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SKIN ACNE SKIN DISEASE CLASSIFICATION BY USING FINE TUNED CONVOLUTIONAL NEURAL NETWORK

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Abstract
Acne vulgaris is a prevalent and chronic inflammatory skin condition, categorized by blackheads, whiteheads, pimples, nodules, and cysts, affecting up to 80% of adolescents and often extending into adulthood. The psychological, social, and economic effect of acne is profound, contributing to issues such as low self-esteem, depression, and in severe cases, suicidal thoughts. Traditional methods for assessing acne rely on the manual expertise of dermatologists, which, while valuable, can be time-consuming, prone to observer inconsistency, and potentially partial. Accurate and timely diagnosis is essential for effective treatment, making the need for automated acne classification systems increasingly apparent. Advances in artificial intelligence, particularly Convolutional Neural Networks (CNNs), present promising opportunities to enhance the accuracy and consistency of acne classification. This study develops acne types classification system using a fine-tuned CNN model and evaluate its performance against well-established pretrained models, including ResNet50, Mobile NetV3, and InceptionV3. The proposed model achieved an accuracy of 71% (proposed model), ResNet50 (62%), MobileNetV3 (49%), and InceptionV3 (46%). By bench-marking the proposed model's effectiveness against these pre-trained architectures and existing research, this research demonstrates improvements in diagnostic accuracy, reliability, and efficiency. Implementing such automated systems has the potential to enhance treatment outcomes, reduce the burden on healthcare professionals, and provide a more consistent and objective approach to acne diagnosis.

INTRODUCTION

Acne vulgaris is a long-lasting inflammatory skin disorder marked by blackheads, whiteheads, pimples, nodules, and cysts [1,2]. These lesions often appear on visible areas of the skin during adolescence, leading to significantpsychological, social, and economic impacts on those affected [3]. Reported effects include low self-esteem, higher rates of unemployment, and depression, sometimes with suicidal thoughts. Acne vulgaris is very common, with cross-sectional studies showing that up to 80% of adolescents experience it to some extent, with no significant difference between males and females during the teenage years [3]. Most individuals have mild to moderate acne, but about 10% of adolescents suffer from severe acne [1]. The condition usually improves by age 25, but adult acne remains prevalent. At least 12% of women over 25 years old are reported to have acne, whereas the incidence in men of the same age is lower, possibly due to ascertainment bias. Given its high prevalence, a recent global disease burden analysis ranked acne vulgaris as the eighth most common disease worldwide [7]. This disease is typically identified and assessed based on the expertise of medical professionals, which can be susceptible to errors. Accurate identification is crucial for effective acne treatment, necessitating a high level of confidence in the diagnosis [16]. To address this issue, technology has significantly advanced the field of dermatology, particularly in the identification and classification of skin diseases like acne. Proposed CNN model have shown remarkable performance in the field ofimage classification, providing more accurate results and reducing human error. This study classifies different types of acne using our proposed model and compare its performance with pretrained models such as ResNet, MobileNet, and Inception V3.

2. Literature Review

A study used a dataset of 420 images, which were labeled into seven categories by an experienced dermatologist. To increase the dataset size, they applied data augmentation techniques. The researchers developed a dual deep CNN model to identify acne and classify it into seven types. Their approach involved two CNN-based units that extracted deep features, which were then combined using a feature aggregation module. The combined features were used as input for a softmax classifier to determine the acne type. When compared to three machine learning classifiers and five pre-trained models, their model achieved strong performance, reaching an accuracy of 97.53% on the developed dataset [4]. Another study introduced an automated system to categorize acne scars using a deep CNN model. They gathered a dataset of 250 images from five different categories, which were labeled by four dermatologists. After preprocessing, the images were fed into their presented model, called ScarNet, to extract deep features. The researchers carefully adjusted various parameters, like loss function, activation functions, batch size etc., to improve classification accuracy while keeping computational costs low. The experimental results showedthat their approach was effective, achieving an accuracy of 92.53%, specificity of 95.38%, and a kappa score of 76.7% [7]. The study caried out with the objective to develop and evaluate a DL model for accurate classification of skin diseases, with a focus on improving the diagnosis of acne and other common conditions. The study focused on classifying various skin diseases, including acne, eczema, and psoriasis, using a deep learning model. The study achieved an overall accuracy of 88.6% for classifying various skin diseases. The study limits comprise overfitting due to small datasets for certain diseases [2]. Furthermore [3], another research was done in year 2023, for acne classification by using CNN with the VGG16 architecture, KNN, and Random Forest. The dataset used in the study consisted of a total of 822 images after data augmentation techniques were applied. The average accuracy across the models used in the study is approximately 65.2%. The study limitations include a small and possibly narrow dataset, also focusing primarily on accuracy overlooks important metrics likeprecision and recall, crucial for evaluating the model diagnostic reliability in practical medical applications. In this research they collected images of seven categories of skin diseases dominant in the Philippines to develop a classification system. Pre-trained weights from various CNN models, including VGG16 was utilized. The VGG16 model had the lowest at 44.1% [12]. A study introduced a deep learning-based approach to differentiate between Alzheimer's disease (AD), mild cognitive impairment (MCI), and cognitively normal individuals using structural MRI (sMRI). The researchers employed a multiclass classification technique utilizing 3D T1-weighted brain sMRI images obtained from the ADNI database. Axial brain images were taken from 3D MRI scans and analyzed using a CNN. Three models were assessed: a CNN developed from scratch, VGG16, and ResNet-50. The convolutional layers of VGG16 and ResNet-50, both pretrained on the ImageNet dataset, functioned as feature extractors. To finalize the classification, an additional densely connected classifier was incorporated on top of these extracted features. VGG-16 reported a training loss of 0.1511, whereas CNN and ResNet-50 exhibited training losses of 0.3102 and 0.2150, respectively [8]. This [11] research focused on classifying six common skin diseases using deep learning techniques. The studyleveraged the DermNet dataset and compared the performance of ResNet-50, MobileNet, and Efficient-B0 models. The ResNet-50 model demonstrated competitive accuracy, highlighting its effectiveness in skin disease classification tasks. The research [10] presents an advanced approach to skin disease classification by employing three advanced deep learning models: VGG19, YOLOv3, and ResNet50. The ResNet50 model demonstrated high accuracy in classifying various skin diseases, showcasing its potential in dermatological applications. The study [14] collected images of seven types of skin diseases prevalent in the Philippines to develop a classification system. The dataset comprised 3,400 images of conditions such as chickenpox, acne, eczema, Pityriasis rosea, psoriasis, Tinea corporis, and vitiligo. The researchers employed transfer learning with pre-trained weights from various CNN models, including ResNet-50. The ResNet-50 model demonstrated competitive accuracy, highlighting its effectiveness in skin disease classification tasks. Another research [15] focused on detecting and classifying Lumpy Skin Disease Virus (LSDV) using deep learning models. Experiments were conducted using various architectures, including ResNet-50. The ResNet-50 model achieved satisfactory results, indicating its potential applicabilityin LSDV detection. This research used Resnet for skin disease classification called Monkeypox. This study developed a prediction model to improve the classification of Monkeypox. A major challenge faced by researchers was the limited availability of images showing monkeypox-infected skin. To address this, they used the Monkeypox Skin Image Dataset from Kaggle. The dataset was enhanced using data augmentation techniques and then processed through various deep learning and machine learning models. Among all the approaches tested, VGG19 and ResNet achieved the highest recognition accuracy of 92% [5]. This research [14] presents an advanced approach to skin disease classification by employing three advanced deep learning models: VGG19, YOLOv3, and ResNet50. The VGG19 model demonstrated high accuracy in classifying various skin diseases, showcasing its potential in dermatological applications. This study aimed to establish a standardized diagnosis and treatment approach for acne vulgaris using a DL model based on Chinese Guidelines. The model training was done using Inception-v3 network. To enhance accuracy, the researchers first used ImageNet dataset. These pretrained networks retain shallow image features, aiding in classification. They then applied transfer learning and trained the model onthe Acne Dataset to help it learn high-level semantic features. The experiment used a learning rate of 0.001. The model resulted an average F1 score of 0.8[6]. The study [11] proposed a deep learning method to correctly identify different types of skin lesions. The Inception V3 model was among the architectures evaluated. The Inception V3 model achieved an accuracy of 90%, demonstrating its capability in distinguishing various skin lesions. This research combined Convolutional Neural Networks with predefined models, including Inception V3, to categorized seven skin disease types. The ensemble approach, incorporating Inception V3, achieved an overall accuracy of 89.90%, underscoring its effectiveness in skin disease classification [12]. This study [9] employed the Inception-V3 model to classify skin cancer images. The Inception-V3 model yielded favorable outcomes withan accuracy of 93.50%. This research introduced a method for categorizing skin diseases using deep learning with MobileNet V2 and LSTM. MobileNet V2 resulted high accuracy while being suitable for lightweight computational devices. The suggested model effectively retains stateful information, leading to accurate predictions. A grey-level co-occurrence matrix was used to assess disease progression. The model performance was compared with other advanced approaches, including FTNN, CNN, VGG, and a modified CNN architecture. Using the HAM10000 dataset, the proposed method outperformed others, achieving an accuracy of over 85% [12]. Another study [13] proposed an approach for skin disease classification using a combination of MobileNet V2 and LSTM networks. MobileNet V2 achieved high accuracy while being suitable for use on lightweight computational devices.

3. Methodology

The following figure. 1 shows the workflow begins with Dataset Collection and Preprocessing, where raw facial images are gathered, resized, normalized, and augmented to enhance model robustness. The next stage, Model Selection and Training, involves implementing a custom CNN model alongside pretrained architectures such asthe benchmark models to assess its effectiveness.

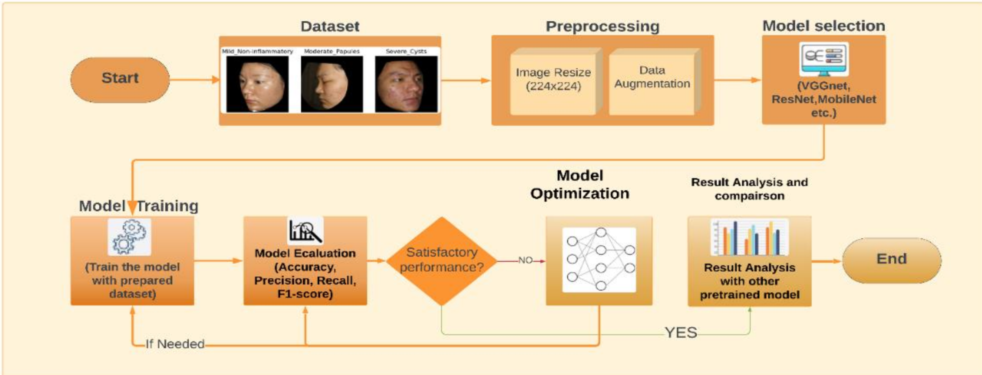

Figure 1. Proposed Methodology

3.1. Dataset Details

The original dataset contains total images of 999 acne images in 3 classes as Mild_Non-inflammatory, Moderate_Papules andResNet, InceptionV3, and MobileNet as shown in figure 2. These models are trained using labeled acne images considered into mild, moderate, and severe classes. The Evaluation Phase measures model performance. The final step involves Result Comparison and Analysis, where the proposed model's classification capability is compared withSevere_Cysts and 2200 total images after augmentation. These are the three different stages and types of acne.

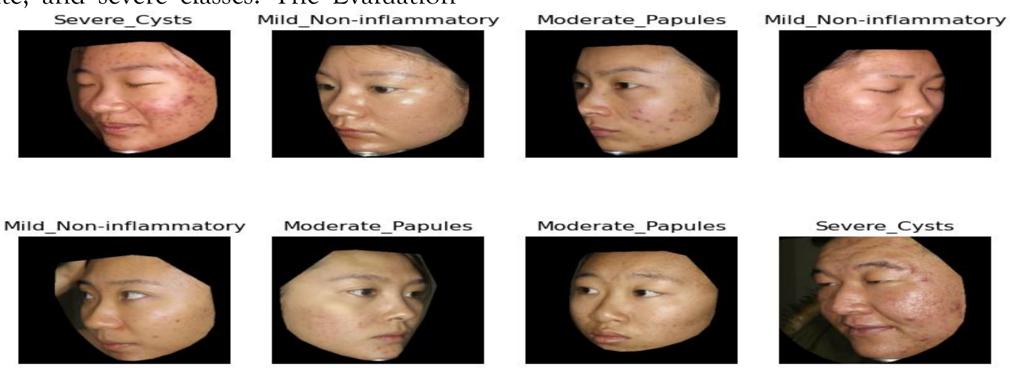

Figure 2. Dataset details

3.2. Data Preprocessing

Data preprocessing is a critical step in deep learning to improve model performance and ensure reliable results. Since the model result heavily depends on the input data, preprocessing techniques were applied to standardize and optimize the dataset. In this study, image resizing, data augmentation, and data splitting were utilized to improve model efficiency and accuracy. These techniques collectively contributed to better generalization, reduced overfitting, and improved classification performance.

3.2.1. Data augmentation

Data augmentation is an essential preprocessing technique used to artificially expand the dataset by making changes like rotation, resizing, flipping, and brightness adjustment to existing images. In this study, data augmentation was applied to the original dataset, which initially contained 999 images in three classes 'Mild_non-inflammatory' class had 387 total images, whereas 'Moderate-Papules' had 473 images and 'Severe_Cysts' had 139 total images only. After augmentation, the total number of images increased to 2200, 'Mild_non-inflammatory' has 870 images, 'Moderate-Papules' contains 930 and 'Severe_Cysts' has 400 images in total.

3.2.2. Image Resizing

Since in most of the cases in pretrained model the essential input size for images is 224x224. As most of the pretrained model are design in way to work with this particular image size which allow algorithm train well as algorithm get consistency in data dimensions in different images. So, in our work we resized all the number of images in size 224x224 as our model supports this size as well, so resizing step is done while doing image preprocessing.

3.2.3. Data splitting

Generally, datasets are split into training and testing sets, where the training set typically accounts for 75-80% of the data, while the testing set constitutes around 20-25%. In some cases, a validation set is also included to fine-tune model parameters before final testing. In this study, the dataset was partitioned into 80% training data and 20% testing data. Since the training set contains a larger portion of the images, it helps the model recognize patterns effectively. Meanwhile, the testing set remains entirely separate from training to ensure an unbiased evaluation. This data split helps assess model performance on unseen data, minimizing overfitting and enhancing generalization

4. Pretrained Models

CNNs are designed to process grid-like data, like images [28]. A typical CNN contains multiple layers, with convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. CNNs are widely used for tasks for example image segmentation, classification, and object detection. In this study, VGG16 was selected as the base model and modified to develop the proposed acne classification model. Additionally, three pretrained CNN models, ResNet-50, MobileNetV2, and InceptionV3 were used for comparative analysis In our model, VGG16 serves as the base model, acting as a feature extractor, while the fully connected layers have been modified to enhance classification performance.

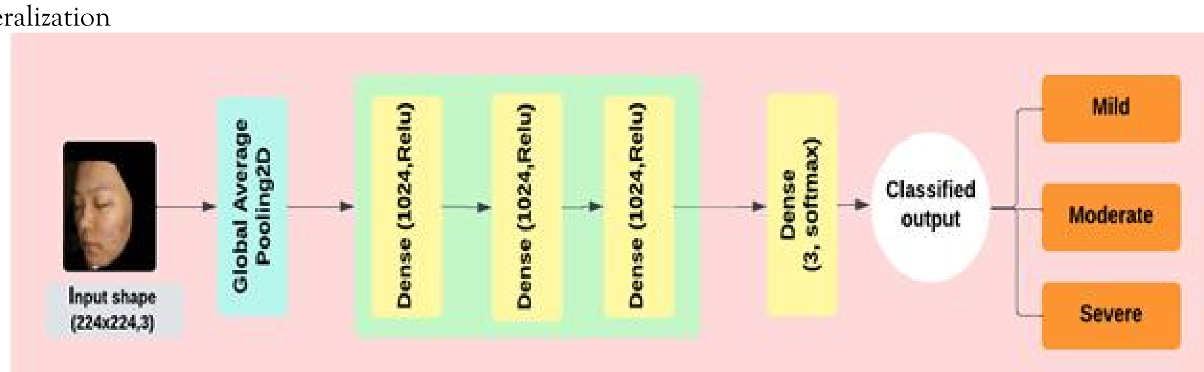

Figure. 3. Proposed CNN model Architecture

The architecture network of VVG16 is working in a way that is starting with an input image typically 224x224 size in input layer. Secondly the network consists convolutional layer that extract features from input image, each block contains multiple convolutional layers which apply filters to detect the patterns such as edges, complex shapes and textures. The convolutional layers are using 3x3 filters and ReLU activation. A max pooling is connected to after convolutional block to reduce the spatial dimensions of feature maps. Filter of 2x2 is used by pooling with stride of 2 to reduce computational complexity and down sampling. After the feature extractionGlobalAveragePooling2D layer is applied to reduce the spatial dimensions of the extracted features while retaining essential information. This is followed by three fully connected (Dense) layers, each consisting of 1024 neurons with ReLU activation,allowing the model to learn complex patterns and relationships in the extracted features. Finally, the output layer consists of three neurons with a Softmax activation function, which classifies input images into three categories—mild, moderate, andsevere acne. These modifications optimize the model's as shown in figure. 3 performance by reducing parameters, improving computational efficiency, and enhancing feature learning for acne classification.

5. Model Summary

This table 1 outlines the training configurations used for the Proposed Model:

Parameters	Proposed Model
Base Model	VGG 16, pre-trained on ImageNet, modified for Acne Classification
Input Image size	224 x 224 x 3
Loss	Sparse categorical cross entropy
Batch size	32
Training and Testing	80% for training and 20% for testing
Performance Metrics	Precision, Recall, Accuracy, F1-Score
Optimizer	Adam
Epochs	10
Final Layer Activation Function	Softmax
Data Augmentation	Yes

Table. 1 Model Summery

6. Model Implementation

The implementation of deep learning models for acne classification was carried out using Python and the TensorFlow/Keras framework. The proposed model, a modified VGG16 architecture, was trained alongside three pretrained models: ResNet-50, MobileNetV2, and InceptionV3. The dataset was preprocessed by using image resizing, data augmentation, and data splitting techniques to enhance model performance. Each model was fine-tuned by adjusting hyperparameters such as learning rate, batch size, and number of epochs. The training process involved optimizing the models using the Adam optimizer and categorical cross-entropy loss function. Performance evaluation was conducted based on accuracy, precision, recall, and F1-score, ensuring a comprehensive comparison of the models.

7. Model Evaluation

To measure the results of the deep learning models for acne classification, various quantitative evaluation metrics were utilized, including accuracy, precision, recall, F1-score, and the confusion matrix. These metrics provide valuable insights into the classification efficiency and help to identify potential biases in the model's predictions.

a. Accuracy

Accuracy reflects the overall performance of a model by measuring the ratio of correctly predicted instances to the total number of predictions. It serves as a general performance indicator.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

b. Precision

Precision measures the reliability of positive predictions by calculating the proportion of correctly identified positive instances among all predicted positives. Higher precision means fewer false positives.

$$Precision = \frac{TP}{TP + FP}$$

c. Recall (Sensitivity)

Recall assesses the model's ability to accurately detect all actual positive cases. A higher recall indicates that the model effectively identifies relevant instances while reducing false negatives.

$$Recall = \frac{TP}{TP + FN}$$

d. F1 Score

The F1 Score is the harmonic mean of precision and recall, offering a balanced evaluation metric for imbalanced datasets. It accounts for both false positives and false negatives in model assessment.

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

These assessment metrics together deliver a comprehensive performance valuation of the model. While accuracy serves as a global measure, precision, recall, and F1-score offer deeper insights into the model's predictive behavior. The confusion matrix further breaks down these aspects, facilitating a detailed analysis of misclassifications. Given the challengesstood by imbalanced datasets, it is crucial to consider multiple metrics rather than relying solely on accuracy to ensure an unbiased evaluation.

8. Comparative Analysis

In this study, a comparative analysis was conducted to evaluate the performance of different deep learning models for acne classification. The models included ResNet-50, MobileNetV2, InceptionV3, and a modified VGG16 (proposed model). Each model was trained and tested on the same dataset, using identical preprocessing techniques such as image resizing, data augmentation, and data splitting (80% training, 20% testing) to ensure fair evaluation. The models were compared based on key performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix results. The goal of this analysis was to determine which model best classifies acne into mild, moderate, and severe categories while maintaining computational efficiency. Additionally, the impact of the proposed modifications in VGG16 was analyzed by comparing its performance against the standard pretrained models.

9. RESULTS

Performance Comparison of Deep Learning Models

This section presents a comparative performance analysis of the deep learning models used for acne classification: Proposed Model (Modified VGG16), ResNet-50, MobileNetV2, and InceptionV3. The evaluation metrics considered include accuracy, precision, recall, and F1-score, as shown in the results table. The proposed model as shown in following figure 1, 2, outperformed the other three models, achieving an accuracy of 71%, with precision, recall, and F1-score values of 66%, 78%, and 72%, respectively. ResNet-50 achieved 62% accuracy, making it the second-best model, while MobileNetV2 and InceptionV3 exhibited lower performance, with 49% and 46% accuracy, respectively. The resultsindicate that the presented model provides the best classification performance, particularly in terms of recall (78%), demonstrating its ability to correctly identify acne severity levels. ResNet-50, though relatively effective, showed slightly lower performance across all metrics. MobileNetV2 and InceptionV3 struggled with classification, suggesting limitations in feature extraction for this particular dataset. This comparative analysis shown in following figure, highlights the effectiveness of the proposed modified VGG16 model in acne classification, reinforcing the importance of architectural modifications and fine-tuning in achieving superior performance.

Proposed Model

Metric	Results(%)
Accuracy	71
Precision	66
Recall	78
F1-Score	72

Resnet 50

Metric	Results(%)
Accuracy	62
Precision	61
Recall	62
F1-Score	59

MobileNetV2

Metric	Results(%)
Accuracy	49
Precision	41
Recall	49
F1-Score	44

InceptionV3

Metric	Results(%)
Accuracy	46
Precision	38
Recall	46
F1-Score	39

Figure 1. Model performance Comparison details

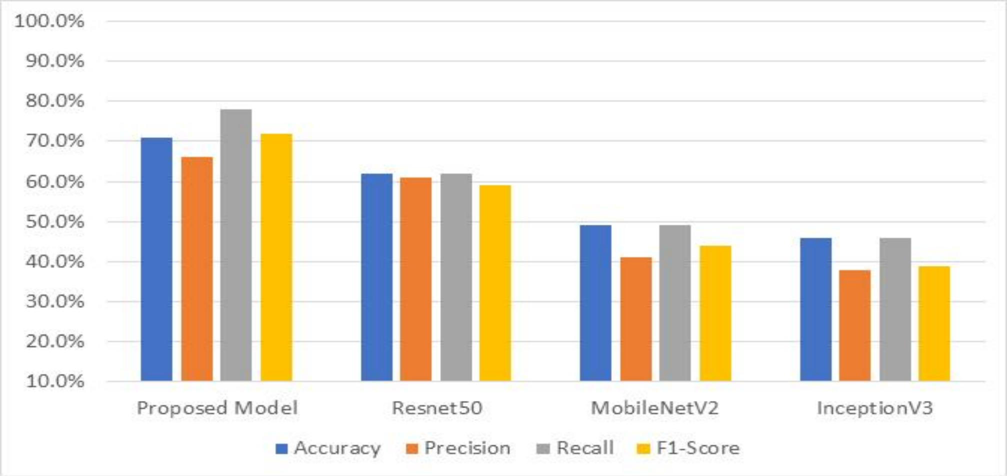

Figure 2. Proposed Model performance Comparison with other pre-trained models

10. Conclusion

The proposed deep learning-based model has successfully achieved 71% accuracy in classifying acne into mild, moderate, and severe categories. This result demonstrates the model's efficiency in identifying different acne severity levels based on facial images. The model's performance, indicating a balanced ability to detect and classify acne correctly. The use of a modified VGG16 architecture has contributed to this accuracy, outperforming traditional models like ResNet-50, MobileNetV2, and InceptionV3 in this specific classification task. A comparative analysis was conducted to evaluate the proposed model against pretrained DL models like ResNet-50,MobileNetV2, and InceptionV3. The results indicate that the proposed model outperformed all baseline models, achieving a higher accuracy. The confusion matrices further highlight the model's ability to correctly classify acne severity, minimizing misclassification rates compared to other models. While the proposed model shows promising results, this comparative analysis also highlights potential areas for improvement, such as enhancing precision for mild acne cases and addressing misclassification between moderate and severe acne.

11. Limitations

Despite its promising performance, the proposed model has several limitations that must be considered. The model's accuracy could be improved with a larger and more

12. Future Directions

To address these limitations and further enhance the model's performance, future research directions may include:

Improving Accuracy: The accuracy of acne classification models can be further improved in the future, leading to more precise and reliable predictions.

Expanding the Dataset: Incorporating a more diverse and larger dataset with different skin tones, lighting conditions, and acne types for better generalization.

Mitigating class imbalance: Future work will focus on mitigating class imbalance to improve model performance and ensure more balance acne classification.

Deployment in Real-World Applications: Integrating the model into mobile applications or web-based platforms for real-time acne assessment and monitoring.

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