

Deep Learning-Based Exploration of YOLOv8 for Acne Vulgaris Type Classification and Lesion Counting

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Abstract—Acne vulgaris is a prevalent skin disorder that considerably affects teenagers and young adults worldwide. The condition is characterized by various lesion types, including papules, pustules, and nodules, each requiring specific treatment approaches. Conventional methods of acne assessment are often inconsistent, subjective, and labor-intensive, making it challenging for dermatologists to provide accurate and timely diagnoses. This study utilizes the You Only Look Once (YOLO) version 8 (YOLOv8) deep learning architecture to develop an automated and objective system for categorizing acne lesions and evaluating acne severity. Renowned for its speed and accuracy in object detection, this model processes facial images through resizing, normalization, and augmentation to maintain data consistency and boost detection precision. Lesions are categorized into papules, pustules, and nodules. The model achieved 80% precision, 81% recall, and a 78% F1-score, illustrating its effectiveness in detecting and classifying acne lesions while minimizing diagnostic delays. Future efforts should address dataset imbalances by integrating underrepresented classes, exploring class-weighted training, and applying advanced augmentation techniques to further enhance performance. This study underscores the potential of AI-powered tools like YOLOv8 to advance dermatological practice, improve patient care, and contribute to public health progress.

Index Terms—acne prediction, acne vulgaris, YOLOv8, CNN

I. INTRODUCTION

Acne vulgaris, commonly referred to as acne, is one of the most prevalent dermatological conditions worldwide, characterized as a chronic inflammatory disorder. It manifests in a variety of forms, including papules, nodules, comedones, blackheads, whiteheads, pustules, erythema, and cysts [1], [2]. These clinical presentations can broadly be categorized into non-inflammatory and inflammatory lesions. While acne predominantly affects adolescents and young adults aged 12 to 24 years, it can impact individuals across all age groups [3]. In regions like Asia, particularly in countries such as Indonesia, acne prevalence is further exacerbated by variable climatic conditions and dietary practices, making it a significant public health concern. Beyond physical symptoms, acne has profound psychological and social implications, affecting self-esteem, interpersonal relationships, and mental health, with severe cases linked to depression and suicidal tendencies. This underscores the importance of accurate acne severity evaluation and lesion quantification in guiding effective treatment strategies.

Traditional acne assessment methods are often subjective, prone to variability among clinicians, and labor-intensive,

highlighting the need for more standardized and precise methodologies. Established tools such as the Global Acne Grading System (GAGS) and the Investigator Global Assessment (IGA) are frequently used to ensure international standardization in acne severity evaluations.

The GAGS evaluates acne severity based on the location and type of lesions across six body areas: forehead, cheeks, nose, chin, chest, and upper back. Each area is assigned a weight proportional to its size and pilosebaceous density, with lesion severity scored from 0 to 4. A global score is calculated by multiplying the severity score by the area weight, classifying acne as mild (1–18), moderate (19–30), severe (31–38), or very severe (over 38) [4]. Conversely, the IGA scale provides a holistic severity rating from 0 to 4, where 0 indicates clear skin and 4 denotes severe acne with extensive lesions, including nodules. This scale does not differentiate between facial regions but defines each level with specific criteria for lesion type and extent [4].

Recent advancements in artificial intelligence (AI) and computational technologies have revolutionized healthcare, particularly in dermatology, by enhancing image analysis and addressing challenges in skin condition detection and classification. Machine learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in identifying and categorizing dermatological conditions. For instance, AcneNet, a specialized CNN for acne detection, achieved an overall accuracy of 95.89% [5], while CNN-based models have also been effective in detecting melanoma and other skin lesions [6]–[10]. Object detection models like YOLO (You Only Look Once) have also been applied to acne detection, with YOLOv4 achieving 91.25% accuracy in detecting facial acne [1]. YOLOv8, the latest iteration, offers enhanced performance, accuracy, and efficiency, making it suitable for diverse applications, including medical imaging. In comparative studies, YOLOv8 achieved higher F1-scores than YOLOv5 and YOLOv7 for helmet detection tasks [11]. Additionally, in fire detection tasks, YOLOv8 demonstrated strong performance in detecting both fire and smoke, whereas YOLOv4 was limited to detecting fire alone [12]. However, it is important to note that YOLOv8 in this study utilized a larger dataset than YOLOv4, which contributed to its performance advantage.

This research employs YOLOv8 to categorize acne lesions into types such as nodules, papules, and pustules, and to quantify them in order to evaluate acne severity. YOLOv8

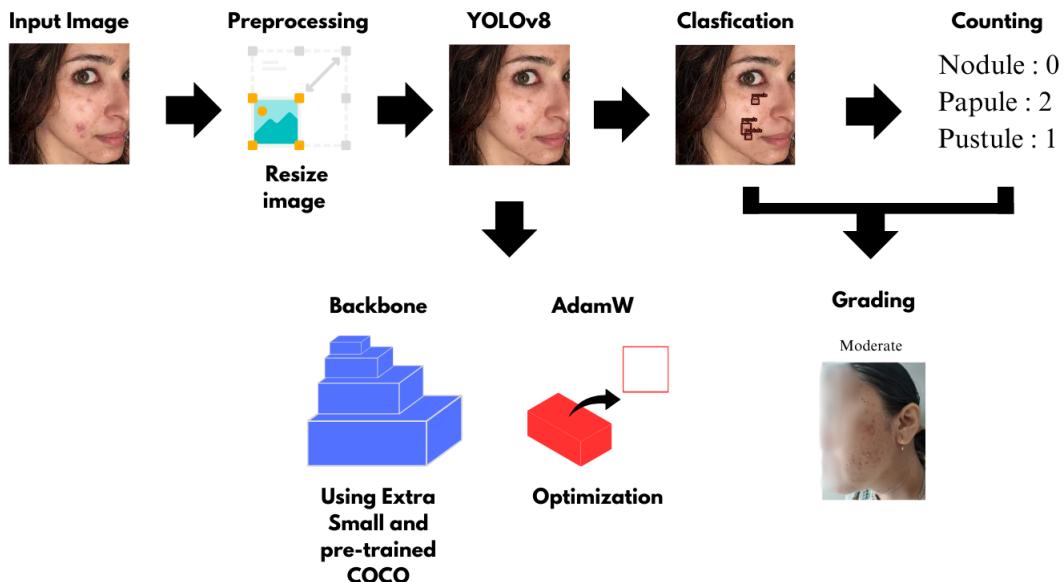


Fig. 1. System flow of YOLOv8 in acne detection.

was chosen for its advanced architecture, which enhances speed, accuracy, and efficiency beyond previous versions, making it well-suited for medical imaging applications. While models like YOLOv4 and AcneNet have excelled in acne detection, this study centers on how effectively YOLOv8 can classify acne lesions and assess their severity. By utilizing these technological advances, the study seeks to investigate YOLOv8's potential to tackle challenges in dermatological imaging, rather than making direct comparisons with older models. Employing cutting-edge deep learning methods, this research aims to establish a dependable, automated system for acne diagnosis and management, boosting precision, efficiency, and patient care.

The structure of this paper is organized as follows: Section II details the Research Methodology, including the system flowchart, dataset description, and evaluation metrics used to assess the model's performance. Section III presents the Results and Discussion, highlighting the model's performance in acne lesion classification, severity assessment, and lesion quantification while addressing its limitations and practical implications. Finally, the Conclusion synthesizes the findings, emphasizing the study's contributions and proposing potential directions for future research.

II. RESEARCH METHODOLOGY

A. YOLO

YOLO is a state-of-the-art, real-time object detection system that has significantly influenced computer vision due to its speed and accuracy. Originally introduced by Redmon et al. in 2016 [13], YOLO has undergone several iterations, each improving upon the last in terms of both performance and efficiency. YOLO itself has several characteristics, such as:

- 1) Single Neural Network: YOLO frames object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. This unified approach enables YOLO to run significantly faster than competitor models, which often apply a two-step process involving region proposals followed by classification.

- 2) Real-Time Processing: YOLO is renowned for its speed, which allows it to detect objects in real-time. This capability is crucial for applications requiring immediate analytical feedback, such as interactive systems and autonomous driving.
- 3) Grid-Based Detection: The image is divided into an $S \times S$ grid and for each grid cell, the model predicts multiple bounding boxes, confidence scores for those boxes, and class probabilities. The confidence score reflects the accuracy of the bounding box and whether the box contains a specific object. Meanwhile, the class probabilities denote the likelihood of the object belonging to a particular class.

YOLOv8 represents the latest advancement in this model series, offering significant improvements in speed, accuracy, and model size, making it suitable for real-time applications [14]. This model is the result of the evolution of the previous version in 2023 by Ultralytics [15]. In medical imaging, particularly in dermatology, the adaptation of YOLOv8 could potentially transform the detection and classification processes of acne lesions. Its ability to rapidly process images and accurately identify and count acne lesions can be pivotal in clinical settings, providing dermatologists with a powerful tool for both diagnosis and severity assessment of acne.

B. Flowchart system

The method employed in this study utilizes a Convolutional Neural Network (CNN) based on the YOLO version 8 (YOLOv8) model. The process begins with inputting a dataset containing various images of facial acne. This dataset is critical as it provides the foundational data required for training and testing the system. The next step involves preprocessing, where the images are adjusted to improve their quality and enhance the diversity of the data. Following preprocessing, the model setup phase is initiated. At this stage, the YOLOv8 architecture is specifically configured for acne detection. Subsequently, YOLOv8 processes the preprocessed images to identify and extract key features indicative of acne lesions. These features play a crucial role in accurately detecting

and classifying acne in the subsequent steps. For a detailed overview, refer to Fig. 1.

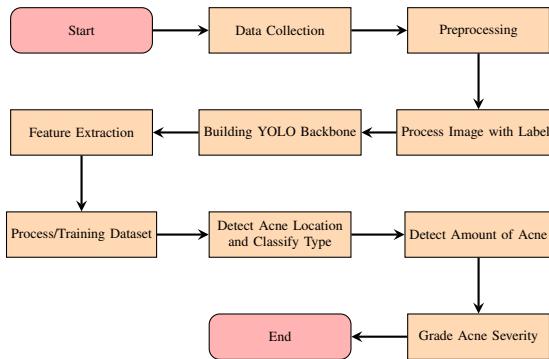


Fig. 2. Research methodology for acne detection.

During the training process, the YOLOv8 model scans the input images to detect and identify potential acne lesions. Each detected lesion is then processed in the Lesion Type Classification step, where the model determines the type of acne, such as blackheads, whiteheads, or pustules, based on extracted features. In the Lesion Count step, the system counts all lesions present on the face, including a breakdown by lesion type, which is crucial for assessing the severity of the acne condition. Finally, in the Severity Grading phase, the system evaluates the severity of acne based on the number and types of detected lesions. The process concludes with the final phase, where the system outputs the results, including the lesion types, counts, and severity grades identified in the images. A detailed illustration of this research methodology is provided in Fig. 2.

C. Dataset

The dataset used in this study was sourced from Kaggle, a well-known open-source platform recognized for its extensive repository of datasets suited for various data science applications. This dataset, published by the Kaggle user Kucev Roman¹, consists of images of individuals with acne severity levels ranging from 3 to 4, as defined by the IGA scale. The dataset includes three types of image perspectives: frontal, left two-thirds, and right two-thirds, as shown in Fig. 3.

To facilitate its use in machine learning workflows, the dataset is systematically organized into three primary folders: testing, training, and validation. Each folder is further divided into two subfolders: one containing facial images depicting various types of acne, and the other holding corresponding labels. These labels are essential as they are formatted specifically to interact with the YOLOv8 model, an advanced object detection system. The labels, stored as .txt files, employ bounding box annotations to identify and locate objects within the images. The label format includes five key variables, which are detailed in Table I.

The dataset initially contains labeled data with a general “acne” object class, as shown in Table II, but lacks the specific acne types required for this study. To meet the training requirements, the dataset will be relabeled to classify acne into three distinct categories: nodules, papules, and pustules. The updated labels will use numerical identifiers:

¹<https://www.kaggle.com/datasets/osmankagankurnaz/acne-dataset-in-yolov8-format>



Fig. 3. Some example images from the test dataset sourced from Kaggle.

TABLE I
EXPLANATION ABOUT VARIABLES LABELS

Variables	Descriptions
Object class	the type of object (in this case, the type of acne lesion)
x coordinate	center point x coordinate for the object or bounding box
y coordinate	center point y coordinate for the object or bounding box
Height	the height of the bounding box
Width	the width of the bounding box

TABLE II
EXAMPLE OF TEXT FILE FOR ANNOTATIONS IN TEST DATA

Class	X Center	Y Center	Width	Height
0	0.71015625	0.28984375	0.040625	0.059375
0	0.76953125	0.37421875	0.04296875	0.07421875
0	0.53125	0.3953125	0.04375	0.06015625
0	0.47421875	0.6015625	0.03671875	0.059375
0	0.57265625	0.43046875	0.0359375	0.05859375

3 for nodules, 4 for papules, and 5 for pustules, as outlined in Table III.

Papules are small, raised lesions less than 1 cm in diameter that appear red and inflamed. Pustules, which are similar in appearance, contain pus at their centers, indicating a heightened inflammatory response. In more severe cases, lesions may develop into nodules—painful, inflamed swellings larger than 5 mm. Papules result from deep skin inflammation, while pustules exhibit additional erythema and edema. Severe and persistent inflammation can lead to the formation of nodules [16]–[18].

TABLE III
EXAMPLE OF TEXT FILE FOR ANNOTATIONS IN TEST DATA AFTER RELABELING

Class	X Center	Y Center	Width	Height
5	0.71015625	0.28984375	0.040625	0.059375
4	0.76953125	0.37421875	0.04296875	0.07421875
4	0.53125	0.3953125	0.04375	0.06015625
5	0.47421875	0.6015625	0.03671875	0.059375
4	0.57265625	0.43046875	0.0359375	0.05859375

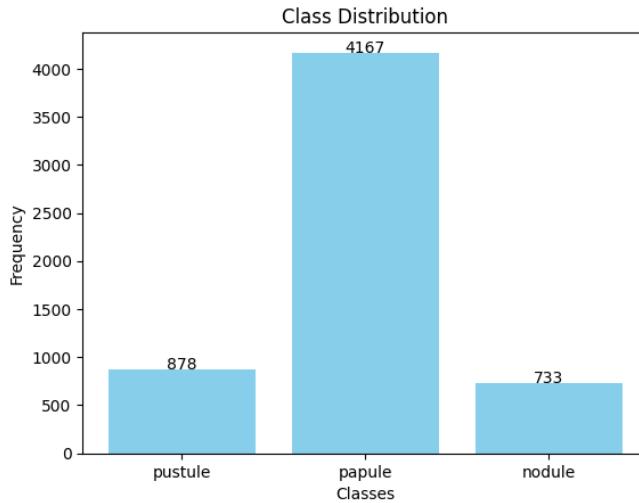


Fig. 4. Distribution of target class.

After the relabeling process, the dataset now consists of 5,778 samples classified into three distinct categories of acne: papules, pustules, and nodules, as illustrated in Fig. 4. The distribution of classes reveals a significant imbalance: papules are substantially more prevalent, accounting for 4,167 samples (72.1%), while pustules and nodules are comparatively less common, comprising 878 samples (15.2%) and 733 samples (12.7%), respectively. This imbalance poses challenges for training the classification model, as the predominance of papules allows the model to learn their characteristics more effectively than those of the underrepresented classes.

D. Evaluation Metrics

The developed acne classification and counting system will be tested using a specific test dataset. The evaluation metrics that will be used in this study are commonly employed to assess models, including accuracy, precision, recall, and F1-score [19]. These metrics will help in evaluating and reporting the effectiveness and efficiency of the YOLOv8 model in classifying different types of acne.

In this research, the evaluation metrics is known as confusion matrix, which consist of several variables, such as:

- True Positive (TP): The number of positive samples that are correctly predicted as positive.
- False Positive (FP): The number of negative samples that are incorrectly predicted as positive (type I error).
- False Negative (FN): The number of positive samples that are incorrectly predicted as negative (type II error).
- True Negative (TN): The number of negative samples that are correctly predicted as negative.

Accuracy is one of the most frequently used metrics to measure the performance of a classification model. It calculates the proportion of samples that are correctly classified compared to the total number of samples [20], [21]. Here is the formula to calculate the accuracy:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \quad (1)$$

Precision represents the proportion of correctly classified positive samples among all samples predicted as positive. It measures the accuracy of positive predictions made by the model [20], [21]. Here is the formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

Recall represents the proportion of correctly classified positive samples among all actual positive samples. It assesses the model's ability to identify all relevant positive cases [20], [21]. Here is the formula to calculate the recall:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

The F-measure combines precision and recall into a single metric that balances both concerns. Its value ranges from 0 to 1. The F1-score is a specific variation of the F-measure where precision and recall are equally weighted, providing a balanced evaluation of the model's performance [21]. Here is the formula to calculate the F1-score:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

All the formulas mentioned above can be explained using a confusion matrix [19].

III. RESULTS AND DISCUSSION

A. Classification Type of Acne Vulgaris

The annotated instances of acne lesions demonstrate the model's capability in detecting and classifying papules, pustules, and nodules, from the sample images (Fig. 3) as illustrated in Fig. 5, by comparing its predictions (green bounding boxes) with the actual ground truth labels (red bounding boxes).

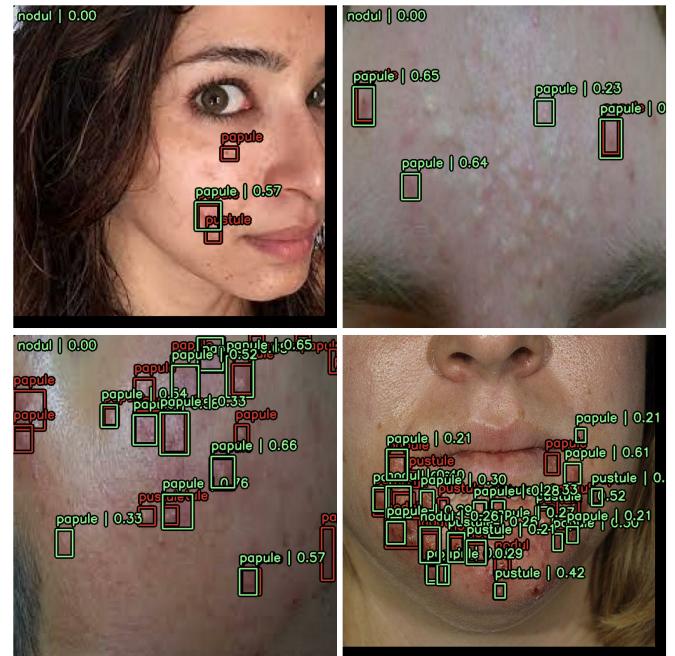


Fig. 5. The results of the YOLOv8 model applied to sample images as illustrated in Fig. 3.

In the upper left panel of Fig. 5, the model demonstrates fair accuracy in forecasting papules and pustules on the cheek, although some pustules are mistakenly identified as papules owing to their visual similarity, highlighting the challenge of distinguishing subtle variations in lesions. The upper right panel illustrates effective detection of papules on the forehead, where green boxes closely match the red

representations of ground truth, despite a few instances of missed or inaccurately placed papules. In the lower left panel, the model adeptly navigates a densely populated cheek area, detecting the majority of papules despite its complexity; nonetheless, minor errors in bounding box positioning expose the difficulty in capturing lesions placed in close proximity. In the lower right panel, which depicts the chin and mouth area, the model correctly identifies most papules and pustules; however, the rarity of nodules in both predictions and ground truth highlights an imbalance within the dataset.

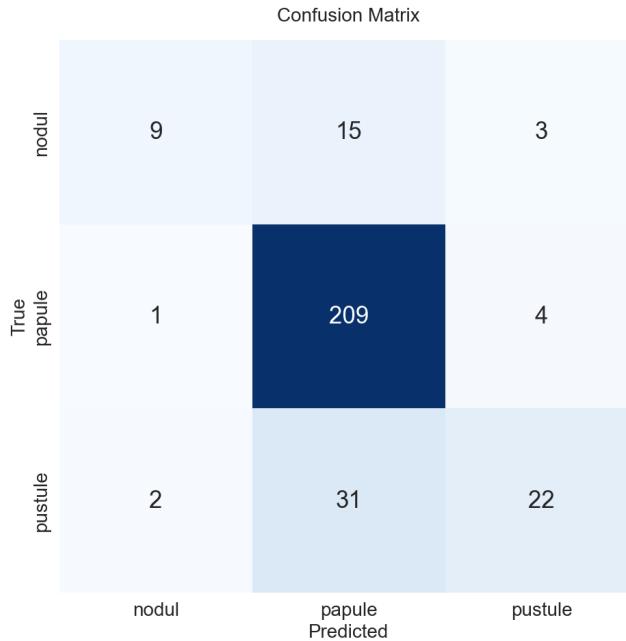


Fig. 6. Confusion matrix for model

The confusion matrix depicted in Fig. 6 assesses the performance of the YOLOv8 model in categorizing acne lesions into nodules, papules, and pustules. The model demonstrates strong proficiency in identifying papules, accurately classifying 209 samples. However, some misclassifications are evident, with one papule misclassified as a nodule and four as pustules.

In contrast, the model faces challenges in accurately classifying pustules, often misidentifying them as papules due to shared visual features, such as redness and inflammation. Among the pustule samples, only 22 were correctly classified, while 31 were misclassified as papules and 2 as nodules. A similar pattern is observed with nodules, where only 9 samples were accurately identified, while 15 were misclassified as papules and 3 as pustules.

These results highlight the impact of dataset imbalance, where the higher prevalence of papules in the dataset enables the model to learn their features more effectively, resulting in superior classification accuracy for this category compared to pustules and nodules.

TABLE IV
OVERALL PERFORMANCE METRICS FOR THE MODEL

Metric	Value
Accuracy	0.81
Precision	0.80
Recall	0.81
F1-score	0.78

The YOLOv8 model demonstrated strong overall performance in detecting and classifying acne lesions, achieving an accuracy of 81%. As shown in Table IV, the model achieved weighted precision, recall, and F1-score of 0.80, 0.81, and 0.78, respectively. These metrics highlight the model's ability to maintain a good balance between precision (the correctness of positive predictions) and recall (its ability to detect relevant instances). The F1-score, as the harmonic mean of precision and recall, underscores the model's robustness in handling classification tasks, even when faced with imbalanced data.

Despite these promising results, the dataset imbalance posed a notable challenge. Papules accounted for approximately 70% of the samples, while pustules and nodules represented only 10–15% each. This imbalance significantly influenced the model's performance, resulting in superior classification accuracy for papules compared to the under-represented categories of pustules and nodules, as evidenced by the confusion matrix.

While these findings demonstrate the potential of the YOLOv8 model for acne lesion classification, they also underscore the importance of addressing class imbalance. Techniques such as data augmentation or weighted training could enhance the model's generalizability and improve its performance across all lesion types. These results affirm the model's effectiveness while identifying areas for refinement, providing a foundation for future advancements in automated acne classification.

B. Severity of acne and lesion counting

To thoroughly assess the robustness and generalizability of the YOLOv8 model, images independent of the training, testing, and validation datasets were used. These supplementary images, collected from volunteers via Google Forms, were entirely distinct from the original Kaggle dataset. They served as a means to evaluate the model's effectiveness in detecting, classifying, and determining acne severity in novel, unseen cases. This evaluation was crucial for gauging the model's performance in real-world scenarios beyond the controlled conditions of the original datasets. Notably, one of the test images included in this evaluation featured the facial image of the second author of this paper, adding an additional layer of practical validation (Fig. 7).



Fig. 7. (a) Example of an input image featuring the second author's face from this paper, and (b) the corresponding output image processed by YOLOv8.

In Fig. 7(a), the input image illustrates the subject's facial region devoid of annotations or true labels, as the dataset was compiled independently of any originally labeled datasets and is without predefined ground truth bounding boxes (red). This configuration simulates a real-world context wherein the

model functions autonomously, absent of pre-existing manual annotations, thereby demonstrating its potential applicability in clinical or diagnostic settings. In Fig. 7(b), the predictions generated by the YOLOv8 model are represented by green bounding boxes, each accompanied by a confidence level and a lesion classification. The model accurately identifies papules and a pustule, demonstrating its ability to classify lesions in unannotated cases. The absence of red bounding boxes highlights that this evaluation was conducted independently, without relying on prior annotations.

TABLE V
CLASSIFICATION AND GRADING OUTPUT OF FIG. 7

Parameter	Value
Image	test.jpg
Total Detections	6
Number of Papules	5
Number of Pustules	1
Number of Nodules	0
Severity Level	3 (Moderate)

The YOLOv8 model was employed not only to classify acne lesions but also to count them and assess the severity of acne in the given image (Fig. 7). Table V summarizes the results of the classification and grading process for an example input image. The model detected a total of 6 lesions, comprising 5 papules and 1 pustule, with no nodules identified. Based on the quantity and types of lesions detected, the acne severity level was graded as 3 (Moderate).

This result highlights the model's capability to automatically analyze and quantify lesions in an image, providing a consistent and objective method for determining acne severity. Such automated lesion counting and severity grading can support dermatologists in tracking patient progress and optimizing treatment plans more effectively.

IV. CONCLUSION

This study focused on the classification and enumeration of acne vulgaris lesions—specifically papules, pustules, and nodules—using the YOLOv8 model. The model demonstrated strong overall performance, achieving an F1-score of 78%, an accuracy of 81%, a precision of 80%, and a recall of 81%. Despite these promising results, the study faced challenges stemming from significant dataset imbalance, with pustules and nodules being underrepresented. This imbalance limited the model's ability to generalize effectively for minority classes, leading to occasional misclassifications. The model's robustness and generalizability were further assessed using additional images that were independent of the original dataset. Furthermore, the YOLOv8 model demonstrated its capability to not only classify but also count acne lesions and assess acne severity. As a result, the model successfully detected a total of 6 lesions (5 papules and 1 pustule) and graded the severity as 3 (Moderate) as shown in Table V.

To address these limitations, future research should aim to expand the dataset for underrepresented classes, employ advanced augmentation techniques, and utilize class-weighted training strategies. Additional improvements could include hyperparameter fine-tuning, exploring deeper YOLOv8 variants, and enhancing post-processing methods for lesion counting. These optimizations would further improve the model's robustness and overall efficiency. Furthermore, this study underscores the potential of the YOLOv8 model as an automated tool for the classification and quantification of acne

lesions, paving the way for more reliable, objective, and efficient dermatological assessments.

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