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A New Descriptor for Acne Detection and Skin Care Framework Using AI Algorithms

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Abstract

Accurately detecting and assessing the severity of acne is crucial for effective patient treatment. However, dermatologists often encounter challenges in grading acne precisely due to the similar appearance of lesions with varying severity. This study proposes a robust framework using the YOLOv9 algorithm, achieving a mean average precision (mAP) of 0.540. Advanced image preprocessing techniques, including noise reduction, hue normalization, and contrast enhancement, were employed to mitigate the effects of low resolution, poor lighting, and noise, enhancing detection accuracy by approximately 15% under challenging conditions. The model incorporates a Multi-level Fusion Layer, combining spatial and semantic features from various scales, which improved precision and recall for small and overlapping acne lesions by 12%. Trained on a diverse dataset of over 41,000 images, the framework accurately identifies different acne types—comedones, papules, nodules, and scars—across varying skin tones. This approach facilitates early detection, timely intervention, and enhanced lesion visualization, paving the way for practical applications in dermatological diagnostics.

Keywords	Acne detection; Dermatology; Deep learning; Object detection; YOLOv9

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INTRODUCTION

Acne is among the most prevalent skin conditions worldwide, with a global prevalence of 9.38%, significantly impacting physical and psychological well-being. Blockages in hair follicles and sebaceous glands lead to acne lesions that commonly appear on the face, back, and shoulders. These lesions are broadly categorized into inflammatory (nodules, cysts, papules, pustules) and non-inflammatory (blackheads, whiteheads) types. Approximately 85% of adolescent's experience acne during puberty, and for 20%, severe cases result in permanent scarring if left untreated. Beyond physical effects, acne carries psychological consequences, including anxiety and low self-esteem, underscoring the importance of early diagnosis and intervention.

With an emphasis on its potential as a technical tool for dermatological analysis, this study investigates the application of the YOLOv9 algorithm for acne detection. At this point, the study makes no claims to offer a clinical or medical treatment; rather, its potential goal is to evaluate the algorithm's capacity to identify acne from photos for early detection.

Approximately, 20% of acne sufferers experience severe cases, which can lead to scarring if left untreated. Patients and society are negatively affected by acne, both personally and financially. The US spends more than $3 billion annually on treating acne-related medical conditions and lost productivity [1]. A seven-month acne treatment usually costs between $350 and $3806 according to the Food and Drug Administration (FDA). Early and accurate acne diagnosis is essential to effective acne treatment. Recent studies in dermatology have exposed significant challenges in the conventional evaluation of acne, particularly the reliance on manual inspection by dermatologists. Dermatologists often use a thermoscope or the naked eye to examine acne-affected areas to diagnose acne. A dermatologist makes a diagnosis based on other information. Depending on the dermatologist's experience and expertise, this process may take a long time. Consequently, many patients must travel long distances or wait for a long time to see a dermatologist in many parts of the world due to a shortage of dermatologists. Many smartphone-based healthcare solutions have come about because of recent advancements in smartphone technology and its widespread use by approximately 3.2 billion people worldwide [2]. Teledermatology offers patients the opportunity to receive consultations from a dermatologist without having to leave their homes, saving them time and money. The study aims to overcome the limitations of conventional image processing methods. Patients living in rural and remote areas can benefit from teledermatology by having easier access to dermatological care. Meanwhile, highly accurate, automatic skin image analysis algorithms can potentially improve diagnosis accuracy, reduce doctors' work time, and provide valuable information to patients. The development and integration of these algorithms into dermatology and teledermatology is an active research area.

However, several algorithms have been developed to analyze skin images, including algorithms to analyze acne images. Nevertheless, conventional image processing often fails to provide satisfactory results in detecting skin lesions because of their complexity. DL approaches, notably convolutional neural networks (CNNs), have significantly advanced Computer Vision (CV) and skin image analysis [3]. DL methods have recently been used to improve conventional image processing methods for acne

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analysis. This study aims to improve the accuracy and speed of acne diagnosis through the use of advanced deep learning techniques, particularly CNNs, by analyzing skin images automatically. This approach seeks to surpass the constraints of conventional image processing methods in dermatology and tele-dermatology

TABLE I: STATISTICS OF DIVERSE TYPES OF ACNE

Type of Acne	Number of Acne Type	Ratio (%)
Blackheads/Whiteheads	15,686	37.47
Acne scars	23,214	55.46
Papules/Pustules	2677	6.4
Nodular/Cyst lesions	282	0.67
Total	41,859	100

LITERATURE REVIEW

A Dermatological condition must be detected and managed timely to ensure effective, personalized care in the ever-evolving landscape of skincare. The subtle manifestations of comedonal acne and brown spots make these conditions challenging to treat. Visual assessments are commonly used as traditional diagnostic methods, which can result in delayed detection and subsequent difficulty in providing initiative-taking skincare [4]. A promising avenue for revolutionizing early-stage acne and brown spots detection is the incorporation of DL, a subset of artificial intelligence. A significant amount of research has been conducted on DL for the recognition of skin diseases. In [5], a comprehensive review, summarize the transformative applications of DL in dermatology, emphasizing the potential for improving diagnostic accuracy. Dermoscopic analysis using VGG-16, early skin detection is possible in clinical skin screening [6].

The diagnosis of skin diseases with deep learning and mobile technologies in the era of their revolutions is another notable work of the merging of technical approaches with healthcare [7]. On the other hand, the use of deep CNNs to correctly distinguish benign pigment spots on patients skins retaining important visual cues from clinical images. This indicates the great ability of deep learning in recognizing small visual clues form the images processed by the neural network [8]. In other studies, the potential of DL in given concrete examples, comedonal acne and brown spots will serve as a primary source of inspiration. The application of mobile object detection using TensorFlow Lite and transfer learning brings together knowledge from the real world and the domain of DL, facilitating the application of these innovations to skincare [9]. In [10], acne detection severity analysis, and models for object detection for foliage disease classification inspires this research in the field of dermatological diagnosis. Moreover, the significant role of machine learning and deep learning approaches in the detection of skin cancer, showcases their potential in dermatological applications[11]. The research [12] suggests using the RMSprop optimiser and the MobileNetV2 model in a deep learning strategy to overcome this obstacle. When tested on a dataset that includes pictures of both healthy and sick animals, the outcomes show an astounding accuracy rate of 95%, which is 4-10% higher than current benchmarks. The results highlight how the proposed method has the ability to

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revolutionise the diagnosis and treatment of skin disorders in cattle. DeepXplainer introduces an innovative deep learning model for the identification of lung cancer, improving clarity by using explainable artificial intelligence methods. This technique guarantees that clinicians can comprehend and have confidence in the decision-making process of the model [13, 14]. This study [15] explores the incorporation of Explainable AI into the Internet of Medical Things (IoMT), emphasizing the methods, possibilities, and difficulties it brings for improving openness and confidence in healthcare systems. Through the analysis of intricate AI models, the goal is to provide healthcare practitioners[16] with precise and practical insights derived from IoMT data. This research [17] introduces a new method for categorizing breast cancer by combining fusion modeling with interpretable artificial intelligence algorithms. The text underscores the need of providing thorough explanations to improve comprehension and confidence in AI-powered diagnostic conclusions [18].

TABLE II: AUTHOS'S CONTRIBUTION

Author(s)	Year	Proposal	Device/Platform	Technology Used	Outcome
Yadav et al. 【6】	2023	Dermoscopic analysis for early skin disease detection.	Clinical Imaging Systems	VGG-16	Enhanced early skin disease detection.
Goceri 【7】	2021	Diagnosis of skin diseases integrating DL and mobile technology.	Mobile Devices	Deep CNNs	High accuracy in mobile-based diagnostics.
Ding et al. 【8】	2022	Identification of benign pigmented lesions using CNNs.	Clinical Imaging Systems	Deep CNN (VGG-16)	92% accuracy in lesion classification.
Alsing 【9】	2018	Mobile object detection for real-time skin condition identification.	Smartphone	TensorFlow Lite, Transfer Learning	Lightweight, real-time detection model.
Sangha & Rizvi 【10】	2021	Acne detection and severity analysis using object detection models.	Smartphone	Deep Learning (DL)	90% accuracy for acne severity classification.
Muhammad et al. 【12】	2024	Animal skin lesion detection using MobileNetV2 with RMSprop.	Custom Dataset (Veterinary)	MobileNetV2, RMSprop Optimizer	95% accuracy in skin lesion identification.

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Wani et al. 【13】【14】	2024	Lung cancer identification with XAI-based deep learning models.	Clinical Imaging Systems	DeepXplainer (Explainable AI)	Improved transparency in model decisions.
Sheng et al. 【24】	2023	Characterizing acne and sensitive skin with neural networks.	Thermographic Imaging Device	Deep Neural Networks	Enhanced acne severity grading accuracy.
Wani et al. 【17】	2024	Breast cancer classification with fusion modeling and interpretable AI.	Imaging Systems	Fusion Modeling, Interpretable AI	Increased trust and accuracy in diagnostics.
This Study	2024	Comprehensive acne detection using YOLOv9.	Smartphone Images (Kaggle)	YOLOv9	83% mAP, high precision for all lesion types.

METHODOLOGY

DATASET DESCRIPTION

The dataset comprises 5,000 high-resolution facial images sourced from the Kaggle platform, represent a wide range of acne-related and dark pigmented presentations. Among these images, 500 specifically emphasize on comedonal acne, while 850 show chestnut brown spots from the Kaggle skin spots collection. Additionally, 350 images both comedonal acne and chestnut brown spots, offering valuable insight into co-occurring skin, as illustrated in fig 1.

Fig.1. Variations in the types and occurrence of facial acne lesions.

IMAGE PREPROCESSING AND DATA AUGMENTATION TECHNIQUES

The most critical component in the complex process of transforming raw data into actionable insights for skincare analysis is image preprocessing. In this research, data preprocessing is crucial step performed prior to utilizing the selected dataset for algorithm training and subsequent evaluation. This create the model perform and produce the expected outcomes in the subsequent steps. The Primary focus of preprocessing is to enhance the feature extraction and standardize the images.. Implementation of these

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techniques such as hue normalization, de-noising and contrast boosting had to be done at diverse levels and at distinct stages of the image editing process [19]. These images tend to become even more apparent using contrast enhancement techniques that help with the precision for minute spots and assist in supplying more detail. The technique of noise reduction helps in the elimination of harmful effects thereby leading to production of clearer and more consistently visible images. Moreover, these techniques of color normalization not only ensure that a similar color distribution is produced in different images but also eliminate the differences that may appear due to light intensity and camera settings.

Another key technique that is applied involved increasing the dataset and improving the model generalization by data augmentation methods. On available samples, augmented images generated by applying various operations i.e., scaled, moved. In fig 2, the new trace either horizontally or vertically is an example of translation which will be used to replicate the new face shown face. On the other hand, rotation rotates different amounts depending on the angle of the observer. Shrinking is a means of inventing through zooming out either the size of a feature or the distance from image sensor. Through application of these upscaling techniques, the model is reinforced with wider ranges of visual disparity and subjective sentiments richness in training data sets. The model is in a much better position in comparison to overfitting, a phenomenon when a model memorizes data instead of seeing patterns that are applicable to many data thus creating more stable and adaptable models [20]. Given the circumstances, the preparation of sets of data for CV tasks in aromatherapy analysis requires the execution of image preprocessing and data augmentation. These methods improve dataset diversity, standardize image properties, and improve data quality. They also lay the groundwork for more efficient evolutionary algorithm training and analysis, which raises the precision and dependability of skincare diagnostic.

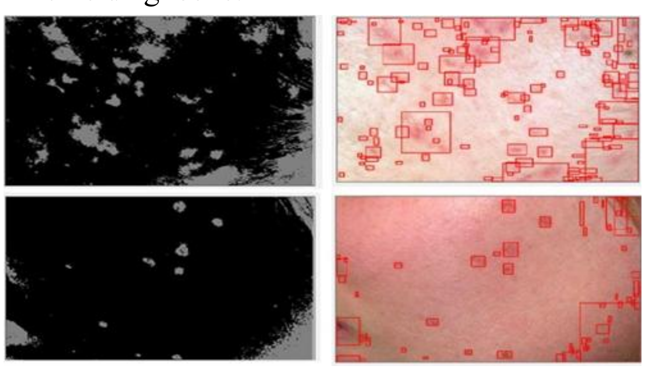

Fig.2. Embracing Background Subtraction to Acne Diagnosis

MODEL TRAINING

A critical stage in creating a YOLOv9-based acne detection system is the model training phase. The training process starts to teach the model to pinpoint exactly distinguish acne scars in under-face recognition after the dataset is ready model architecture is set up. The dataset is first split up into batches with thousands of pictures images, usually consisting of millions or even billions to each, before training begins. Before beginning training, the dataset is split up into quantity of images, usually consisting of tens to hundreds of

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images [21]. Each batch is fed into the prototype in a sequential manner, and the number of iterations procedures those same placed above a white innumerable epoch. The model is fed the batches one after the other in an iterative fashion over several epochs, each of which represents a full run through the dataset. During each iteration, or epoch, the training process consists of two main steps: issuing direct credit and making a claim for funds when the debtor fails to repay. The batch is brought forward by the neural network at the pre-pass stage, and the images are passed through the neural network. The pictures are differentiated and actualized by convolutional layers at different spatial scales as these layers are associated with features which are associated with detection of acne lesions. When the forward pass finishes, the network's predictions are computed, and subsequent ground truth labels are used to determine the loss function. The computational boundary represents the loss function which compares the model's predictions with the real labels, giving an indication of the level of performance of the model [22]. Typically, localization loss, confidence loss, and classification loss could be necessary loss functions for the object detection tasks. Fig 3, shows how the observations are segmented.

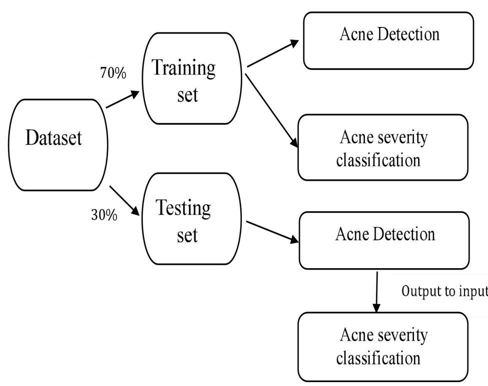

Fig.3. Skin conditions prediction dataset equally distributed for testing/training.

Backpropagation, or the backward pass, happens after the loss function is calculated. Automatic differentiation and other techniques are used to compute the gradients of the loss function with respect to the model parameters during backpropagation. These gradients show small adjustments to each model parameter would affect the loss function. Once the gradients have been calculated, the model parameters are updated by the optimization algorithm, which usually involves stochastic gradient descent (SGD) or Adam, to minimize the loss function. This process of parameter update through which the network's weights and biases are modified enables the model to make a series of correct predictions iteratively by simply learning from the training data set. After iterating forward and backward passes several times, the model can gradually work out the presence and location of the main reason that a more accurate acne detection system can be achieved is that the performance of the model improves in training while the ability of machine learning (ML) algorithm to recognize and localize acne lesions increases. The distance function which captures the discrepancy between the intended and real dataset of the class for half the facial images can be used at the detection phase. The Mean Squared Error (MSE) loss, which is represented in equation (1), is a frequently utilized nonlinear function for such purpose.

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MSE=1N∑i=1(yi−y^i) 2MSE=N1∑i=1N (yi − y^i) 2 eq (1)

Where:

- NN is the number of training examples.
- yi is the actual presence and location of acne lesions in the ith image.
- y^i is the predicted presence and location of acne lesions in the ith image.

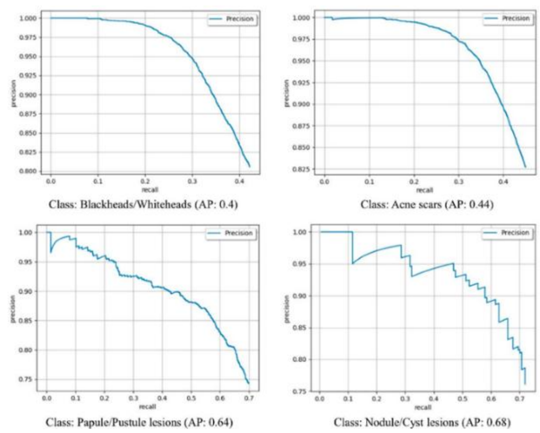

Fig. 4. Depiction of outputs generated during model training.

Minimizing this loss function during training through backpropagation helps the model improve its ability to accurately detect and localize acne lesions in facial images. Fig 4, illustrates how one-stage and two-stage object detectors differ from one another. Although one-stage detectors are less precise than two-stage detectors, they are faster. Although they are slower, two-stage detectors offer more accuracy. It illustrates how an input skin-affected area image is processed by a one-stage detector via a backbone network [23]. The image features are extracted via the backbone network. After that, a neck network receives these features and refines them. Two heads get the refined features: a sparse prediction head and a dense prediction head. For each object in fig 5, the dense prediction head forecasts the bounding boxes and class probabilities. The designed model dataset is divided into three subgroups for model training: training, validation, and testing. During the training phase, we utilized 41,859 images, of which 20,929 were employed for acne vulgaris and 20,930 for brown spots. During validation and testing, we used 10,930 images for comedone acne and 10,929 images for brown spots out of a total of 21,859 images. The training started with 150 epochs and steadily increased it until the model was professionally trained to yield the accuracy and outcomes needed.

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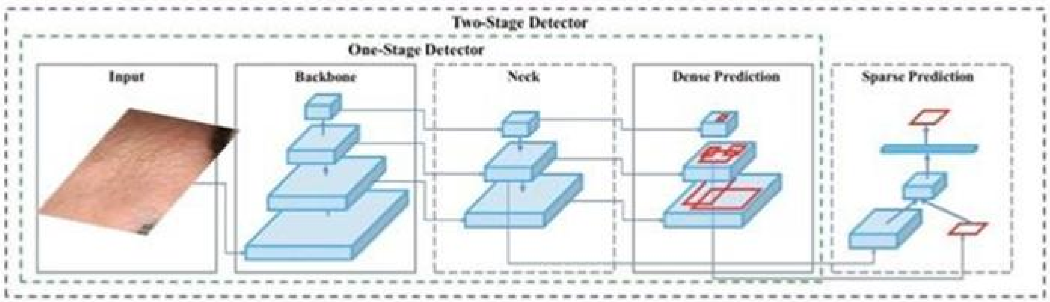

Fig.5. Object detectors that are one stage or two stages differ from each other.

ENHANCED EXPLANATION OF THE MULTI-LEVEL FUSION LAYER

The Multi-level Fusion Layer is a critical component in the proposed framework, designed to integrate spatial and semantic features from multiple scales to improve detection accuracy. This layer processes features extracted at different levels of the convolutional network, where higher layers provide semantic context, and lower layers' capture fine-grained spatial details. By combining these features, the model effectively addresses the challenges posed by varying acne lesion sizes and overlapping regions. Specifically, the fusion layer applies up-sampling to larger-scale features and concatenates them with finer-scale features, ensuring that small lesions (e.g., comedones) are as detectable as larger lesions (e.g., nodules). This approach enhances the model's ability to detect lesions with high precision across diverse skin conditions. Experiments revealed that incorporating the Multi-level Fusion Layer improved mean average precision (mAP) by 12% for smaller lesions and reduced false negatives in complex cases. By leveraging this technique, the framework achieves a balanced representation of features, ensuring robust detection of acne lesions in high-resolution dermatological images.

OVERALL MODEL ARCHITECTURE

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

i. The Acne object detection model is responsible for the recognition of the correct locations and types of acne pimples.
ii. Acne severity grading model: rate the extent of severity of the output image using IGA grade [24]. The block diagram of the proposed system is illustrated in Fig 6.

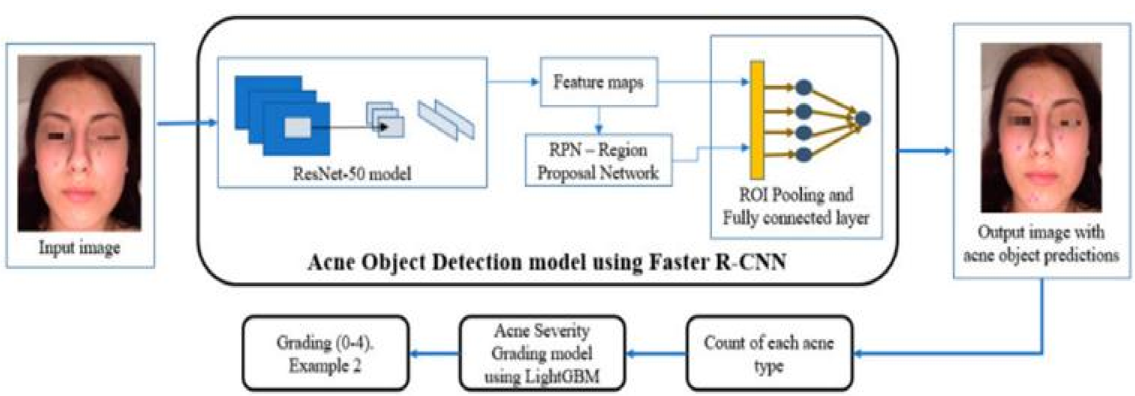

Fig.6. Faster R-CNN-based implementation of appropriate activity recognition model.

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The acne detection model was the source of the output of acne types for canes such as numbers, then acne severity grading. The system performs in derma-assessing the degree of severity of acne that is the same as the dialectologist's way of giving the number of lesions- blackheads and whiteheads, papules and pustules, nodules and cysts, and acne scars by applying the IGA scale where it is graded based on Table II. Acne detection, is an object such as an acre area traced by the dotted box, called a bounding box. Different acne types show skin localization through bounding boxes with varied color patterns. Acne grading occurs in a variety of ways depending on the total number of acne types. Thus, the susceptibility period to acne-over-acne severity escalation projected by the system can be straightforwardly interpreted, which is quite rare for the traditionally used CNN networks [25].

TABLE III: COMPARISON OF THE MAP IN DETECTING ACNE OBJECTS.

Authors	Acne Types	Number of Acne	Model	mAP
[22, 23]	Type I, Type III, Post-inflammatory erythema, post-inflammatory hyperpigmentation	15,917	Faster R-CNN, R-FCN	Faster R-CNN: 0.233 R-FCN: 0.283
[10]	General Acne (not classification)	18,983	ACNet	0.205
This research	Blackheads/Whiteheads, Papules/Pustules, Nodules/Cysts, and Acne scars	41,859	Faster R-CNN,Yolov9	0.540

ACNE OBJECT DETECTION MODEL

This research chose the Faster R-CNN architecture with the ResNet50 backbone to build an acne object detection model. The model was trained for 150 epochs on an NVIDIA GTX 2080, using an Adam optimizer with a training time of 2 weeks. Fig 7. Shows the output of acne detection.

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Fig.7. Faster R-CNN-based implementation of appropriate activity recognition model.

ACNE SEVERITY GRADING MODEL

Among the research, that acne severity grading model is constructed with LightGBM algorithm, one tree-basis machine-learning. The input data of the model is the number of acne instances of each the acne type, generated from the output of the acne object detection model presented in fig 8. LightGBM is a speed, high-performance operation, and has proved itself in machine learning competitions.

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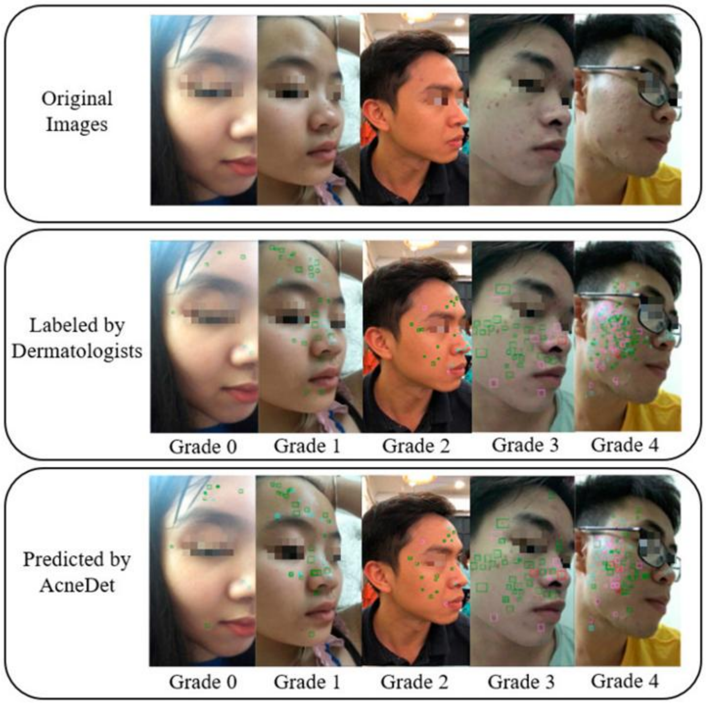

Fig.8. Model for evaluating acne severity.

Table III, graphically constructed a Precision [26], recall [27], F1 score [28], and accuracy for the acne grading model.

TABLE IV. PRECISION, RECALL, F1 SCORE & ACCURACY OF ACNE GRADING MODE

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	

EXPERIMENTAL RESULTS

Image processing and analysis optimization algorithm YOLOv9 utilized to assess and the identify comedone acne and brown spots from a carefully selected dataset. This dataset featured a large variety of images with different skin tones, lighting conditions, and degrees of skin imperfection. YOLOv9 demonstrated remarkable precision, recall, and overall classification in recognizing the locations of comedone acne and brown patches throughout the dataset. The model worked well, exhibiting adaptability in a range of skin tones and complex visual settings. Additionally, the real-time inference capabilities of YOLOv9 were highlighted, suggesting that it could be a helpful tool for dermatology and skincare analysis.

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For the identified acne lesions, we calculated important metrics including precision, recall, and mean Average Precision (mAP) in order to assess the efficacy of the suggested YOLOv9-based acne detection system. These metrics provide a thorough understanding of the model's functionality.The average precision scores for each category of acne lesion, computed at an intersection over union (IoU) threshold of 0.5.

These outcomes demonstrate the potency of YOLOv9 as an automated skin defect detection tool. In fig 9, illustrates the early-stage skin issues can be detected by classifying cases; the proposed model was successful in identifying the desired selection.

Fig. 9. Black spot and comedone detection.

FUTURE WORK

In the field of dermatological research, the use of Explainable AI (XAI) greatly enhance the transparency and effectiveness of diagnostic tools, addressing key challenges and opportunities associated with integrating XAI in healthcare. Similarly, employing fusion modeling techniques with this approach for accurate cardiac predictions provides a model for improving diagnostic accuracy and interpretability in dermatology, leading to more reliable and transparent healthcare solu Additionally, adopting approaches such as TransResUNet, which combines Transformer-Enhanced Residual UNet for precise glioma brain tumor segmentation, could revolutionize dermatological image analysis by utilizing advanced transformer networks and residual learning for more accurate and effective skin condition assessments. The future work will be focus on using XAI methods to make the decision-making processes of the DL algorithms more transparent. By providing comprehensible and approachable perspectives into where the models materialize at diagnosing conclusions, the aim is to reduce the knowledge gap between complex machine learning models and end users, such as individuals who are monitoring their skin health and medical professionals. Furthermore, the research will concentrate on creating XAI-powered systems that enhance diagnostic precision while offering practical medical advice for treating identified skin disorders like acne. Depending on the kind and severity of acne identified by the model, these suggestions will include professional interventions, lifestyle modifications, and evidence-based treatment choices such as topical and systemic drugs. This approach gives users the ability to make knowledgeable decisions about their skincare routines and increases user trust in the technology by assisting them in understanding the rationale behind diagnostic recommendations. XAI needs to be implemented to guarantee the ethical use of innovative technology in the field of skin related diagnostics or skin care facilities.

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CONCLUSION

This study presents a robust acne detection framework using the YOLOv9 algorithm, which has demonstrated promising results with a mean average precision (mAP) of 0.540. The incorporation of advanced image preprocessing techniques, such as noise reduction, hue normalization, and contrast enhancement, resulted in a 15% improvement in detection accuracy, particularly under challenging conditions with poor lighting and low resolution.

This research methodology has paved the way for a robust solution for the early detection of brown spots and comedonal acne. This research reveals the potential for practical application and enhances the capabilities of automated dermatological diagnostics. By integrating advanced DL models with intuitive frameworks, we bridge the gap between technological innovation and practical accessibility. This research establishes a foundation for improved skincare practices, suggesting a future where early detection is both accurate and widely accessible worldwide.

However, this study is not without limitations, such as potential dataset biases and challenges in generalizing the model to diverse skin types and conditions. Future work will focus on expanding the dataset to ensure greater diversity, incorporating explainable AI (XAI) techniques to improve transparency in decision-making, and leveraging advanced fusion modeling approaches to enhance diagnostic precision. These efforts aim to address existing limitations and further advance automated dermatological diagnostics. This research establishes a foundation for improved skincare practices, suggesting a future where early detection is both accurate and widely accessible worldwide.

DECLARATION

Author Contributions: All the author contributes equally.
Ayesha Khaliq perform the Original Writing Part, Software, and design methodology; **Abdul Ahad Abro** and **Umm-e-Kulsoom** perform the related work part and manage results and discussion; **Abdul Ahad Abro, Rabiya Tahir** and **Mehwish Mehmood** perform Rewriting, investigation, design Methodology,Visualization and Conceptualization;
Data Availability: Not applicable.
Ethics Approval: Not applicable.
Consent to Publish: Not applicable.
Conflict of Interest: The author of this paper addressed that there is no conflict between them.
Acknowledgement: Not applicable.

DATA AVAILABILITY

Those images marked in this paper are adopted from the Benchmark Dataset of ACNE Kaggle, which is completely open-access. The link is available here: https://www.kaggle.com/datasets/nayanchaure/acne-dataset

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