. Preparation and Transformation of the Dataset

The Acne21 dataset was employed in this study, with annotations in the YOLOv11 format, including class identifiers and bounding box coordinates. To train the detection model, all lesion types were merged into a single label ("acne"), preserving only bounding box information. This transformation was automated through a Python script to ensure annotation consistency, following practices adopted in related work [51].

For training the EfficientNet-B0 classifier, the dataset was reorganized into a directory structure with six subfolders, each corresponding to one acne category: blackhead, whitehead, papule, pustule, nodule, and cyst. Cropped regions were extracted using bounding boxes from the original dataset and assigned to their respective class folders. This step ensured compatibility with classification models and follows recent dermatology studies that leverage lightweight convolutional networks such as EfficientNet [52].

B. Training the Models

Detection stage. For lesion detection, we employed YOLOv11-L with 640x640 input resolution, trained for 50 epochs (batch size 8, GPU, no AMP). YOLOv11 was chosen for its effectiveness in detecting small objects [17], crucial for early acne lesions. The model was restricted to localization only, since (i) preliminary tests showed overlapping low-confidence predictions even after NMS, and (ii) fine-grained subtype classification is outside YOLO's scope. To address this, we set a lower confidence threshold to maximize recall and delegated subtype classification to a specialized model on cropped regions.

Classification stage. The EfficientNet-B0 model was used to categorize cropped lesion images. Preprocessing included resizing to 384×384 pixels and applying data augmentation (RandomHorizontalFlip, RandomRotation, and ColorJitter). Training was performed for 50 epochs with a batch size of 32 and a learning rate of 1×10^{-3}, using the AdamW optimizer with CrossEntropyLoss. Two learning rate schedulers (CosineAnnealingLR and ReduceLROnPlateau) were applied, and early stopping was configured with patience of 5 epochs. The best-performing model was saved via checkpoint ("best_model.pth"). EfficientNet-B0 was selected for its balance between accuracy and computational efficiency, as noted in [53].

C. Integration of the Models

After training, the models were integrated into a unified pipeline. YOLOv11 was responsible solely for detecting and cropping lesion regions, while EfficientNet-B0 classified each region into one of the six categories. The system generated a JSON file containing: the original image, a list of detected classes, a count of each lesion type, and the Investigator's Global Assessment (IGA) score. The IGA score was calculated using clinical weights (blackheads and whiteheads = 1, papules = 2, pustules = 3, nodules = 4, cysts = 5), following standard dermatological practice [54]. This design enables both precise localization and clinically interpretable severity scoring, providing a scalable solution for mobile health applications.

IV. Results and Discussion

This section examines ClearFace results, including detection performance, classification, IGA score estimation, qualitative analysis of predictions, and comparison with related studies.

A. Detection Performance

The YOLOv11-m model reached a precision of 42. 4%, a recall of 35. 2%, 31. 5% mAP@50, and 10. 3% mAP@50–95. These values indicate reasonable but limited performance, particularly considering the visual subtlety of certain acne lesions and variability in skin tone, lighting, and image quality.

The large gap between precision and recall suggests that the model behaves conservatively: when a lesion is detected, it is usually correct (high precision), but many lesions are missed (low recall).

The 31.5% mAP@50 aligns with results observed for lightweight models in medical tasks. However, the low mAP@50–95 score highlights the model's limited ability to localize lesions precisely across multiple IoU thresholds.

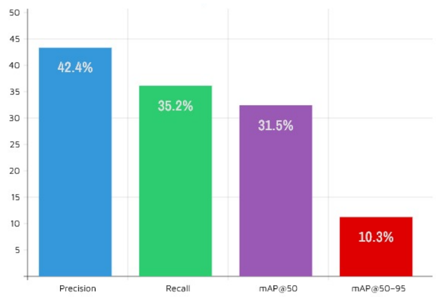

Figure 2. Performance metrics of the YOLO model results.

B. Classification Performance

The EfficientNet-B0 classifier achieved 66.3% accuracy, 67.1% precision, 65.8% recall, and 66.2% F1-score. These results were computed using cropped images derived from bounding boxes in the Acne21 dataset, ensuring alignment between regions of interest and their labels.

This pattern is consistent with findings by Shen et al. [51], who also reported significant confusion among certain lesion types when training skin condition classifiers.

Although the performance is moderate, potential improvements may be achieved by integrating attention mechanisms, using deeper EfficientNet versions (e.g., B3 or B5), or applying stronger supervision techniques.

C. IGA Score Estimation

The IGA score regression resulted in a mean absolute error (MAE) of 17.65, mean squared error (MSE) of 726.57, root mean squared error (RMSE) of 26.95, and mean absolute percentage error (MAPE) of 252.16%.

These high errors indicate substantial inconsistency in severity estimation, likely related to incorrect classification of severe lesion types, such as pustules and nodules.

Table I
REGRESSION ERROR METRICS FOR THE IGA SCORE

Metric	Abbreviation	Value
Mean Absolute Error	MAE	17.65
Mean Squared Error	MSE	726.57
Root Mean Squared Error	RMSE	26.95
Mean Absolute Percentage Error	MAPE	252.16%

D. Qualitative Examples and Discussion

Evaluation of visual examples revealed that, when predictions were correct, the system localized lesions and assigned the appropriate classes with confidence.

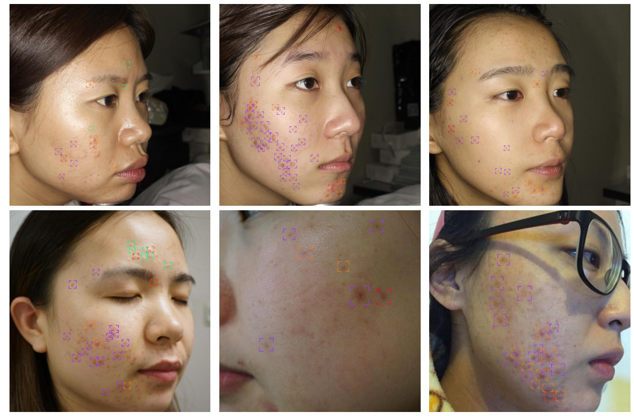

Figure 3. Examples of successful acne detections and classifications.

Failure cases included mislocalizations, missing lesions, or classification confusion. These issues were particularly frequent among lesions that were small, clustered, or visually ambiguous.

Figure 4. Examples of incorrect acne detections and classifications.

Most visual errors were concentrated among pustules, papules, and nodules, reinforcing the difficulty in differentiating between these visually similar forms.

E. Comparison with Related Studies

ClearFace achieved 66.3% accuracy in classification using the EfficientNet-B0 model on cropped lesion images. This result is lower than that reported by Huynh et al. (2022), who achieved 85% accuracy on images captured with mobile phones. This performance gap is likely related to the fact that Huynh et al.'s model was jointly optimized for detection and classification, resulting in fewer errors across pipeline stages. Additionally, their dataset included greater diversity in acquisition conditions.

In terms of severity estimation, ClearFace produced a MAPE of 252.16%, compared to 118% reported by Gao et al. (2025) using a combined classification and regression approach. Incorporating regression alongside classification, as in Gao et al., could potentially reduce errors in severity assessment. ClearFace also produced significant errors in severe lesion types, such as pustules and nodules, consistent with previous observations by Shen et al. (2018).

Overall, this analysis highlights the simplicity of ClearFace's two-stage architecture. However, performance may be improved by integrating multitask models or attention mechanisms to enhance detection and classification of subtle lesions.

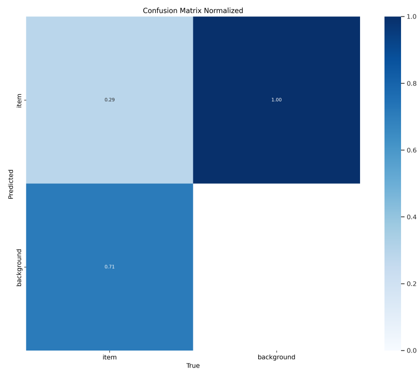

Figure 5. Normalized confusion matrix of YOLOv11 detection.

Furthermore, an error matrix was generated for the YOLOv11 model's detection phase, going beyond basic performance metrics. Results reveal that a substantial number of lesions were wrongly categorized as background, resulting in a high false-negative rate. In absolute and normalized matrices, nearly 71% of real lesions were missed. The model struggled to detect smaller or low-contrast lesions, particularly in lower-quality images captured under challenging lighting or overlapping skin conditions.

V. Conclusion

The primary objective of this study was to develop an artificial intelligence model based on computer vision, designed to classify the severity of facial acne and to provide users with a preliminary self-assessment of their skin condition through a mobile application. The results indicated that, despite the limitations of the YOLOv11 model in complex scenarios, the EfficientNet-B0 classifier performed more consistently, achieving an accuracy of 67.1%. This result suggests that the model is capable of correctly identifying the majority of lesions in cropped images, even when faced with moderate variations in the input conditions. Thus, this study represents an initial advance in the application of deep learning models to support dermatological assessment, contributing to the development of accessible and scalable solutions in the clinical context.

A. Future Work

Although the results obtained are promising, especially with the EfficientNet-B0 classifier, the quality of the classifications still depends directly on the previous detection stage, which, as shown, has significant limitations. To enable the system to achieve a level of reliability appropriate for potential clinical or personalized recommendation applications, several essential improvements are required.

The first is the adoption of the GAGS (Global Acne Grading System) method, widely used by dermatologists because it considers not only the type of lesions, but also their distribution in the different anatomical regions of the face. To make this feasible, it will be necessary to incorporate facial semantic segmentation techniques, which will allow the precise delineation of areas such as the forehead, cheeks, chin, and nose. This stage will contribute significantly to adapting the system to recognized clinical standards.

In addition, future versions of the project could investigate the use of alternative detection models beyond YOLOv11, such as YOLOv8, Faster R-CNN, or architectures that demonstrate superior performance in contexts with small lesions and minimal texture variation. Another promising line involves replacing or supplementing the current dataset with larger, more diverse databases annotated with standardized clinical criteria, which would enable the training of more robust and generalizable models.

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References

[1] A. L. Zaenglein, "Acne vulgaris," *New England Journal of Medicine*, vol. 379, no. 14, pp. 1343–1352, 2018.

[2] D. V. Samuels, R. Rosenthal, R. Lin, S. Chaudhari, and M. N. Natsuaki, "Acne vulgaris and risk of depression and anxiety: a meta-analytic review," *Journal of the American Academy of Dermatology*, vol. 83, no. 2, pp. 532–541, 2020.

[3] I. Vallerand, R. Lewinson, L. Parsons, M. Lowerison, A. Frolkis, G. Kaplan, C. Barnabe, A. Bulloch, and S. Patten, "Risk of depression among patients with acne in the uk: a population-based cohort study," *British Journal of Dermatology*, vol. 178, no. 3, pp. e194–e195, 2018.

[4] X. Wu, N. Wen, J. Liang, Y.-K. Lai, D. She, M.-M. Cheng, and J. Yang, "Joint acne image grading and counting via label distribution learning," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

[5] Y. Akpinar Kara and D. Ozdemir, "Evaluation of food consumption in patients with acne vulgaris and its relationship with acne severity," *Journal of cosmetic dermatology*, vol. 19, no. 8, pp. 2109–2113, 2020.

[6] E. Nasr-Esfahani, S. Samavi, N. Karimi, S. Soroushmehr, M. Jafari, K. Ward, and K. Najarian, "2016 38th annual international conference of the ieee engineering in medicine and biology society (embc)," *Melanoma detection by analysis of clinical images using convolutional neural network*, pp. 1373–1376, 2016.

[7] Y. Fujisawa, Y. Otomo, Y. Ogata, Y. Nakamura, R. Fujita, Y. Ishitsuka, R. Watanabe, N. Okiyama, K. Ohara, and M. Fujimoto, "Deep-learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumour diagnosis," *British Journal of Dermatology*, vol. 180, no. 2, pp. 373–381, 02 2019. [Online]. Available: https://doi.org/10.1111/bjd.16924

[8] K. R. Glines, W. Haidari, L. Ramani, Z. M. Akkurt, and S. R. Feldman, "Digital future of dermatology," *Dermatology online journal*, vol. 26, no. 10, 2020.

[9] N. Saranummi, "Ieee transactions on information technology in biomedicine (t-itb)," *IEEE Transactions on Information Technology in Biomedicine*, vol. 7, no. 4, pp. 226–226, 2004.

[10] J. D. Bernhard, "Journal of the american academy of dermatology editorial office," *Journal of the American Academy of Dermatology*, vol. 49, no. 6, p. 1028, 2003.

[11] K. Byamba, S. Syed-Abdul, M. García-Romero, C.-W. Huang, S. Nergyi, A. Nyamdorj, P.-A. Nguyen, U. Iqbal, K. Paik, L. Celi *et al.*, "Mobile teledermatology for a prompter and more efficient dermatological care in rural mongolia," *British Journal of Dermatology*, vol. 173, no. 1, pp. 265–267, 2015.
[12] F. M. Walocko and T. Tejasvi, "Teledermatology applications in skin cancer diagnosis," *Dermatologic clinics*, vol. 35, no. 4, pp. 559–563, 2017.
[13] S. Ouellette and B. K. Rao, "Usefulness of smartphones in dermatology: a us-based review," *International Journal of Environmental Research and Public Health*, vol. 19, no. 6, p. 3553, 2022.
[14] R. S. Azfar, J. L. Weinberg, G. Cavric, I. A. Lee-Keltner, W. B. Bilker, J. M. Gelfand, and C. L. Kovarik, "Hiv-positive patients in botswana state that mobile teledermatology is an acceptable method for receiving dermatology care," *Journal of telemedicine and telecare*, vol. 17, no. 6, pp. 338–340, 2011.
[15] I. Radosavovic, R. P. Kosaraju, R. Girshick, K. He, and P. Dollár, "Designing network design spaces," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2020, pp. 10 428–10 436.
[16] R. A. Diptho and S. Basak, "Enhancing dermatological diagnosis through medical image analysis: How effective is yolo11 compared to leading cnn models?" *NDT*, vol. 3, no. 2, p. 11, 2025.
[17] G. Jocher and J. Qiu, "Ultralytics yolo11," 2024. [Online]. Available: https://github.com/ultralytics/ultralytics
[18] J. Torous, H. Wisniewski, B. Bird, E. Carpenter, G. David, E. Elejalde, D. Fulford, S. Guimond, R. Hays, P. Henson *et al.*, "Creating a digital health smartphone app and digital phenotyping platform for mental health and diverse healthcare needs: an interdisciplinary and collaborative approach," *Journal of Technology in Behavioral Science*, vol. 4, no. 2, pp. 73–85, 2019.
[19] H. Cortés, M. Rojas-Márquez, M. L. Del Prado-Audelo, O. D. Reyes-Hernández, M. González-Del Carmen, and G. Leyva-Gómez, "Alterations in mental health and quality of life in patients with skin disorders: a narrative review," *International journal of dermatology*, vol. 61, no. 7, pp. 783–791, 2022.
[20] A. C. Brewer, D. C. Endly, J. Henley, M. Amir, B. P. Sampson, J. F. Moreau, and R. P. Dellavalle, "Mobile applications in dermatology," *JAMA dermatology*, vol. 149, no. 11, pp. 1300–1304, 2013.
[21] K. Tran, M. Ayad, J. Weinberg, A. Cherng, M. Chowdhury, S. Monir, M. El Hariri, and C. Kovarik, "Mobile teledermatology in the developing world: implications of a feasibility study on 30 egyptian patients with common skin diseases," *Journal of the American Academy of Dermatology*, vol. 64, no. 2, pp. 302–309, 2011.
[22] H. Kim, J. Kim, E. Jung, D. Park, and J. Roh, "Mobile application in dermatology: a useful tool for better communication and patient education," *Hong Kong Journal of Dermatology & Venereology*, vol. 2, no. 26, pp. 67–70, 2018.
[23] S. J. Lofgreen, K. Ashack, K. A. Burton, and R. P. Dellavalle, "Mobile device use in dermatologic patient care," *Current Dermatology Reports*, vol. 5, no. 2, pp. 77–82, 2016.
[24] L. C. De Guzman, R. P. C. Maglaque, V. M. B. Torres, S. P. A. Zapido, and M. O. Cordel, "Design and evaluation of a multi-model, multi-level artificial neural network for eczema skin lesion detection," in *2015 3rd International conference on artificial intelligence, modelling and simulation (AIMS)*. IEEE, 2015, pp. 42–47.
[25] U. P. Sudhakara, H. Hebbar, G. Arunkumar, and N. Sampathila, "A technology framework for remote patient care in dermatology for early diagnosis," *Informatics in Medicine Unlocked*, vol. 15, p. 100171, 2019.
[26] E. Göçeri, "Impact of deep learning and smartphone technologies in dermatology: Automated diagnosis," in *2020 tenth international conference on image processing theory, tools and applications (IPTA)*. IEEE, 2020, pp. 1–6.
[27] E. Goceri, "Diagnosis of skin diseases in the era of deep learning and mobile technology," *Computers in Biology and Medicine*, vol. 134, p. 104458, 2021.
[28] S. Wongvibulsin, M. J. Yan, V. Pahalyants, W. Murphy, R. Daneshjou, and V. Rotemberg, "Current state of dermatology mobile applications with artificial intelligence features," *JAMA dermatology*, vol. 160, no. 6, pp. 646–650, 2024.
[29] P. P. Rebouças Filho, S. A. Peixoto, R. V. M. da Nóbrega, D. J. Hemanth, A. G. Medeiros, A. K. Sangaiah, and V. H. C. de Albuquerque, "Automatic histologically-closer classification of skin lesions," *Computerized Medical Imaging and Graphics*, vol. 68, pp. 40–54, 2018.
[30] A. De, A. Sarda, S. Gupta, and S. Das, "Use of artificial intelligence in dermatology," *Indian journal of dermatology*, vol. 65, no. 5, pp. 352–357, 2020.
[31] T. J. Brinker, A. Hekler, A. H. Enk, J. Klode, A. Hauschild, C. Berking, B. Schilling, S. Haferkamp, D. Schadendorf, S. Fröhling *et al.*, "A convolutional neural network trained with dermoscopic images performed on par with 145 dermatologists in a clinical melanoma image classification task," *European Journal of Cancer*, vol. 111, pp. 148–154, 2019.
[32] M.-J. Yim, J. M. Lee, H.-S. Kim, G. Choi, Y.-M. Kim, D.-S. Lee, and I.-W. Choi, "Inhibitory effects of a sargassum miyabei yendo on cutibacterium acnes-induced skin inflammation," *Nutrients*, vol. 12, no. 9, p. 2620, 2020.
[33] A. Sangha and M. Rizvi, "Detection of acne by deep learning object detection," *medRxiv*, 2021.
[34] "Automatic acne object detection and acne severity grading using smartphone images and artificial intelligence," *Diagnostics*, vol. 12, no. 8, 2022.
[35] "Acne detection by ensemble neural networks," *Sensors*, vol. 22, no. 18, 2022.
[36] "Acne8m: An acne detection and differential diagnosis system using ai technologies," 2023, study link provided, no DOI available.
[37] "Acne vulgaris detection and classification: A dual integrated deep cnn model," *Informatica (Slovenia)*, vol. 47, no. 4, 2023.
[38] C. Huang *et al.*, "A computer vision application for assessing facial acne severity from selfie images," https://arxiv.org/abs/1907.07901, 2019.
[39] Z. Xu *et al.*, "Acnet: Mask-aware attention with dynamic context enhancement for robust acne detection," https://arxiv.org/abs/2105.14891, 2021.
[40] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.
[41] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2016.
[42] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR)*, 2016.
[43] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," 2017.
[44] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR)*, 2016.
[45] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, "Ssd: Single shot multibox detector," in *European Conference on Computer Vision (ECCV)*. Springer, 2016.
[46] S. Vijayarani and S. Dhivya, "Facial acne classification using image processing and machine learning," *International Journal of Computer Applications*, vol. 123, no. 9, 2015.
[47] P. K. Kalra, A. Ghosh, and A. Kumar, "Acne detection using clustering based image segmentation and texture feature extraction with svm classifier," *Procedia Computer Science*, vol. 167, pp. 2391–2400, 2019.
[48] M. Everingham, L. Van Gool, C. Williams, J. Winn, and A. Zisserman, "The pascal visual object classes (voc) challenge," *International journal of computer vision*, vol. 88, no. 2, pp. 303–338, 2010.
[49] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft coco: Common objects in context," in *European Conference on Computer Vision*. Springer, 2014, pp. 740–755.
[50] H. Zhang and T. Ma, "Acne detection by ensemble neural networks," *Sensors*, vol. 22, no. 18, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/18/6828
[51] X. Shen, J. Zhang, C. Yan, and H. Zhou, "An automatic diagnosis method of facial acne vulgaris based on convolutional neural network," *Scientific reports*, vol. 8, no. 1, p. 5839, 2018.
[52] R. Sabir and T. Mehmood, "Classification of melanoma skin cancer based on image data set using different neural networks," *Scientific Reports*, vol. 14, no. 1, p. 29704, 2024.
[53] J. Frederich, J. Himawan, and M. Rizkinia, "Skin lesion classification using efficientnet b0 and b1 via transfer learning for computer aided diagnosis," in *AIP Conference Proceedings*, vol. 3080, no. 1. AIP Publishing, 2024.
[54] H. Alsulaimani, A. Kokandi, S. Khawandanh, and R. Hamad, "Severity of acne vulgaris: comparison of two assessment methods," *Clinical, cosmetic and investigational dermatology*, pp. 711–716, 2020.