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Acnelytix - Acne Severity Classification and Type using Lighweight Deep Learning Approach

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Abstract: Acne vulgaris is a common dermatological condition that affects individuals across all age groups and can lead to physical scarring and psychological distress. Traditional diagnosis relies on manual visual examination, which is subjective and dependent on specialist availability. This paper presents Acnelytix, an AI-powered system for automatic acne type detection and severity classification using lightweight deep learning models. The system employs Convolutional Neural Networks (CNNs) such as MobileNetV2 and EfficientNet-Lite for efficient feature extraction and classification. Facial images collected from publicly available datasets on Kaggle are preprocessed, augmented, and used to train the model. The system is implemented as an offline desktop application using ONNX Runtime and ML.NET for real-time inference. Experimental evaluation is conducted using standard performance metrics. The proposed system provides accurate, fast, and scalable diagnostic support, making it suitable for deployment in resource-limited healthcare environments.
Keywords: Acne detection, Deep learning, CNN, Medical image analysis, Lightweight neural networks, Severity classification

I. INTRODUCTION

Artificial Intelligence (AI) and Deep Learning (DL) are rapidly transforming modern healthcare by enabling automated, fast, and reliable diagnostic support systems. Skin disorders, especially acne vulgaris, affect a large portion of the global population and can lead to both physical scarring and psychological stress. Although acne is not life-threatening, improper or delayed assessment may worsen the condition.

Traditional diagnosis depends on dermatologists' visual examination, which can be subjective and limited in rural or resource-constrained areas. The increasing availability of computer vision and lightweight neural networks provides an opportunity to develop intelligent systems that assist in dermatological evaluation.

Recent advances in lightweight Convolutional Neural Networks (CNNs) such as MobileNetV2 and EfficientNet-Lite have made it possible to perform high-accuracy image classification on systems with limited computational resources. These technologies enable real-time medical image analysis without requiring expensive hardware or continuous internet connectivity. By integrating such models into a standalone application, accessible and affordable preliminary skin assessment becomes feasible.

This project, Acnelytix, proposes an AI-powered system that detects acne lesions and classifies their severity using facial images. The system focuses on efficiency, offline usability, and clinical support, ensuring it can be deployed in hospitals, clinics, and even remote healthcare centers.

A. Research Problem

Acne severity assessment is often subjective and varies between medical professionals. Access to dermatologists is limited in many regions due to cost, distance, and shortage of specialists. Existing automated skin analysis systems typically rely on heavy deep learning models that demand high computational resources and cloud connectivity. Therefore, there is a need for a lightweight, accurate, and offline-capable AI system that can automatically detect acne and classify severity while remaining practical for real-time use.

B. Purpose of the Study

The purpose of this project is to design and implement a deep learning-based system capable of automatically analyzing facial images to detect acne and determine its severity level. The system utilizes lightweight CNN architectures for efficient inference and integrates them into a desktop software application. The solution aims to assist dermatological assessment, provide early screening, and reduce dependence on continuous specialist availability

C. Contribution
The project contributes a complete AI-based acne analysis system that combines image preprocessing, feature extraction, deep learning classification, and software integration in a single platform. Unlike many existing works, the system emphasizes lightweight implementation for real-time performance and offline operation. The project also demonstrates how AI models can be embedded into practical healthcare applications through tools such as ML.NET and ONNX Runtime.

D. Motivation
The growth of AI, increased computational capabilities, and the demand for accessible healthcare solutions motivate this research. Skin conditions significantly impact quality of life, yet access to dermatological care remains unequal. By leveraging AI and computer vision, the project aims to bridge this gap and offer a cost-effective, scalable, and intelligent support system.

E. Paper Organization
The remainder of this work describes the system methodology, model architecture, and implementation process. It further presents interim results, discusses system scalability and limitations, and outlines future enhancements for expanding the system's clinical capabilities.

II. RELATED WORK

A. Background
Skin disease diagnosis using artificial intelligence has become an active research area due to the rapid advancement of computer vision and deep learning technologies. Dermatological conditions such as acne, eczema, psoriasis, and skin cancer are commonly diagnosed through visual inspection, which makes them suitable for automated image-based analysis. However, traditional clinical diagnosis depends heavily on the experience of dermatologists and may vary between professionals. Moreover, access to dermatological services is limited in rural and low-resource regions, creating a need for intelligent support systems.

Several research works have explored automated skin lesion and acne detection using machine learning and deep learning approaches. Early systems relied on handcrafted features such as texture descriptors, color histograms, and edge detection techniques combined with classical classifiers like Support Vector Machines (SVMs). Although these methods provided moderate success, their performance was limited due to their inability to capture complex patterns in medical images.

With the emergence of deep learning, Convolutional Neural Networks (CNNs) became the dominant approach for medical image analysis. CNN-based systems automatically learn hierarchical features directly from image data, improving accuracy and robustness. Studies have demonstrated the use of deep CNN architectures such as ResNet, VGGNet, and Inception for skin disease classification tasks. However, many of these models are computationally heavy and require high-end GPUs, which restricts their real-time and offline deployment.

Recent research has shifted towards lightweight architectures like MobileNet and EfficientNet, which are optimized for low memory usage and faster inference. These models maintain high accuracy while being suitable for mobile and desktop applications. Data augmentation techniques such as rotation, flipping, brightness adjustment, and noise injection are also widely used to enhance model generalization and handle variations in lighting and skin tone.

Despite these advancements, most existing works focus either on acne detection alone or severity estimation alone, with limited integration into a complete clinical workflow. Additionally, many systems operate as research prototypes rather than practical applications. The proposed system addresses these gaps by combining lightweight CNN-based classification with a standalone desktop application and role-based clinical interaction.

B. Convolutional Neural Networks (CNNs)
Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for image processing and visual recognition tasks. CNNs are inspired by the structure of the human visual cortex and are capable of automatically learning spatial hierarchies of features from input images. They have become the foundation of modern computer vision systems, including medical image analysis.

A CNN typically consists of multiple layers, each performing a specific function in feature extraction and classification.

1) Convolution Layer: The convolution layer is responsible for extracting important visual features from the input image. It applies learnable filters (kernels) across the image to generate feature maps that highlight patterns such as edges, textures, and shapes. This allows the network to detect acne lesions and skin irregularities effectively

2) Pooling Layer: Pooling reduces the spatial dimensions of feature maps while preserving essential information. Max-pooling, the most common type, selects the maximum value from a region of the feature map. This reduces computational complexity and helps the model become more robust to small variations in image position or orientation
3) Shift Invariance: CNNs exhibit shift invariance, meaning small changes in the position of features in an image do not significantly affect the output prediction. This property is important in acne detection, as lesions may appear in different regions of the face.
4) Feed-Forward Operation: In CNNs, data flows in one direction from input to output through multiple layers. Each layer transforms the data into a higher-level representation, enabling the network to learn complex visual patterns
5) Fully Connected Layer: After convolution and pooling operations, the extracted features are flattened and passed to fully connected layers. These layers perform high-level reasoning and combine features to make final predictions about acne severity
6) Softmax Function: The Softmax activation function is used in the output layer to convert network outputs into probability values for each severity class (mild, moderate, severe). The class with the highest probability is selected as the predicted result
7) Dropout: Dropout is a regularization technique used to prevent overfitting. During training, some neurons are randomly ignored, forcing the model to learn more generalized features rather than memorizing the training data.

The use of CNNs, particularly lightweight variants like MobileNetV2 and EfficientNet-Lite, enables the proposed system to achieve accurate acne severity classification while maintaining low computational requirements, making it suitable for real-time and offline deployment.

III. METHODOLOGY

A. System Overview

The proposed system follows a structured methodology that integrates data preprocessing, deep learning model training, acne detection, and software implementation into a unified framework. The methodology ensures a systematic flow from raw image input to final acne severity classification and result presentation.

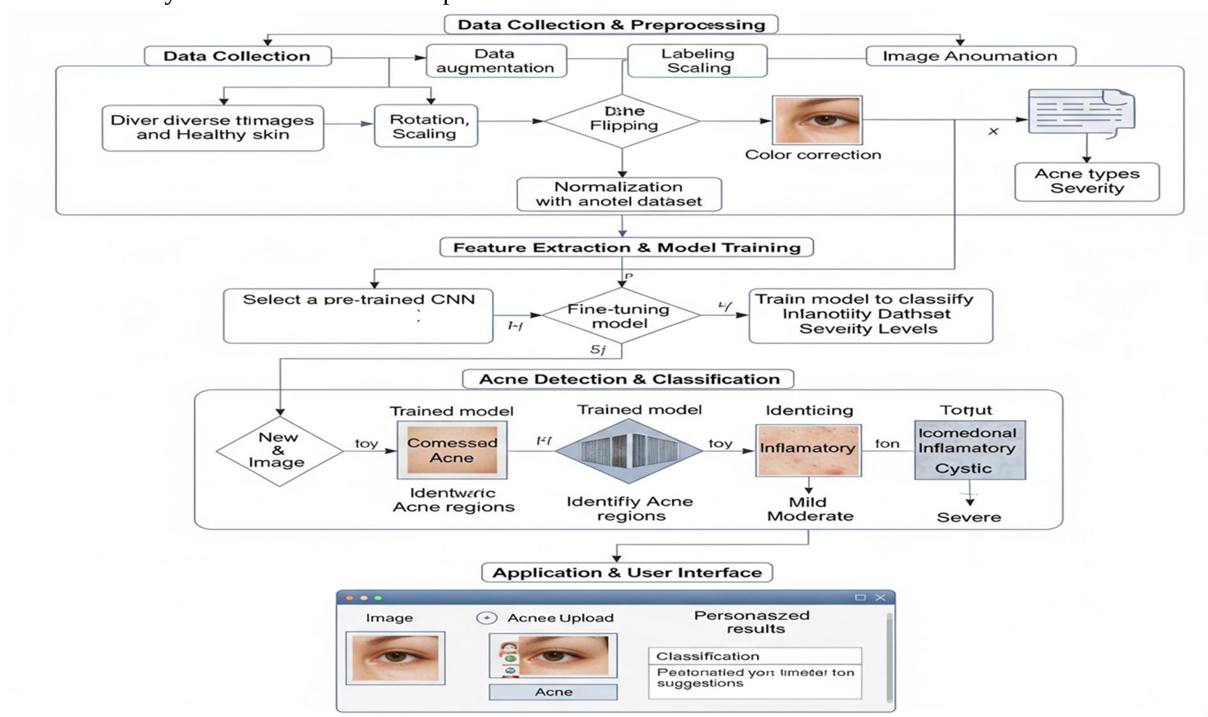

Fig 1. Overall system architecture of the proposed Acnelytic

B. Data Acquisition

The first step involves collecting facial images containing acne lesions and healthy skin from publicly available datasets on Kaggle. The dataset comprises images captured under diverse lighting conditions, skin tones, and background variations to improve model generalization.

To enhance dataset quality and variability, several preprocessing and augmentation techniques are applied. All images are resized and normalized to maintain consistent input dimensions. Noise reduction is performed using filtering methods, and segmentation techniques are employed to isolate facial skin regions from the background. Data augmentation operations such as rotation, flipping, scaling, zooming, and brightness adjustment are used to increase data diversity and address class imbalance.

Each image is annotated according to acne type and severity level (mild, moderate, and severe), which serve as the ground truth labels for supervised learning.

C. Feature Extraction and Model Training

In this stage, a pre-trained Convolutional Neural Network (CNN) model such as MobileNetV2 or EfficientNet-Lite is selected. Transfer learning is applied to adapt the model to the acne dataset. The earlier layers of the network capture general visual features, while the later layers are fine-tuned to learn acne-specific patterns such as lesion texture, redness, and distribution.

The model is trained using labeled data and optimized through hyperparameter tuning. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. Regularization techniques like dropout and data augmentation help prevent overfitting and improve model robustness.

D. Acne Detection and Severity Classification

Once the model is trained, it is used for real-time acne detection and classification. When a new facial image is provided, it first undergoes preprocessing steps such as resizing, normalization, and noise reduction. The processed image is then passed into the CNN model for analysis.

The system initially detects acne-affected regions by identifying visual patterns such as redness, texture variation, and lesion structures. Based on the learned feature representations, the model performs two levels of classification:

1) Acne Type Identification – The system categorizes acne into types such as comedonal (blackheads/whiteheads), inflammatory (papules and pustules), and cystic forms. This helps in understanding the nature of the skin condition.
2) Severity Classification – After identifying the acne type, the system determines the overall severity level of the condition, typically classified as mild, moderate, or severe, depending on lesion density and spread.

The final output presented to the user includes both the acne type and severity level, along with a confidence score indicating the reliability of the prediction. This dual classification approach provides more detailed diagnostic support compared to systems that only estimate severity.

E. System Implementation

The trained model is exported in ONNX format and integrated into a desktop application developed using the .NET framework. ML.NET and ONNX Runtime are used for efficient inference within the application. The system operates offline, making it suitable for deployment in clinics with limited internet access.

The graphical user interface allows users to upload images, view classification results, and manage patient records. Image preprocessing within the application is handled using OpenCV/Emgu.CV libraries. Role-based access control ensures secure handling of patient data and restricts system functions based on user roles.

F. Overall Workflow

The system workflow begins with user image input, followed by preprocessing and normalization. The processed image is analyzed by the trained CNN model, which predicts acne severity. Results are displayed through the application interface and stored for future analysis. This structured methodology ensures accuracy, efficiency, and scalability of the system.

IV. EXPERIMENTAL SETUP AND EXPECTED RESULT

A. Experimental Setup

The experimental setup for the proposed Acnelytix system focuses on evaluating the performance of the deep learning model for acne type detection and severity classification. The dataset used for training and evaluation consists of facial images with visible acne lesions collected from publicly available datasets on Kaggle. The dataset includes variations in skin tone, lighting conditions, and image backgrounds to ensure robustness of the model.

The dataset is divided into three subsets: training, validation, and testing. The training set is used to train the CNN model, the validation set is used to tune hyperparameters and prevent overfitting, and the testing set is used for final performance evaluation.

Data augmentation techniques such as rotation, flipping, scaling, zooming, and brightness adjustments are applied to increase dataset diversity and improve generalization.

A lightweight pre-trained CNN model such as MobileNetV2 or EfficientNet-Lite is used as the base architecture. Transfer learning is applied by fine-tuning the model using the acne dataset. The model is trained using supervised learning, where labeled images correspond to acne types (comedonal, inflammatory, cystic) and severity levels (mild, moderate, severe). Training is performed over multiple epochs with optimized hyperparameters such as learning rate and batch size.

The model performance is evaluated using standard classification metrics, including:

1) Accuracy – Overall correctness of predictions
2) Precision – Proportion of correctly predicted positive cases
3) Recall – Ability of the model to detect actual acne cases
4) F1-Score – Harmonic mean of precision and recall

The system is implemented and tested on a standard computer with at least 8 GB RAM and CPU-based processing, demonstrating that the model can operate without high-end hardware.

B. *Expected Results*

The proposed system is expected to achieve high accuracy in detecting acne regions, identifying acne types, and classifying severity levels. Due to the use of lightweight CNN architectures and data augmentation, the model is expected to generalize well to images captured under different real-world conditions.

The system is anticipated to provide:

1) Reliable classification of acne into type categories such as comedonal, inflammatory, and cystic
2) Accurate severity prediction (mild, moderate, severe)
3) Fast inference suitable for real-time desktop use
4) Consistent performance even with limited computational resources

The output of the system includes the predicted acne type, severity level, and confidence score. These results can support dermatologists in preliminary diagnosis and help users monitor skin conditions over time.

Overall, the expected outcome is a lightweight, accurate, and scalable AI system that bridges the gap between medical image analysis research and practical healthcare application.

V. CONCLUSION

This project presented Acnelytix, an AI-powered system designed for automatic acne type detection and severity classification using deep learning and computer vision techniques. The system addresses the limitations of traditional dermatological assessment, which can be subjective and dependent on specialist availability. By leveraging lightweight Convolutional Neural Network (CNN) architectures such as MobileNetV2 and EfficientNet-Lite, the proposed solution achieves a balance between accuracy and computational efficiency.

The system integrates image preprocessing, feature extraction, model training, and desktop application deployment into a unified framework. It is capable of identifying acne types such as comedonal, inflammatory, and cystic, while also classifying severity levels into mild, moderate, and severe categories. The use of transfer learning and data augmentation enhances the robustness of the model under varying lighting conditions, skin tones, and image qualities.

One of the key strengths of the system is its lightweight and offline-capable design, making it suitable for deployment in clinics, hospitals, and remote healthcare centers without requiring high-end hardware or continuous internet access. The user-friendly interface ensures accessibility for both medical professionals and general users.

Although the system shows promising performance, further improvements can be made by expanding the dataset, incorporating more diverse skin conditions, and enhancing explainability features such as heatmaps for lesion visualization. Future enhancements may include cloud integration, mobile application support, and extension to other dermatological diseases.

In conclusion, the proposed system demonstrates how artificial intelligence can be effectively applied in healthcare to provide fast, reliable, and scalable diagnostic support, contributing to improved accessibility and early assessment of skin conditions.

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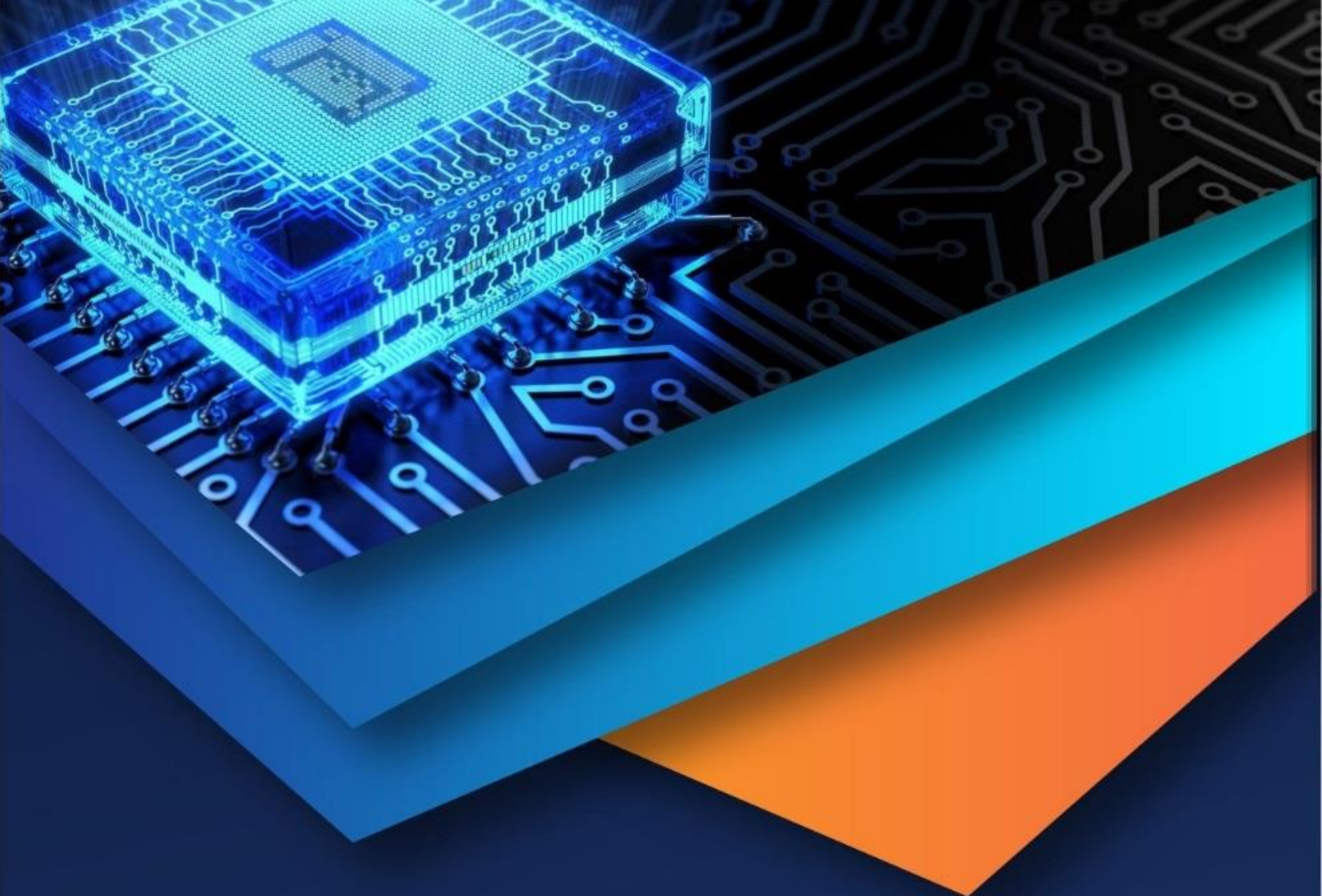

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