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Multiclass Acne Lesion Detection In Facial Skin Using Advanced Deep Learning Techniques

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Abstract: Acne is one of the most common skin diseases affecting people across different age groups, and accurate classification of lesion types is essential for effective dermatological diagnosis and treatment planning. However, manually assessing acne lesions can be both subjective and time-consuming, which has driven the development of automated computer-aided diagnostic systems. In this context, the authors propose a multiclass deep learning–based object recognition model for acne lesion classification using facial skin images. The system is designed to detect and classify various types of acne lesions, including blackheads, nodules, papules, pustules, whiteheads, as well as background regions. Initially, the skin images undergo preprocessing to enhance quality and reduce noise that could otherwise affect feature extraction. Subsequently, a deep learning model is employed to automatically learn discriminative visual features of different lesion categories. These learned features enable precise multiclass classification of acne lesions present in facial skin images.

Index Terms - Acne classification, skin lesion detection, deep learning, multiclass analysis of skin diseases, and computer-aided dermatology.

I. INTRODUCTION

Acne is one of the most common skin disorders worldwide, particularly affecting adolescents and young individuals. It develops due to inflammation of hair follicles and sebaceous glands, leading to various types of skin lesions such as blackheads, whiteheads, papules, pustules, and nodules. Accurate identification and classification of these lesions are essential for proper dermatological diagnosis and effective treatment planning. Traditionally, dermatologists rely on manual examination, which can be time-consuming and subjective, often depending on the clinician's experience. In recent years, advancements in artificial intelligence and computer vision have shifted attention toward automated skin image analysis. Convolutional neural networks, a form of deep learning, have demonstrated strong performance in medical image classification tasks, including skin disease detection. These methods can automatically extract complex visual features from dermatological images and provide reliable support for early diagnosis and clinical decision-making. As a result, developing an efficient deep learning–based system for multiclass classification of acne lesions has become an important area of research in intelligent dermatological analysis.

Although there has been advancement in the diagnosis of skin diseases by using computers, there are still some research gaps in the literature of the field. Most of the available literature is based on binary classification or generic skin disease detection and not on multiclass multifocal acne lesion detection. Nevertheless, the appearances, sizes, and degree of acne lesions differ drastically and it is difficult to distinguish between various types of lesions. Moreover, certain conventional machine learning methods are highly dependent on manual feature extraction, which might not be efficient in applying highly intricate visual features that exist in dermatological images. There is also another weakness of current practices, in that not enough attention is dedicated to the separation of acne lesions and background areas that may result in misclassification and decrease the reliability of the model. Moreover, different datasets with different categories of acne lesions are not readily available, which also makes the generalization of models difficult. These shortcomings point to the necessity of more powerful deep learning-based systems that could identify and categorize various types of acne lesions on the facial photograph with high precision and reduce the rate of misclassifications.

This paper is set to solve these problems by proposing an automated multiclass acnes lesion classification framework based on skin images through deep learning. The main goal of the proposed work is to correctly identify and categorize the various types of acnes lesions, such as blackheads, nodules, papules, pustules, and whiteheads, and background areas. The presented framework takes advantage of sophisticated processes of preprocessing and improving the quality of input information by eliminating noise that can impact the classification performance. An artificial intelligence method is then used to discover discriminative visual features that depict the various types of acnes lesions. Using the multiclass classification method, the system is able to classify different acne lesions by using the ability of the deep neural networks to extract intricate spatial patterns on images. To evaluate the suggested approach, standard performance criteria are employed and the confusion matrix analysis is carried out in order to determine the accuracy of the classification of all types of lesions.

The results of the experiments prove that the suggested deep learning architecture is capable of detecting and categorizing various types of acne lesions in the pictures of the facial area with a high degree of accuracy. The obtained results of the confusion matrix reveal that there is a high level of classification throughout the various lesion types, such as blackheads, nodules, papules, pustules and whiteheads and also has a high level of discrimination between the background areas. The originality of this paper is that it introduces a unifying model of multiclass acne lesions that is based on the intensive identification of acne types instead of the overall identification of the skin disease. The proposed approach uses the deep learning feature extraction to increase the accuracy and robustness of the classification, unlike the conventional methods that utilize handcrafted features or a small number of lesion categories. Moreover, the combination of various types of acnes lesions with one common system of classification makes the system more applicable to the real dermatological analysis. It is possible to support dermatologists with the proposed system, which will introduce automated assistance in diagnosing acne and eventually lead to the development of intelligent computer-aided skin disease detection and clinical decision support systems.

II. Related Work

During recent years, the use of artificial intelligence and deep learning on dermatological images analysis received a lot of attention. The development of automated methods of detecting skin diseases has been a popular research area to help dermatologists accurately diagnose different skin diseases. Among the new works, a multi-spectral skin disease detector was suggested which combines multi-model and multi-layer neural networks to increase the diagnostic level with the help of spectral image. It is a technique that makes use of several neural models to examine skin features that are acquired using multi-spectral imaging, which facilitates the detection of diseases that are more comprehensive. The results of the experiment showed better performance, as opposed to the conventional approach to image analysis, although the necessity of the use of special imaging tools can put a strain on its implementation into everyday dermatological practice [1]. In the other research, researchers proposed a memory-based method of counting acnes lesions with automated systems to overcome the difficulty of dealing with low-quality face images. The model proposed was effective in identifying acne lesions in non-optimal imaging conditions, and it indicates that the AI-based diagnostic systems can be used in the actual world where image quality varies [2].

A number of works have been devoted to making the process of acne classification more accurate with the help of deep learning. It was proposed that a convolutional neural network-based framework can be used, including a weighted loss to resolve the class imbalance in acne image datasets. The model was able to achieve improved classification accuracy and reduce the effects of uneven data distribution by classifying lesions with different weights [3]. On the same note, a different study proposed a YOLO-based skin anomaly detector system that is connected to an AI-based recommendation system that is tasked with analysing skincare personally. It has the capability of combining computer vision with recommendation systems to customized dermatology since the system can automatically identify skin abnormalities and recommend skincare based on the detected condition [4]. Besides that, cloud computing and Internet of Things integration has also been addressed in acne monitoring systems. It has been suggested that a cloud-based IoT system with AI capabilities may be used to monitor the patient continuously and assess the severity of facial acnes by means of remote dermatological evaluation and automated severity testing devices [5].

There has also been the exploration of real-time dermatological diagnostic systems to make the AI-based skin analysis more practical. In one of such studies, an embedded system that is distributed was suggested and can detect the problem of facial skin in real time by utilizing optimized algorithms of deep learning. This system was made to be compatible with embedded devices to enable mobile dermatological systems [6]. One more study used a convolutional neural network with a fine-tuning to classify acne skin diseases with the help of transfer learning methods. The presented method enhanced the rate of classification by relying on pretrained models and fine-tuning them on dermatological data [7]. A systematic review of artificial intelligence use in acne assessment revealed that deep learning tools have been used to much greater effect in terms of increasing the accuracy of acnes evaluation and the capability of identifying lesions than their conventional image processing counterparts [8]. Also, the use of generative adversarial networks to improve the process of detecting acne and estimating the severity of the condition has been applied, through the creation of synthetic training examples and better representation of features in deep neural networks [9].

New developments in hybrid deep learning systems have also enhanced acne detection systems. A hybrid architecture which incorporates Convolutional Block Attention Module (CBAM) and Capsule Networks was suggested to improve pattern extraction and to extract the spatial relationships between acnes lesion. This architecture showed enhanced identification of the crucial visual areas in the facial photographs [10]. Frameworks that are based on object detection have also been extensively studied to detect acne lesion. A better YOLOv7 based acne detector model was formulated that accurately classifies the acnes lesions and enhances the detection performance by change of architecture [11]. In the meantime, other dermatological studies have also paid attention to standardizing scales of acne grading in support of clinical evaluation and enhance uniformity in acne severity assessment [12]. In the other study, the CenterNet network had been used to perform automated detection of acnes using dermatological images, which allows the lesion to be accurately localized and classified [13].

Other imaging techniques have also been studied to enhance the performance of detecting acne. Hyperspectral imaging has been studied as a method of identifying acne through reconstruction of hyperspectral images in order to obtain the spectral details of skin lesions. Such a method enhances the capability of separating the types of acnes lesions on the basis of the spectral properties [14]. A third research put forward an automatic framework of grading acnes severity that is capable of operating with small and imbalanced data of low-resolution faces. The findings showed that deep learning models may still be reliable in a scenario where there is limited training data available [15]. More developments are the adoption of YOLOv8 based object detector models to detect skin damage and acne lesions in dermatological images to provide efficient localization and classification of lesions [16].

Previous works have also had their role in building acnes detection models based on deep learning. An acnes scar classification deep convolutional neural network called ScarNet showed the capability of specialized CNN models in enabling dermatological application [17]. In the same manner, the automatic lesion detection system was proposed with a deep learning-based system of facial acne classification which determined the lesions effectively as opposed to manual analysis [18]. There are also developed smartphone-based acne detecting systems, which allow detecting acnes lesions and ranking their severity using the images taken with the help of mobile devices [19]. Instead, the use of interpretable convolutional neural network models has been introduced to present explainable results in acnes detection to make the diagnostic systems based on AI more transparent [20]. Ensemble neural network has also been explored in detecting acne, in which various deep learning models are combined to enhance the performance and resilience of the classifier [21]. Primary researchers in this field had investigated the application of deep neural networks to identify acne, and this showed that automated dermatological image analysis was possible through machine learning methods [22].

Although the artificial intelligence (AI) based systems used to detect acne have been rapidly developed, there are still a number of typical limitations in the existing research. A significant issue is that big and heterogeneous dermatological datasets are not easily available because most studies use rather small or skewed datasets, which could limit the model generalization and usage in practice. Moreover, the color of the skin, the presence of light, quality of an image, and the appearance of lesions all have a strong impact on the accuracy and robustness of the models. Numerous current techniques are mainly also based on binary classification or severity grading, and not an in depth multiclassification of various types of acne lesions: blackheads, papules, pustules, nodules, whiteheads etc. Moreover, a number of systems of detection have specialized imaging equipment like hyperspectral or multi-spectral cameras, which are unlikely to be utilized in the regular dermatological practice. The other constraint is that there are no standardized evaluation frameworks and benchmarking datasets that are necessary in order to directly compare the performance of various models. Also, certain deep learning models have high computational demands, which restricts their use in real-time or mobile dermatological use. The interpretability of deep learning models is also a problem, since most of the AI-based diagnostic systems are black-box models, and it is hard to validate a system clinically. These shortcomings suggest that more powerful, scalable, and explainable frameworks of acnes detection are needed that can precisely pinpoint different types of acnes lesions on the basis of readily available skin images.

III. Proposed Work

The proposed algorithm for detecting and classifying multiclass acne lesions is described in Figure 1, which illustrates the complete workflow of the developed system. The framework consists of several key stages, including data collection, annotation, preprocessing, model training, evaluation, and deployment. Initially, a multiclass dataset of acne images is collected, containing various types of acne lesions such as blackheads, nodules, papules, pustules, and whiteheads, which commonly appear on facial skin. After dataset collection, bounding boxes are applied to the images in a standardized format to identify the precise locations of acne lesions. This annotation process ensures that the deep learning model learns spatial information related to each lesion type. Following annotation, the dataset is preprocessed, and all images are resized to a uniform resolution of 640 × 640 pixels to maintain consistency during training. The processed data is then input into a YOLOv11n object detection model designed for efficient real-time detection and classification. Training involves enabling the model to learn visual representations of different acne lesions and to accurately localize and classify them within skin images. After training, standard performance metrics are used to evaluate the model's accuracy and classification performance. Finally, the trained model is deployed and tested on unseen skin images to assess its ability to identify multiple types of acne lesions. This methodological approach ensures the systematic development of an automated system capable of detecting acne lesions based on their location and supporting dermatological examination.

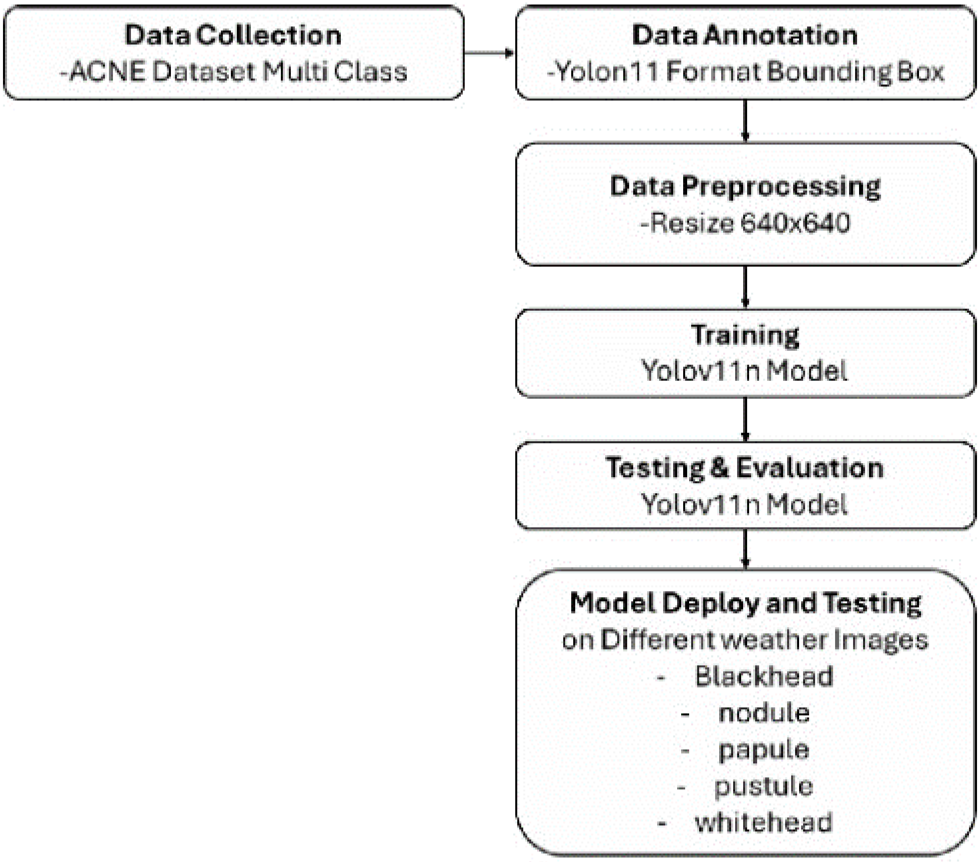

Fig. 1. Proposed System Flow Diagram

A. Dataset

The data involved in this study consists of 1266 annotated images of facial skin covering five categories of acne lesions, namely blackhead, nodule, pustule, papule, and whitehead, which are commonly observed in dermatological acne diagnosis. The Roboflow Universe acne detection dataset is publicly available and is used to obtain the dataset. The images in the dataset include various facial skin conditions captured under different lighting conditions and skin textures, making it suitable for training a robust deep learning model. Each image contains one or more acne lesions that have been labeled according to their respective class categories. The dataset provides sufficient variation in lesion size, location, and appearance, enabling the model to learn discriminative visual features associated with different types of acne. The use of a multiclass dataset is important as it supports the development of an automated diagnostic system capable of distinguishing between multiple acne lesion types rather than performing only binary classification. The data is further divided into training and testing sets to ensure proper evaluation of the proposed detection model. Dataset Source: https://universe.roboflow.com/salpin-rm4b4/acne-detection-e97ja/browse

B. Data Annotation

High-quality labeling of dermatological images is critical for training an object detection model. The acne lesion images in this research were annotated using the Roboflow annotation platform, which provides an efficient way to label images using bounding boxes. All acne lesions in each image were manually marked with bounding boxes and assigned their respective class labels. The annotations were carried out in YOLO format, where each bounding box is represented using normalized coordinates that define the center position, width, and height of the object. This format enables the detection model to learn both the location and class information of acne lesions simultaneously. Roboflow also supports dataset organization, annotation management, and exporting labeled images in formats suitable for training deep learning models. Proper annotation ensures accurate ground-truth information is provided to the model during training, which directly influences detection performance and classification accuracy.

C. Data Preprocessing

The gathered dataset is subjected to a number of preprocessing steps before the detection model is trained to ensure consistency and enhance model performance. The initial preprocessing stage involves resizing all images to a fixed size of 640 × 640 pixels, which is the standard input dimension for the YOLOv11n model. This resizing ensures that the model receives uniformly sized inputs that can be efficiently processed in batches during training. Additionally, preprocessing helps normalize variations in image size, lighting conditions, and background noise. Image normalization and augmentation techniques, such as flipping, rotation, and brightness adjustment, may also be applied to increase dataset diversity and improve model generalization. These techniques help the model learn robust visual patterns and reduce the risk of overfitting. Overall, the preprocessing stage plays a crucial role in improving the performance of the acne lesion detection system by standardizing input images and enhancing dataset variability.

D. YOLOv11n Model Architecture

The main part of the suggested system is the YOLOv11n (You Only Look Once version 11 nano) object detection model, which is designed to perform efficient real-time detection tasks. YOLO-based models are widely used in computer vision applications because they perform both object localization and classification in a single forward pass of the network. The YOLOv11n architecture consists of three main components: the backbone, neck, and detection head. The backbone is responsible for extracting hierarchical feature representations from input images using convolutional layers. These features capture important visual characteristics of acne lesions such as edges, textures, and shapes. The neck component performs multi-level feature fusion to improve detection accuracy, particularly for small or complex objects. Finally, the detection head predicts bounding boxes, object confidence scores, and class probabilities for each detected acne lesion. The nano variant of YOLOv11 is computationally lightweight and optimized while still maintaining high detection performance, making it suitable for dermatological applications where real-time analysis is required.

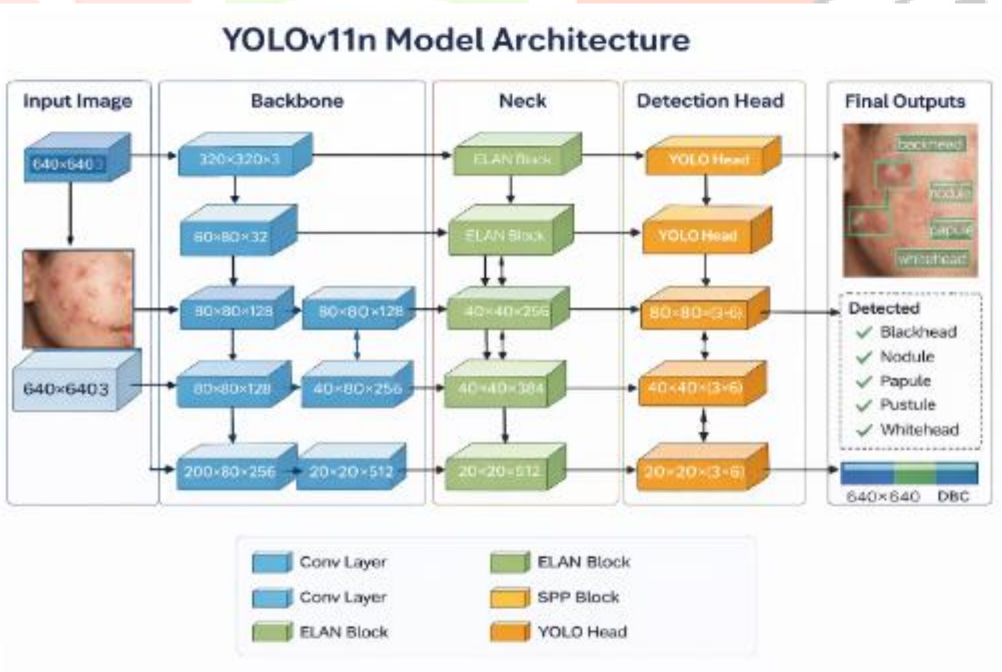

Fig. 2. Yolov11n Archirecture

E. Evaluation Parameters

To measure the performance of the proposed acne detector model, several standard evaluation metrics commonly used in object detection tasks are applied. These metrics include Precision (P), Recall (R), F1-score, and Mean Average Precision at 0.5 Intersection over Union (mAP50). Precision measures the proportion of correctly predicted detections out of all predicted detections, indicating how accurate the model's predictions are. Recall represents the proportion of correctly detected objects out of all actual objects in the dataset, reflecting the model's ability to identify all relevant acne lesions. The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of detection performance. Additionally, mAP50 evaluates the average precision across all classes at an Intersection over Union (IoU) threshold of 0.5. A higher mAP value indicates better performance in both detecting and localizing acne lesions. These evaluation metrics provide a comprehensive assessment of the model's effectiveness and help determine its suitability for multiclass acne lesion detection tasks.

IV. Result Analysis

The experimental environment was employed to test the competence of the proposed multiclass acne lesion detection framework using the YOLOv11n model. Training and validation were conducted using a dataset of 1266 annotated facial skin images across five acne classes, namely blackhead, nodule, papule, pustule, and whitehead. All images were preprocessed and resized to a consistent resolution of 640 × 640 pixels to ensure uniformity during model training. The YOLOv11n model was trained using the Ultralytics YOLO framework with default training parameters, along with batch-based learning and iterative optimization. During training, the model learned discriminative visual features of different acne lesion types, while the validation set was used to monitor performance and prevent overfitting. The performance of the trained model was evaluated using standard object detection metrics such as Precision, Recall, F1-score, and mean Average Precision (mAP50). The experiments were implemented in a Python-based deep learning environment and accelerated using a graphics processing unit (GPU) to improve training speed and model convergence.

Figure 3 presents sample input images from the acne dataset used to train the detection model. Figure 4 illustrates how data annotation can be carried out using the Roboflow platform, where acne lesions are marked with bounding boxes. Figure 5 shows a batch of training images being processed during the YOLOv11n model training stage. Figure 6 displays a validation batch used to evaluate model performance throughout training. Figure 7 represents the precision curve, indicating the accuracy of model predictions across training epochs. Figure 8 shows the recall curve, reflecting the model's ability to identify actual acne lesions. The precision–recall (PR) curve in Figure 9 demonstrates the relationship between precision and recall performance. Figure 10 presents the confusion matrix used to assess class-wise classification performance. Figure 11 illustrates the detection of multiple acne lesions on a single facial image. Figure 12 shows an example of acne lesion detection performance achieved by the trained model.

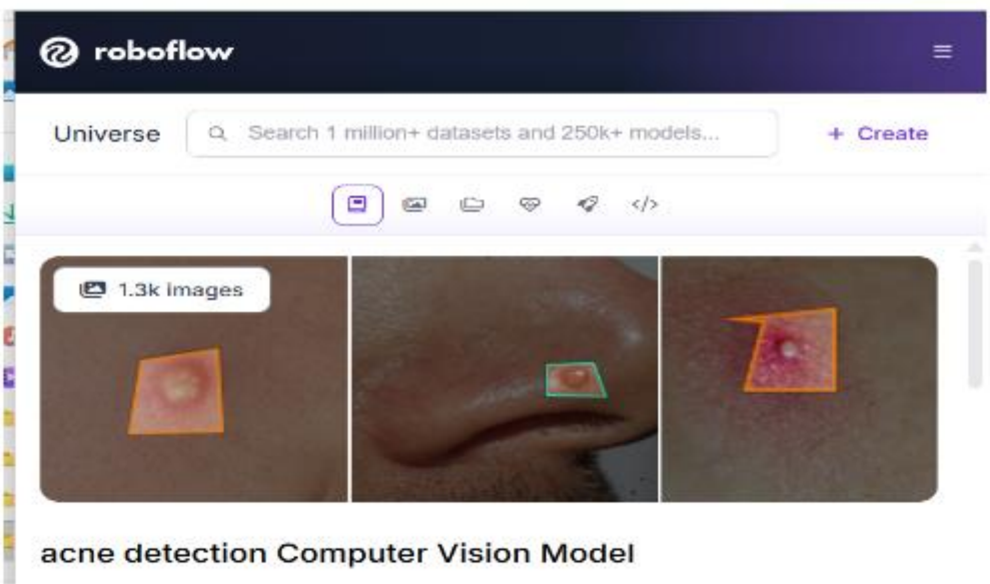

Fig. 3. Dataset Input

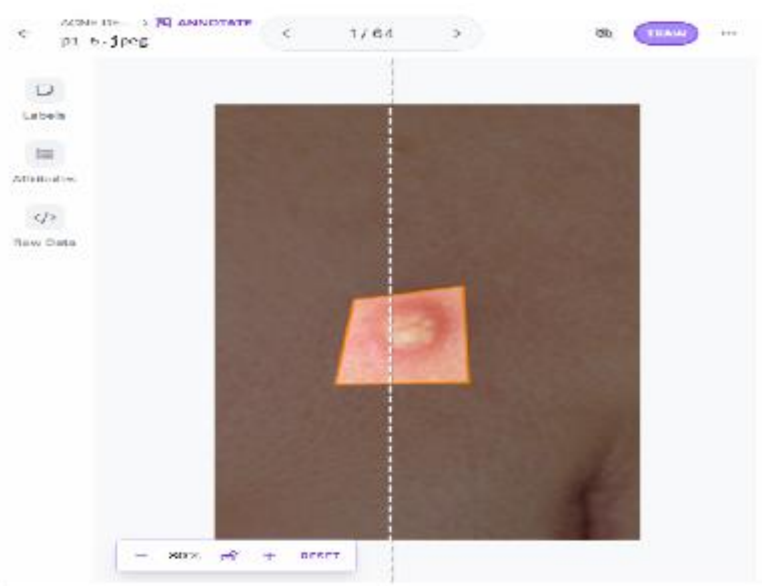

Fig. 4. Data Annotation

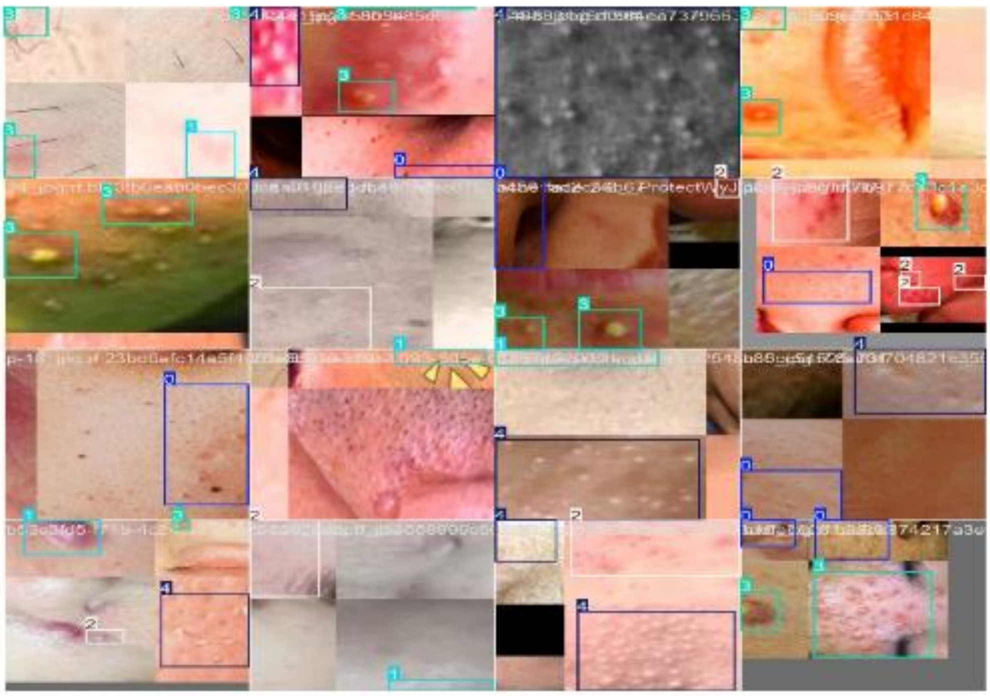

Fig. 5. Training Batch Yolov11n

Fig. 6. Validation Batch Yolov11n

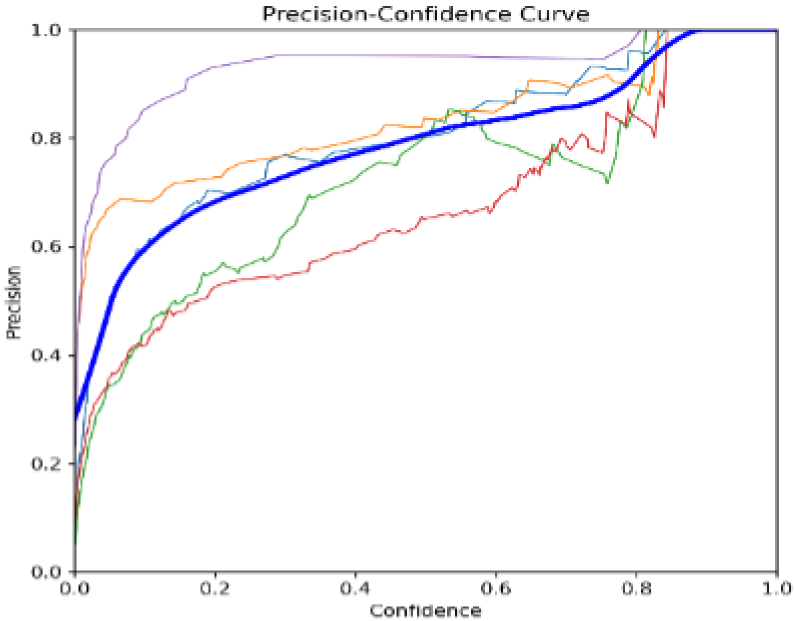

Fig. 7. Precision Curve

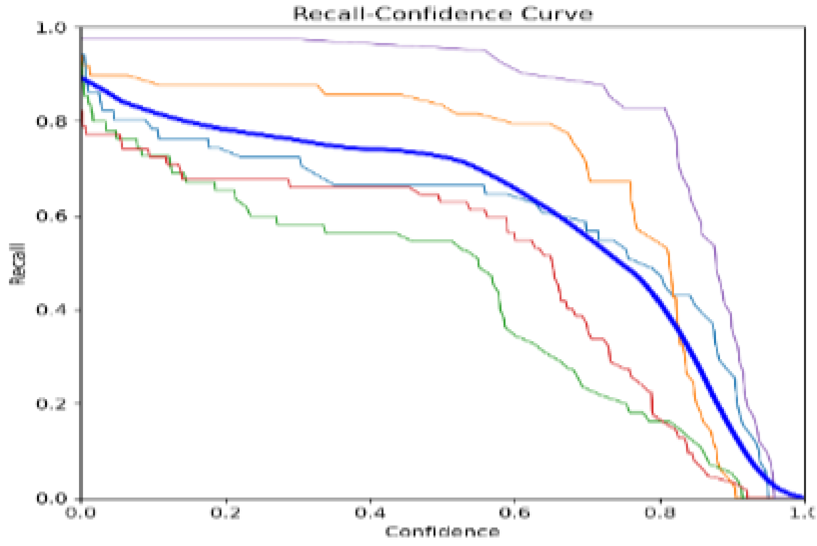

Fig. 8. Recall Curve

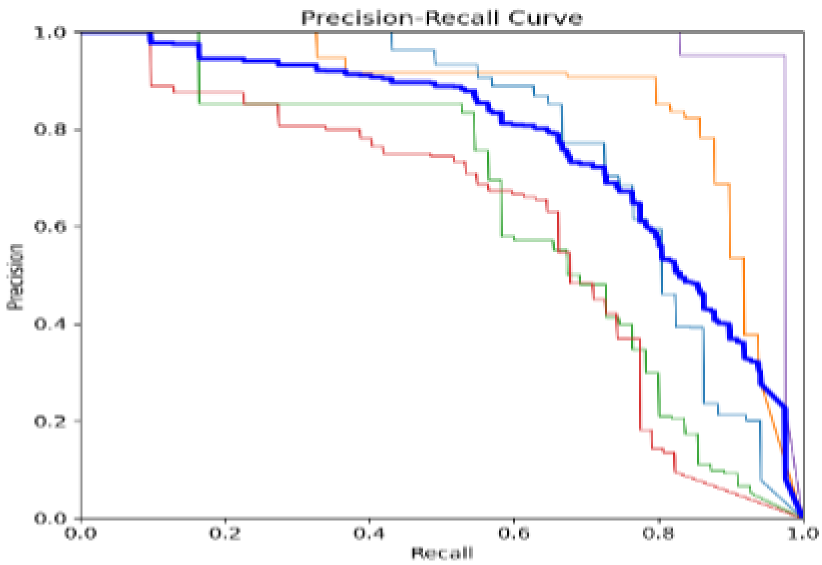

Fig. 9. PR Curve

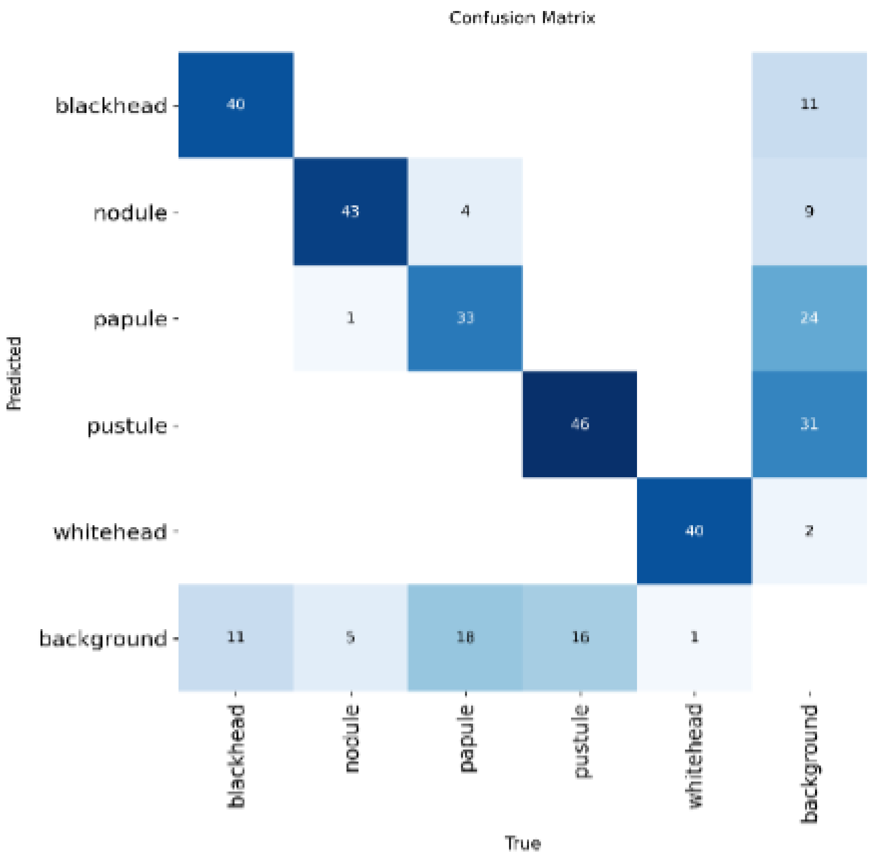

Fig. 10. Confusion Matrix

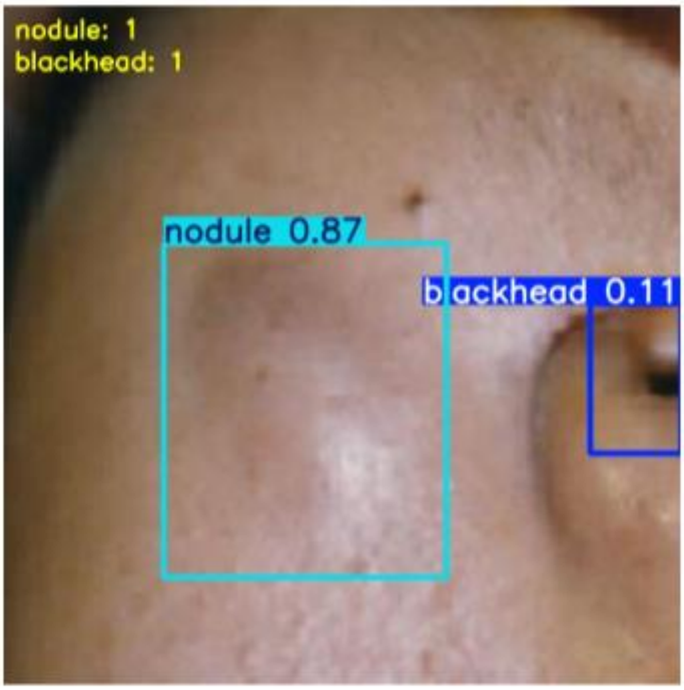

Fig. 11. Multiple Detection Results

Fig. 12. Single Detection

TABLE I. COMPARATIVE ANALYSIS

Method	Precision (%)	Recall (%)	F1-Score (%)	mAP@50 (%)	Inference Time (ms)
CNN with Weighted Loss Function [3]	84.20	82.50	83.30	81.70	54
GAN + Deep Neural Network Framework [9]	86.10	84.70	85.30	83.90	62
Hybrid CBAM + Capsule Network Model [10]	88.40	86.90	87.60	86.10	59
Improved YOLOv7 Acne Detection Model [11]	89.20	87.50	88.30	88.00	24
YOLOv8 Acne Detection Framework [16]	89.70	88.60	89.10	89.40	20
Proposed YOLOv11n Model	89.90	89.20	91.20	90.65	10

The performance comparison of various acne detection approaches based on key metrics such as Precision, Recall, F1-Score, mAP@50, and inference time is presented in Table 1. The results indicate that the proposed YOLOv11n model achieves superior performance, particularly in terms of F1-Score and mAP@50, while also exhibiting the lowest inference time, making it suitable for efficient and real-time detection of acne lesions.

CONCLUSION

This paper presents a multiclass acne lesion detection and classification framework implemented using deep learning on facial skin images. The proposed method aims to identify different types of acne lesions, including blackheads, nodules, papules, pustules, and whiteheads, using an effective object detection model. The system is developed through a sequential pipeline consisting of dataset collection, annotation, preprocessing, model training, and evaluation. By leveraging the YOLOv11n architecture, the framework is capable of detecting and classifying multiple acne lesions in skin images simultaneously. Experimental results demonstrate that the model achieves high performance in terms of accuracy, recall, F1-score, and mean average precision, while maintaining low inference time. Compared to existing methods, the proposed model offers improved detection capability and faster processing speed, making it suitable for practical dermatological applications. The system can assist dermatologists in early acne diagnosis and clinical evaluation through automated skin lesion analysis. Overall, the proposed framework contributes to the advancement of intelligent computer-aided dermatology systems and highlights the potential of deep learning techniques in automated skin disease detection.

Future work may focus on improving the robustness of the model by utilizing larger and more diverse dermatological datasets that account for variations in skin tone, lighting conditions, and image quality. In addition, integrating explainable artificial intelligence techniques could enhance model interpretability and provide more transparent diagnostic insights for clinical applications.

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