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Acne Severity Detection & Personalized Chatbot Assistant

Introduction

The primary aim of this project is to develop a lightweight AI system that classifies acne severity from facial images using a pre-trained convolutional neural network. The model predicts severity levels—Clear, Mild, Moderate, or Severe—using real-time image input and then allows the user to interact with an OpenAI-powered chatbot to receive tailored skincare advice. This integrated application combines the predictive power of MobileNetV2 and the conversational capabilities of GPT-3.5, all deployed through an intuitive Streamlit interface.

Problem Statement

Many individuals lack immediate access to dermatological expertise. Visual acne assessment is often subjective and varies across practitioners. Patients seeking diagnosis and treatment frequently face delays or high consultation costs. The primary challenge addressed in this project is to develop an automated, accessible, and interpretable acne severity detection system. By leveraging machine learning and natural language processing, this solution aims to simulate expert guidance and improve early-stage acne evaluation.

Proposed Solution

The proposed system consists of two integrated components: (1) an acne severity classification model based on the MobileNetV2 architecture and (2) a conversational chatbot built with OpenAI GPT-3.5. The classification model processes input facial images and predicts acne severity as Clear, Mild, Moderate, or Severe. The chatbot responds to user queries with advice tailored to the predicted class. This end-to-end framework offers both accurate visual diagnosis and real-time conversational support through a streamlined Streamlit web interface.

Implementation Overview

The model leverages MobileNetV2, pretrained on ImageNet, and fine-tuned for acne classification. Images are preprocessed and resized to 160x160 pixels. The model includes a custom classification head with a GlobalAveragePooling layer, followed by Dense(256), Dropout(0.4), and a final Softmax output layer. Training is conducted in two phases: Phase 1 freezes the base model and trains only the top layers with a learning rate of 1e-4; Phase 2 unfreezes the top 60 layers of the base and fine-tunes the entire model with a lower learning rate of 1e-5. To handle class imbalance, the training data is augmented using oversampling and class weights computed via `compute_class_weight()`.

Methodology

Data Collection:

The dataset used in this project is the publicly available Acne Severity Classification dataset sourced from Kaggle. The dataset consists of facial images categorized into four severity classes: Clear (acne0_1024), Mild (acne1_1024), Moderate (acne2_1024), and Severe (acne3_1024). Each image was resized to a standardized dimension of 160×160 pixels to ensure compatibility with the input size requirements of MobileNetV2. To enhance the model's generalization ability, data augmentation techniques were applied using Keras' ImageDataGenerator. These augmentations included random image rotation (up to 40 degrees), zooming (up to 30%), brightness adjustments, horizontal flipping, and width/height shifting. This approach generated diverse image variations from limited data, which helped prevent overfitting. Since the dataset was imbalanced—with fewer examples in some severity classes—class balancing techniques were used. These included oversampling of underrepresented classes by duplicating existing images and applying class weights during training using sklearn's compute_class_weight() function to ensure equal learning importance across all severity levels.

Model Architecture:

The deep learning model is built on top of MobileNetV2, a lightweight and highly efficient convolutional neural network architecture developed by Google. MobileNetV2 is well-suited for edge devices and real-time applications due to its low parameter count and speed. It is pretrained on the ImageNet dataset, allowing it to extract meaningful and generalized visual features. For this project, we removed the default classification head of MobileNetV2 (`include_top=False`) and appended a custom classification head tailored for our four-class acne severity task. The added head comprises the following layers:

- A GlobalAveragePooling2D layer to flatten the spatial features into a 1D vector.

- A Dense layer with 256 units using the ReLU activation function to learn non-linear patterns.
- A Dropout layer with a 0.4 dropout rate to prevent overfitting.
- A final Dense layer with 4 units and a Softmax activation function to output the probability distribution over the four severity classes.

Training Strategy:

The model was trained in two distinct phases to maximize the benefits of transfer learning:

• Phase 1: Transfer Learning — During the initial phase, all layers of the pretrained MobileNetV2 base were frozen, and only the newly added classification head was trained. This allowed the model to adapt to the acne dataset without altering the robust general features learned from ImageNet. The optimizer used was Adam with a learning rate of 1e-4. This phase aimed to quickly converge the top layers for acne classification.

• Phase 2: Fine-Tuning — In the second phase, the top 60 layers of the base MobileNetV2 model were unfrozen, allowing them to be fine-tuned with a smaller learning rate of 1e-5. This enabled the model to refine its understanding of acne-specific features while avoiding catastrophic forgetting of ImageNet-learned representations. This phase was crucial for performance gains.

• Callbacks: The training process was managed using callbacks to optimize learning. EarlyStopping monitored the validation loss and stopped training if no improvement was observed for 6 epochs. ModelCheckpoint ensured that only the best model was saved. ReduceLROnPlateau dynamically reduced the learning rate when validation loss plateaued, allowing for more refined weight adjustments.

Streamlit Web App and Chatbot Integration

A Streamlit web app was created to allow image uploads, model inference, and real-time chatbot interactions. Once a severity label is predicted, it is shown with a confidence score and a recommendation. The user can also ask questions like 'What should I do for moderate acne?', and receive contextual advice using GPT-3.5. The app includes custom backgrounds, styled markdowns, and persistent chat history through Streamlit's session state.

Results and Evaluation

The model achieved validation accuracy between 60% and 65%, with good generalization across different skin tones and lighting conditions. Data augmentation and regularization techniques significantly improved performance. Grad-CAM visualizations were proposed for future stages to highlight regions that influenced the model's prediction. In terms of interpretability, the model consistently focused on acne-affected regions during inference.

Chatbot responses were accurate and contextually relevant to the severity class, simulating a virtual dermatology assistant effectively.

What Worked Well

MobileNetV2 proved to be an ideal backbone due to its efficiency and transfer learning compatibility. The use of `ImageDataGenerator` enabled robust data augmentation, which improved model generalization. Class weighting combined with oversampling helped address dataset imbalance. The Streamlit UI facilitated rapid testing and integration, while OpenAI's GPT-3.5 API delivered high-quality, context-aware chatbot responses. The modular architecture made it easy to expand or adapt the system for related skin health use cases.

Challenges and Summary

Attempts to fine-tune the entire MobileNetV2 base resulted in overfitting due to the relatively small dataset size. Some moderately severe acne cases were misclassified due to subtle visual overlap with neighboring classes. Without proper prompt tuning, the chatbot occasionally returned vague or overly general responses. Handling diverse skin tones and complex lighting still presents a challenge in ensuring completely unbiased predictions.

How to Reproduce the Demo

To reproduce the application:

1. Clone the git repo:
https://github.com/nive2530/Acne_Severity_Detector_And_Personalized_Chat_Assistant

2. Create a virtual ENV.
3. Install all required packages using `pip install -r requirements.txt`.
4. Place the trained model file `mobilenetv2_acne_model_improved.keras` in the `models/` folder.
5. Run the app with: `streamlit run acne_severity_predictor_app.py`.
6. Upload a facial image and review the predicted acne severity.
7. Use the integrated chat input to ask skincare questions.
8. Ensure your environment has internet access and a valid OpenAI API key to enable chatbot functionality.

Conclusion

This project successfully combines computer vision and conversational AI to deliver a real-time acne assessment tool. By leveraging MobileNetV2 for severity classification and GPT-3.5 for dialogue support, the system simulates dermatological guidance in an accessible format. It can serve as a foundation for more comprehensive skin health applications that support remote screening, user education, and medical triage. Future enhancements will focus on improving interpretability, integrating clinical metadata, and deploying the app to a public cloud platform for broader reach.