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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that Project Report entitled **"Acne Detection and Care System by Using Deep Learning**" which is submitted by **Rohit Yadav** and **Aashika Jain** in partial fulfillment of the requirement for the award of degree **B. Tech. in Department of Computer Science & Engineering** of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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ABSTRACT

Millions of people worldwide suffer from acne, a common dermatological ailment that frequently causes both physical and psychological discomfort.The prevalence of acne, a common skin condition, poses a significant challenge to derma-tologists and individuals seeking effective skincare solutions.This research introduces ’Acne Care’, an innovative system that leverages deep learning techniques and Reset18 application for the detection and personalized care of acne.This model analyse various skin abnormalities and make a severity detection system based on the classification using deep learning algorithms.This ensemble model could accurately predict the number, location, and severity of acne at the same time. It might also be a useful tool for the patient to self-test and help the doctor diagnose them.This paper presents the development, methodology, and potential impact of this model, addressing the growing need for more efficient and effective acne management.The findings of this research paper contribute to the development and advancement of deep learning based regression models to assess the severity level of acne lesions from selfie images and their management. Acne detection, utilizing prior knowledge to diagnose acne severity, number or position through facial images, plays a very important role in medical diagnoses and treatment for patients with skin problems. Recently, deep learning algorithms were introduced in acne detection to improve detection precision. However, it remains challenging to diagnose acne based on the facial images of patients due to the complex context and special application scenarios. Here, we provide an ensemble neural network composed of two modules: a classification module aiming to calculate the acne severity and number; a localization module aiming to calculate the detection boxes. This ensemble model could precisely predict the acne severity, number, and position simultaneously, and could be an effective tool to help the patient self-test and assist the doctor in the diagnosis.

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LIST OF ABBREVIATIONS

AP	Average precision
BB	Bounding box
BEC	Bottleneck and expansion convolution
Faster R-CNN	Faster region-based convolutional neural networks
FCN	Fully convolutional networks
FPN	Feature pyramid networks
GPU	Graphics processing unit
IoU	Intersection over union
Mask R-CNN	Mask region-based convolutional neural networks
PAN	Path aggregation network
RoI	Region of interest
RPN	Region proposal network
RUS	Random under-sampling
SOTA	State-of-the-art
SPP	Spatial pyramid pooling
Tiny-SPP	Tny spatial pyramid pooling
WCL	Wing convolutional layer
YOLO	You only look once
YOLOv3	You only look once version 3
YOLOv4	You only look once version 4

CHAPTER 1

INTRODUCTION

1.1 Introduction

Acne vulgaris, as it is technically called, is a condition where oil and dead skin cells clog pores[3]. This results in whiteheads, blackheads, and red pimples as the inflamma-tion gets greater.Without a doubt, most of the human face acne's problems. This widespread skin condition, which affects more than 85% of teenagers, is characterized by clogged pores,pimples, and occasionally hard, deep lumps on the face, neck and upper arms. Based on the statistic by the American Academy of Dermatology Association, it is known that ap-proximately 85% of people between 12 and 24 experience at least minor acne. Moreover, acne occur in adult is upto 15% of women [1]. Figure 1 shows the different types of acne.

Acne manifests in various types, each characterized by distinct features and severity levels. Whiteheads, for instance, are small, raised bumps with a white or flesh-colored center, resulting from the blockage of hair follicles by a combination of oil and dead skin cells. Conversely, blackheads share similarities with whiteheads but have an open pore, and their dark appearance is attributed to the oxidation of the exposed clogged material when in contact with air [2].Papules, on the other hand, present as small, red, inflamed bumps without a visible center and can be tender to the touch, often stemming from bacterial activity and inflammation. Pustules, similar to papules, contain pus at their tips, giving them a distinctive ap pearance of white or yellowish bumps with a red base.Nodules represent a more severe form of acne, characterized by large, painful, and solid lumps located beneath the skin's surface. These deep-rooted nodules often require medical intervention due to their prolonged healing time and potential for com-plications. Understanding the unique characteristics of each type of acne is crucial for effective diagnosis and tailored treatment approaches, especially in the case of nodular acne, where medical attention is frequently necessary for proper management.Understanding one's skin's functioning is necessary to comprehend acne. Oil glands can be found in skin pores. Androgens, the sex hormones, are released in greater amounts when a person reaches puberty. One’s oil glands grow, become hyperactive, and generate excessive amounts of oil, or sebum, as a result of having too many hormones. Skin cells clog pores and hair follicles when sebum production is excessive. Additionally, as oil levels rise, Cutibacterium acnes germs proliferate. Acne, which is characterized by a raised red spot with a white center, is caused by infection or inflammation of blocked pores. A whitehead is present if the pore becomes clogged, shuts, and then bulges.When a pore clogs, remains open, and the top turns black from oxidation or air exposure, this is known as a blackhead. A pustule, or red, inflammatory pimple, may develop when bacteria multiply in the clogged pore. Cysts develop when there are big, painful lumps beneath the skin’s surface due to deep-seated pore blockage and inflammation.Acne can be brought on by hormonal changes brought on by birth control medications, menstruation, and pregnancy. Hair dyes, oily hair ointment, and thick face creams and cosmetics are some other external acne causes that can clog pores. Wearing clothing that scrapes against the skin can exacerbate acne, particularly on the chest and back. As might excessive perspiration while exercising in hot, muggy weather [6]. Since stress has been linked to an increase in oil production, many teenagers get a fresh round of pimples right before or on the first day of school. Dermatologists evaluate Different types of Acne in Fig. 1.1 Likes Nodules, Pustules, cysts , Papules , Blackheads And Whiteheads, the severity of acne in a clinical setting traditionally. Dermatologists administer prescribed treatments, or depending on the severity, over-the-counter skin care items are suggested. Due to the prevalence of the condition, there is a greater demand from acne sufferers to have their acne severity professionally evaluated on a regular basis than there are dermatologists available to do so [4]. Patients with acne are thought to have to wait an average of more than 32 days to see a dermatologist. For acne sufferers, this poses a significant obstacle and source of irritation as it postpones advice regarding food, lifestyle, and skin care products.

Deep learning and computer vision developments recently opened the door for quick and automated illness diagnosis systems.This paper focuses on the application of ResNet-18, a neural network architecture that was introduced to address the challenges of training very deep neural networks. ResNet introduces the concept of residual learning, which involves using shortcut connections to skip one or more layers and assists in detection of acne severity at a deeper level. ResNet-18 consists of 18 layers (hence the name), organized into several blocks. These blocks include convolutional layers, batch normalization, rectified linear unit (ReLU) activations, and residual connections.Utilizing ResNet-18 in acne detection involves leveraging the capabilities of this deep convolutional neural network architecture for image classification tasks.This architecture has been widely used and adapted for various computer vision tasks, including image classification, object detection, and segmentation. Researchers often use pre-trained versions of ResNet-18 on large datasets, like ImageNet, for transfer learning in specific applications, including medical image analysis such as acne detection. ResNet-18, along with its deeper variants like ResNet-50, has become a foundational architecture in the field of acne detection using deep learning algorithms [5]. The aim to detect Different stages of acne shown in fig 1.2 model is to combine techno-logical advancements with dermatological expertise to enhance early detection, provide personalized skincare guidance, and contribute to the overall well-being of individuals by fostering awareness and accessibility in the realm of skincare. Acne is a common skin condition that can take various forms, each with its own characteristics and treatment approaches. Here are the main types of acne:

1.1 Types Of Acne

i. Comedonal Acne:

Whiteheads: Closed comedones that appear as small, flesh-colored or white bumps.

Blackheads: Open comedones that appear as small, dark spots due to oxidation of the material inside the pore.

ii. Inflammatory Acne:

Papules: Small, red, tender bumps without pus.

Pustules: Similar to papules but with a white or yellow center filled with pus.

Nodules: Large, painful, solid lumps beneath the surface of the skin.

Cysts: Deep, painful, pus-filled lumps that can cause scarring.

iii. Acne Mechanica:

Caused by friction, pressure, or heat, often from sports equipment, helmets, or tight clothing.

iv. Acne Conglobata:

A severe form of acne with interconnected nodules and cysts, often leading to significant scarring.

v. Acne Fulminans:

An acute and severe form of acne conglobata, characterized by sudden onset of painful nodules, systemic symptoms like fever, and joint pain.

vi. Hormonal Acne:

Often found around the jawline and chin, related to hormonal fluctuations, commonly seen in women.

vii. Fungal Acne (Pityrosporum Folliculitis):

Caused by an overgrowth of yeast in the hair follicles, leading to itchy, uniform pustules.

viii. Excoriated Acne:

Resulting from picking or scratching acne lesions, leading to more inflammation and scarring.

Each type of acne may require different treatment strategies, ranging from topical treatments and oral medications to lifestyle changes and professional procedures like laser therapy or chemical peels. Consulting a dermatologist is crucial for accurate diagnosis and appropriate treatment.

Fig.1.1 Types of Acne

1.2 Different Stages of Acne

Acne can progress through different stages, each characterized by varying severity and types of lesions Show on Fig. 1.2 Understanding these stages helps in determining the appropriate treatment and management strategy.

i. Mild Acne

Characteristics: Few comedones (whiteheads and blackheads), occasional papules and pustules.

Common Areas: Face, particularly the forehead, nose, and chin.

Treatment: Over-the-counter (OTC) topical treatments such as benzoyl peroxide, salicylic acid, or alpha hydroxy acids. Regular cleansing and non-comedogenic skincare products.

ii. Moderate Acne

Characteristics: More widespread and noticeable presence of comedones, papules, and pustules. May involve inflammation.

Common Areas: Face, and possibly the back, shoulders, and chest.

Treatment: Prescription topical treatments such as retinoids or antibiotics. In some cases, oral antibiotics or hormonal treatments (e.g., birth control pills for females) may be recommended. Consistent skincare routine and possible lifestyle adjustments.

iii. Moderately Severe Acne

Characteristics: Numerous papules and pustules, along with a greater number of inflamed nodules.

Common Areas: Face, chest, back, and shoulders.

Treatment: Combination of topical treatments and oral medications. Oral antibiotics or isotretinoin (Accutane) may be prescribed. Hormonal treatments for females. Dermatological procedures like chemical peels or light therapy might be considered.

iv. Severe Acne

Characteristics**:** Extensive inflammation, numerous large, painful nodules or cysts. High risk of scarring and hyperpigmentation.

Common Areas: Face, neck, chest, back, and shoulders.

Treatment: Stronger oral medications such as isotretinoin (Accutane). Intralesional corticosteroid injections for large nodules. Close supervision by a dermatologist is essential. Comprehensive skincare regimen to support treatment and reduce irritation.

v. Nodulocystic Acne

Characteristics: Severe form with large, painful nodules and cysts. Significant inflammation and potential for deep scarring.

Common Areas: Face, neck, chest, back, and shoulders.

Treatment: Oral isotretinoin (Accutane) is commonly prescribed due to its effectiveness in severe cases. Other treatments may include oral antibiotics, hormonal therapy, and possibly surgical intervention for cyst drainage. Continuous monitoring by a dermatologist

Mild Acne Moderate Acne Severe Acne Nodulocystic Conglobata

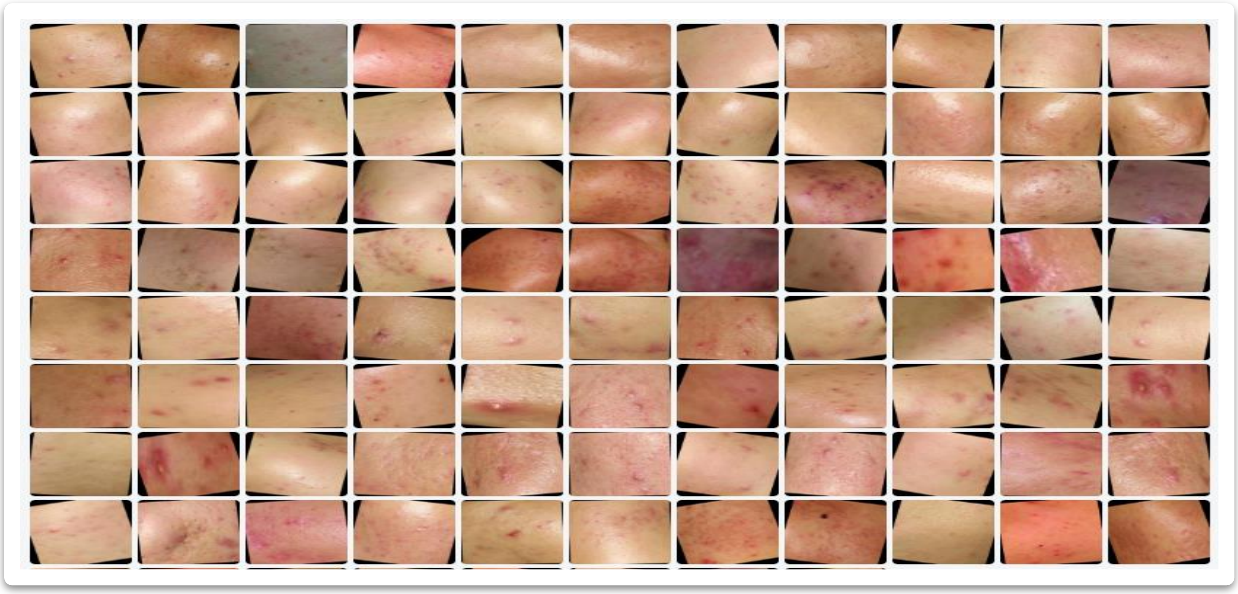

Fig.1.2 Stages of Acne

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vi. Acne Conglobata

Characteristics: One of the most severe forms, characterized by interconnected nodules and cysts, extensive inflammation, and abscesses. Commonly leads to scarring.

Common Areas: Face, neck, chest, back, buttocks, and arms.

Treatment: Aggressive treatment often required, including oral isotretinoin (Accutane), oral antibiotics, and corticosteroids. Dermatological procedures like laser therapy or surgery may be necessary to manage scars and lesions. Ongoing medical supervision is critical.

Each stage of acne requires a tailored approach to treatment, emphasizing early intervention to prevent progression and minimize scarring. Consulting a dermatologist ensures that the most effective treatment plan is implemented based on the specific stage and characteristics of the acne.

1.3 Project Description

Skin diseases are very common and nowadays easy to get remedy from. But, sometimes properly diagnosing these diseases can be quite troublesome due to the stiff hard-to-discriminate symptoms they exhibit. Individuals especially youths are not familiar the level of seriousness of their skin issues. Moreover, individuals do not take the correct and prompt action towards the solution of their acne issues due to the lack of knowledge. The omnipresent issue fortunately is inevitable, however, lacklustre measures and insufficient self-awareness are being practiced by the general public, thus resulting in the exponential increase of individuals having critical acne issues.

1.Teenagers-Acne usually begins in **puberty** and affects many adolescents and young adults. Approximately 85 percent of people **between the ages of 12 and 24** experience at least minor acne. Acne is caused by overactive oil glands in the skin and a buildup of oil, dead skin cells, and bacteria, which leads to inflammation (swelling and redness) in the pores. Oil glands get stimulated when hormones become active during puberty. That's why people are likely to get acne in their teens.

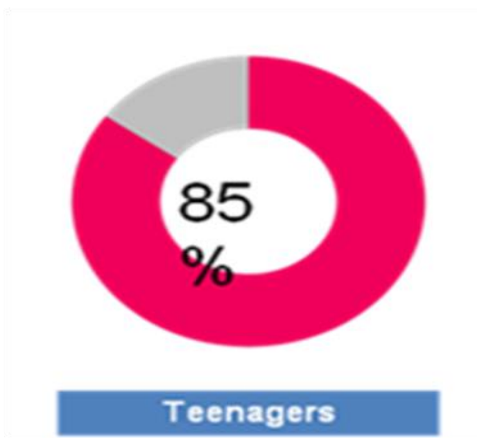

Fig. 1.3 Teenagers Most Common Skin Condition

2.Adult Women-Acne can occur at **any stage of life** and may continue into one’s 30s and 40s. Acne **percentage increases** during **pregnancy**. Yes, adults get acne. Some adults continue to get acne well into their 30s, 40s, and even 50s. It is even possible to get acne for the first time as an adult. Dermatologists call this “adult-onset acne.” It is most common among women going through menopause.

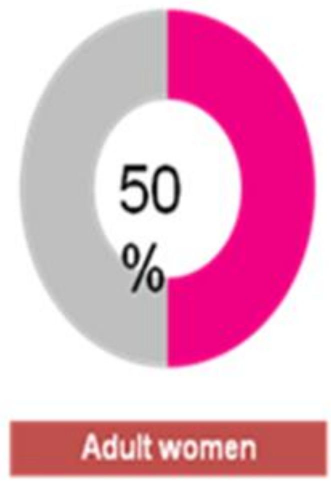

Fig. 1.4 Adult Women Most Common Skin Condition

1.4 Reason for Acne

Women tend to get adult acne more often than men do. If you're getting acne as an adult, it is likely due to one or more of the following reasons.

Fluctuating hormone levels**:** An imbalance can lead to breakouts.

Women often experience fluctuating hormones:

- Around their periods
- During pregnancy, peri-menopause, and menopause
- After discontinuing (or starting) birth control pills

Stress: Researchers have found a relationship between stress and acne flare-ups. In response to stress, our bodies produce more androgens (a type of hormone). These hormones stimulate the oil glands and hair follicles in the skin, which can lead to acne. This explains why acne can be an ongoing problem when we find ourselves under constant stress.

Family history**:** Does a close blood relative, such as a parent, brother, or sister have acne? Findings from research studies suggest that some people may have a genetic predisposition for acne. People who have this predisposition be more likely to get adult acne.

Hair and skin care products**:** If you have adult acne, you should read the labels on your skin care and hair care products. Make sure that you see one of the following terms on every container:

- Non-comedogenic

- Non-acnegenic
- Oil-free
- Won’t clog pores

You want to make sure your moisturizer, cleanser, sunscreen, and all other products contain one of these terms. These products are least likely to cause acne.

Medication side effect: Acne is a side effect of some medicines. If you suspect that a medicine is triggering your acne or making it worse, continue taking the medicine, but talk with the doctor who prescribed it. Ask if acne is a possible side effect. If acne is a possible side effect, ask if you can take a different medicine. If you cannot take another medicine, you may want to see a dermatologist who can help you control the acne.

Undiagnosed medical condition: Sometimes, acne is a sign of an underlying medical condition. Once the medical condition is diagnosed and treated, the acne often clears.

Effective treatment available for adult acne

If nothing clears your acne, you should see a dermatologist. Effective treatment is available. Often a dermatologist will use two or more treatments. With a dermatologist’s help and a bit of patience, virtually every case of acne can be controlled.

CHAPTER 2

LITERATURE REVIEW

Numerous algorithms for the analysis of skin images have been created, including ones for the analysis of acne. However, techniques based on traditional image processing frequently fail to produce satisfactory results due to the intricacy of skin lesions. The advent of deep learning techniques, particularly the convolutional neural network (CNN), has revolutionized the field of computer vision in general and skin image analysis in particular [5].In 2018, a CNN-based approach to automat-ically identify face acne was presented by Xiaolei Shen et al.The process allowed for the distinction of seven groups of acne lesions: modules, cysts, blackheads, whiteheads, papules, pustules, and normal skin. The accuracy of any class 81% was shown in the results.However, the study by Xiaolei Shen et al. used non-smartphone facial pictures [6]. In 2019, Junayed et al. used the AcneNet model—which is based on a deep residual neural network—to classify five different types of acne lesions: cystic, open comedo, keloidalis, closed comedo, and pustular.1800 photos in total were split equally across the classes,360 pictures for every class. With an accuracy of 99.44% for the Keloidalis class, the accuracy was over 94%. But the pictures utilized in the research by Junayed et al. were also not from smartphones [7].Seite et al. published a deep learning-based artificial intelligence method for facial acne analysis using smartphone photos at the end of 2019. The method can evaluate the severity of facial acne using the Global Evaluation Acne (GEA) scale and differentiate between multiple types of acne lesions, including comedonal lesion, in-flammatory lesion, and post-inflammatory hyperpigmentation[8]. The approach made use of a dataset consisting of 5972 photos that were gathered from 1072 acne sufferers using both iOS and Android cellphones. However, the method's accuracy in evaluating the severity of acne was just 68% [9].Yin Yang et al. created a new acne assessment system in 2021 that graded the severity of face acne based on Chinese guidelines by utilizing deep learning [10]. Using Fujifilm and Canon cameras, 5871 clinical photos of 1957 patients were gathered to create a dataset. The method consisted of three steps: preprocessing the image data to remove interference from the eyes, nose, and mouth; second, identifying the acne lesions using an Inception-V3 network; and finally, evaluating the model's effectiveness in acne vulgaris patients[11]. The findings revealed that the deep learning model had an average F1 score of 0.8 and a Kappa coefficient of 0.791,it quantifies the level of association between dermatologists and the deep learning model[12].

In Paper [1] Differentiating between inflammatory and quasi-inflammatory lesions of acne and determining lesion numbers are critical components of acne evaluation. For decades, systematic lesion count has consistently proved the therapeutic efficacy of anti-acne medications. In Paper [2] "Healthcare Solutions Extraction Based on ANN-GOA and TDES." In 2022 Second International Conference on Artificial Intelligencen and Smart Energy (ICAIS), pp. 45-52. IEEE, 2022.In Paper [3] In this article, we use a classification system that includes non-infammatory lesions (open comedones known as blackheads and closed comedones known as whiteheads, infammatory lesions (papules and pustules), and more serious forms, nodules and cysts1. In Paper [4] Acne is a prevalent pathology that affects individuals of any age, genders, and ethnicities. A dermatologist should evaluate the kind and severity of a patient's acne, but the growing wait time for an inspection makes treatment less accessible and, as a result, less effective.

2.1 Existing Image Processing Techniques for Acne Detection

In previous image processing approaches to detect acne, Ramli et al. [13] used CIELAB color space to do skin lesion segmentation. Firstly, sample images were converted from RGB color space to CIELAB color space by calculating the Euclidean distance. They applied Otsu’s thresholding method to extract foreground (acnes) from background (skin). The system had 80% sensitivity and specificity. Khan et al. [3] applied Fuzzy C-means (FCM) Clustering Technique which clustered associated pixel in one or more clusters. They applied FCM on 4 color spaces which were RGB, OHTA, YIQ and I1I2I3. They noted that RGB was very sensitive to illumination variations. YIQ color space solved illumination problem by separating the luminance (Y) from chrominance information (I, Q). The results showed that optimum clusters number was 3. Specificity / sensitivity and accuracy is varying in different clusters number from 45-95%. Alamdari et al. [14] used k-means clustering (2 levels) with Hue Saturation Value (HSV) color space, which had more meaningful color component over RGB. They achieved 70% accuracy. They also used Fuzzy c-means (FCM) clustering technique and Support Vector Machine (SVM) to differentiate acne scar from inflammatory lesions with 80% and 66.6% accuracy, respectively. They found that the accuracy of classifying detected acne from normal skin was 100% using FCM. In addition, they applied wathershed segmentation and multi thresholding but the application was failed to detect acne properly. Liu and Zerubia [15] used Markov random fields (MRFs) with Chromophore Descriptors by applying iterated conditional modes (ICM). The algorithm was robust to large-dynamic-range intensity that would work on images captured under Ref. code:25605822040035JYO8uncontrolled environment. The result highly agreed to human visual inspection(estimated).Chen et al. [16] developed imaging system on Android device as an alternative to expensive skin probe. They used normal and Ultraviolet (UV) lighting with YCbCrcolor space. The system used simple thresholding to extract acne features. Their systems had drawback that required user to manually mark Region of Interest (ROI).They achieved 82% accuracy by simply counting positive and negative samples.Malik et al. [17] used K-means clustering and SVM classifier to detect and classify acnes into 4 categories: comedo, papule, pustule, and nodule with severity level, and resulted in 93% accuracy in average (with post processing).Huamyun and Malik [18] used Multilevel thresholding on RGB images. The result needed more improvement and they suggested a use of Multispectral and Thermal images with more color bands. There would be an improvement in detection result.

Lucut and Smith [19] proposed their own K-means clustering algorithm that applied Hough Transform and First Order Derivative to find thresholding point. This approach automatically found actual number of clusters, resulting in 59-99% accuracy. Chantharaphaichit et al. [1] detected acnes by using image processing technique in MATLAB module. They converted the image from RGB color space to Gray Scale, applied normalization with maximum intensity, converted RGB to HSV color space then applied brightness extraction process. The system marked the Region of Interest(ROI) by image subtraction then applied Binary thresholding with user defined value to apply spot and region. Lastly, acnes detection result was marked on original image.The system had fair accuracy. Chantharaphaichit et al. [2] applied feature extraction with supervised learning: “Training” and “Testing” algorithm on 10 acne images. The system did Blob detection, Feature extraction for each candidate and then applied Bayesian Classification, Supervised Training and Unsupervised Testing. The system had accuracy at 70.65%. Chang and Liao [20] did facial region extraction from captured image by using skin color filtering and region-filling method to detect the largest connected region and remove unrelated facial feature which were eyes, eyebrows, nostrils and mouth through Fourier descriptor. Then, they used feature extraction with co-occurrence matrix and the sequential floating forward selection (SFFS) to select features. Vector Machine (SVM) to classify normal patterns, acnes and spot. They applied a decision tree structure which consisted of two SVMs. Chang's methods worked effectively at 98% accuracy. The system sensitivity was medium at 64% because of the different features in various types of acnes.Chandra et al. [21] used segmentation with color-based technique, Mahalanobis distance (MD) Minimum distance classifier, then compared with Bayesian Classifier. The experimental result showed that Mahalanobis distance was superior to Bayesian Classifier but with limitations such as photographic session ambience light.Khongsuwan et al. [22] applied Ultra-Violet fluorescence lighting in imagecapturing process to detect P. acne, a gram positive anaerobic microorganism, which causes the acne, They converted UV image to RGB and to Gray-Scale, applied adaptive histogram equalization which used a bilinear interpolation to eliminate artificially induced boundaries of the acne, and then applied extended maxima transform to separate close objects from each other. The experiment was done on cropped-part of the skin area only. The system had 83.75% accuracy.Singh and Kanwal [23] did facial marks detection techniques comparison survey. They found that to extract facial features, Active Apperance Model (AAM) was the most efficiency technique. For acnes detection, various techniques were reviewed such as Laplacian-of-Gaussian (LoG), Speeded Up Robust Features (SURF), BLOB detection and Morphological operators. They could identify various types of acne [8]. Fujii et al. [12] applied image processing techniques on Multispectral Image captured from 16 bands and 12 bits depth multispectral camera. Two tungsten lamps were used to illuminate Patient's face. The measurement of spectral energy distribution was done by Spectroradiometer. The classification process was done by Fisher linear discriminant function (LDF's) and thresholding. The 3 Fisher LDF's and thresholding value were experimentally calculated. The system showed good results.

CHAPTER 3

PROPOSED METHODOLOGY

As part of our effort to develop a customized acne detec-tion algorithm, we carefully selected a Kaggle dataset that only included people with fair skin. With 999 photos in all, the dataset includes a wide variety of viewpoints and face expressions to guarantee a thorough portrayal of real-world situations. We found three unique classes in our carefully selected dataset, each of which captured a unique facet of acne manifestation. The careful selection of images allows us to address the complexities associated with acne detection, particularly in individuals with light skin tones. By including a variety of skin conditions and acne manifestations, our dataset aims to enhance the robustness and generalization capabilities of the acne detection model. The diversity within the dataset not only reflects the natural variability in skin conditions but also accommodates the potential nuances associated with different acne types. The model used in the acne classifier is pretrained Resnet-18 model.ResNet-18, short for Residual Network with 18 layers, represents a convolutional neural network (CNN) ar-chitecture renowned for its depth and effectiveness in image recognition tasks.ResNet 18 has 18 layers with a 7 X 7 kernel as 1st layer. It has four layers of ConvNets that are identical. Each layer consists of two residual blocks.Each residual block consists of two convolutional layers and introduces a shortcut or skip connection that bypasses one or more layers.

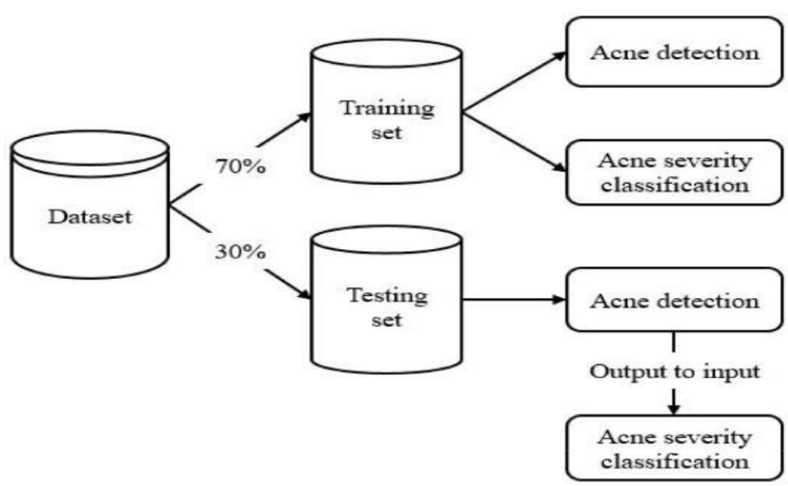

Fig. 3.1 Flowchart

This skip connection facilitates the direct flow of information from the input to the output, enabling the model to learn residual mappings. Figure 3.1 provides a visual representation of the architecture, showcasing the intricate design of ResNet-18.

3.1 Image data processing

To train and validate our algorithm, we collected 212,374 original acne lesion images from dermatology clinical clinics in 15 hospitals in different provinces of China using smartphones from January 2020 to October 2022. For assessing the suitability of each image, we employed Google's advanced machine vision technology, Mediapipe, which evaluates images based on clarity and exposure. Firstly, the face region of the image is cropped and six feature values of the cropped image are calculated, and the sharpness is predicted by logistic regression model. Then, the image was converted from RGB three channels to H(hue)S(saturation)V(lightness), and according to the pixel value of V channel, whether the image was too dark or over-exposed was judged. Finally, based on these criteria,

Fig. 3.2 Image Data Processing

we excluded occluded lesions, non-face images, overexposed, underlit, and blurred images shown in fig. 3.2 .were taken from kaggle , a subsidiary of Google LLC, Through image usability testing and inclusion criteria, 153,183 acne lesions images were finally selected, from which a training set containing 150,219 images and a validation set containing 2,322 acne lesions images were constructed for subsequent modeling.

3.2 Data annotation and review

In the process of labeling the collected facial acne images, in order to label the lesion types efficiently and accurately, we design annotation rules. First, for relatively regular and uniform size acne lesions, such as comedones, papules, pustules, and nodules, we use rectangular boxes for labeling. However, for lesions with more complex and irregular morphology, such as cysts and scars, we choose to use polygonal boxes for annotation. In this way, we can ensure that no critical morphological information is missed during the data annotation process, thus increasing the diagnostic accuracy of the model.

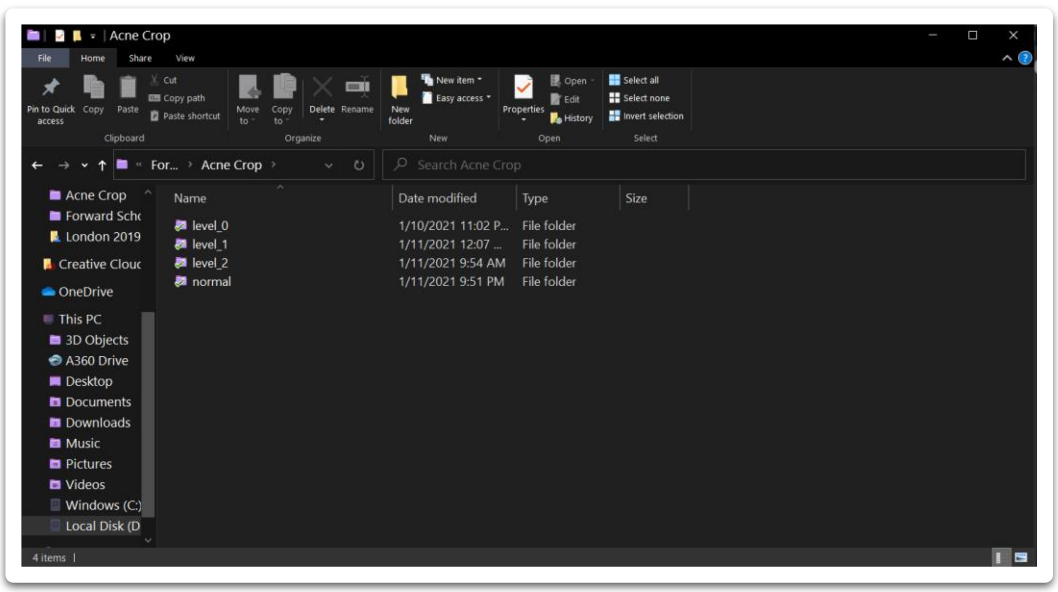

Fig. 3.3 Data Annotation.

To ensure the accuracy and consistency of labeling, all participants received standardized training before the start of the study to ensure ,shown in fig. 3.3 that they were proficient in operating the assessment tool and had a thorough understanding of the classification criteria for acne lesions. In addition, the labeling results were reviewed by two dermatologists. These two experts will correct any labeling errors and omissions to ensure the accuracy of the data. When there are differences of opinion among experts, they will reach consensus through discussion.

3.3 Acne detection module Resnet architecture

Our proposed acne detection algorithm is based on the CenterNet target detection framework and aims to accurately locate acne lesions and classify their types. CenterNet uses anchor-free detection to directly predict the center point, width and height of the target, enabling efficient target location and identification . This method avoids matching problems that may be caused by fixed size and proportion of anchor frames in traditional target detection algorithms. In addition, due to the small size and irregular shape of acne lesions, predefined anchor boxes are less effective, while CenterNet's frame-free approach eliminates the complexity of finding the right anchor box, providing a distinct advantage for acne detection. In view of the many clinical forms of acne, such as comedones, papules, pustules and nodules, especially cysts and scars that are irregular in shape and vary in size, we have optimized CenterNet's infrastructure by integrating a specialized submodule for segmentating cysts and scars, enhancing the model's credibility and transparency in the medical diagnostic process. Finally, we mapped the model results to the rating criteria of China Acne Treatment Guidelines (2019), and compared the performance of the model with that of the most popular models, Faster RCNN, RetinaNet, YOLOV3, YOLOX, and EfficientDet. At the heart of CenterNet lies its adoption of the deep hierarchical aggregation (DLA) strategy, utilizing DLA34 as the foundational feature extraction network. Within DLA34, two pivotal modules, namely iterative depth aggregation (IDA) and hierarchical depth aggregation (HDA), play a crucial role. They effectively amalgamate feature information across various levels. Firstly, DLA34 enhances the model's object recognition capability through semantic aggregation. This enhancement is realized by fusing feature information in the channel directions, equipping the model with a superior understanding of the semantic information present in acne images. As a result, the model becomes adept at identifying and distinguishing between various types of acne, cysts, and scars. Secondly, DLA34 incorporates spatial fusion, which includes the use of deformable convolutions. These convolutions introduce orientation parameters for each element, broadening their coverage during training. This ensures a more thorough analysis of images, especially when addressing irregularly shaped cysts and scars. Such features empower the model to precisely identify, locate, and segment different acne lesions, offering robust support for multi-classification tasks.Implementing ResNet-18 for acne detection involves several steps,

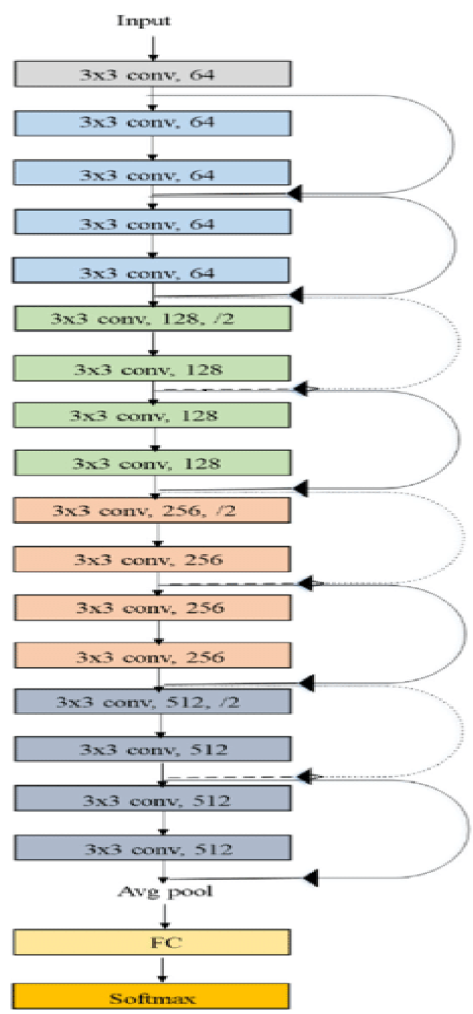

Fig. 3.4 Architecture of ResNet-18.

including data preparation, model creation, training, and evaluation.In our pursuit of creating a specialized acne detection model, we meticulously curated a dataset from Kaggle, focusing specifically on individuals with a light skin complexion.

3.4 Data Pre-processing.

Data pre-processing plays a pivotal role in optimizing model accuracy during training and testing phases.

Target Image Cropping Manually to Remove Unwanted Noise (i.e. eyes, nose, mouth)

Flip:	Horizontal, Vertical
90° Rotate:	Clockwise, Counter-Clockwise, Upside Down
Crop:	0% Minimum Zoom, 50% Maximum Zoom
Rotation:	Between -15° and +15°
Blur:	Up to 10px
Rotate:	30 degree

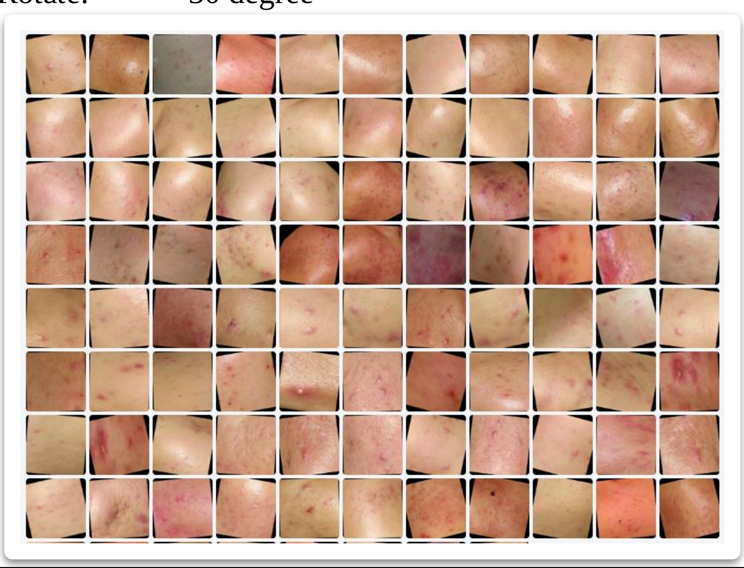

Fig. 3.5 Data Pre-processing.

To address the lim-itation of available open-source data, we employ various data augmentation techniques to diversify the dataset. In the domain of data architecture and modeling for the acne classifier, we adopted the ResNet-18 architecture. ResNet-18 is often pre-trained on large-scale image datasets, such as ImageNet, before being fine-tuned for specific tasks like acne detection.Its ability to capture intricate features in facial images makes it well-suited for the task of acne detection, contributing to the overall efficacy and accuracy of the model in identifying and classifying different levels of acne severity.

The types of data pre-processing shown in fig. 3.5 methods applied, includes horizontal and vertical flips, 90° rotations (clockwise, counter-clockwise, and upside down), cropping with minimum zoom (0%) to maximum zoom (50%), rotation within a range of -15° to +15°, blur effects up to 10 pixels, and a fixed rotation of 30 degrees. These techniques contribute to the augmentation of the dataset, effectively increasing its size and introducing variability that aids in robust model training.

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CHAPTER 4

RESULTS AND DISCUSSION

The results of using the ResNet-18 architecture for acne detection can be evaluated based on various performance metrics. The specific outcomes will depend on factors such as the dataset used for training and testing, the preprocessing techniques applied, and the overall model configuration. In evaluating the performance of an acne detection model, several key metrics are considered. Accuracy, a fundamental measure, reflects the overall correctness of the model's predictions by calculating the ratio of correctly classified samples to the total number of samples.

4.1 Accuracy Table.

This indicates the percentage of correctly classified cases among all instances, providing a general measure of the model's effectiveness.Table 4.1 represents the accuracy on the used dataset and model. By using ResNet-18 pretrained model. we optimize the model to our custom dataset and achieve an accuracy up to 90%**.**

The data set in this study was designed to reflect the clinical incidence and diversity of acne lesions. The distribution of lesions in the training set was characterized by a high prevalence of comedones, papule and scar (40.18, 27.31, and 27.16%, respectively, in the dataset), which was consistent with the commonality of diseases in the clinical environment. The incidence of pustules, nodules, and cysts is low, but the incidence of this type of acne is low in the general patient population. The validation set reflected the distribution of the training set, with slightly higher incidences of cysts and scars, which accounted for 7.84 and 31.01% of cases, respectively. This adjustment ensures that the validation of the model is robust for a wider range of lesion types. In contrast, the test set presented a different Acne distribution, with a greater proportion of comedones (46.27%) and a reduced prevalence of nodules and pustules. This variance is instrumental in assessing the model's adaptability and performance across different clinical settings. The composition of the test set encompasses the multifaceted nature of acne and validates the breadth of manifestations that acne detection models may encounter in real-world clinical Settings. In summary, the composition of these data sets fully considers the various situations that acne detection models may encounter in practical clinical applications, ensuring the generalization ability and accuracy of the models.

Table No.4.1 Accuracy Table

Epoch	**Train_loss**	**Valid_loss**	**Accuracy**	**Time**
0	**1.275670**	**0.998098**	**0.765677**	**00:08**
1	**0.892795**	**0.754339**	**0.811881**	**00:08**
2	**0.880464**	**1.525807**	**0.821782**	**00:07**
3	**0.871721**	**1.643567**	**0.808581**	**00:07**
4	**1.088481**	**1.965398**	**0.656766**	**00:07**
5	**1.044595**	**1.901653**	**0.762376**	**00:07**
6	**0.863624**	**0.809342**	**0.858086**	**00:07**
7	**0.710001**	**0.676677**	**0.896549**	**00:07**
8	**0.532705**	**0.652870**	**0.864357**	**00:07**
9	**0.408114**	**0.615403**	**0.896467**	**00:08**
10	**0.343163**	**0.756864**	**0.897690**	**00:08**
11	**0.276528**	**0.694668**	**0.897643**	**00:07**
12	**0.217420**	**0.605304**	**0.897549**	**00:07**
13	**0.181705**	**0.625304**	**0.900990**	**00:08**
14	**0.141823**	**0.635878**	**0.900990**	**00:07**

4.2 Confusion Matrix

The Confusion Matrix offers a detailed breakdown of the model's predictions, distinguishing true positives, true negatives, false positives, and false negatives. This matrix provides valuable insights into the specific types of errors the model is making, aiding in the identification of areas for improvement. The confusion matrix is typically represented in a matrix format, with the rows representing the actual classes (presence or absence of acne) and the columns representing the predicted classes by the model. Figure 4.1 represents the confusion matrix on the used dataset and model. A confusion matrix is a table that analyses the expected and true labelled classes of a set of tests data to describe the classification model's efficiency. The confusion matrix displays the total amount of genuinepositives (TP), erroneous positives (FP), real negatives (TN), and erroneous negatives (FN) in each dataset type.

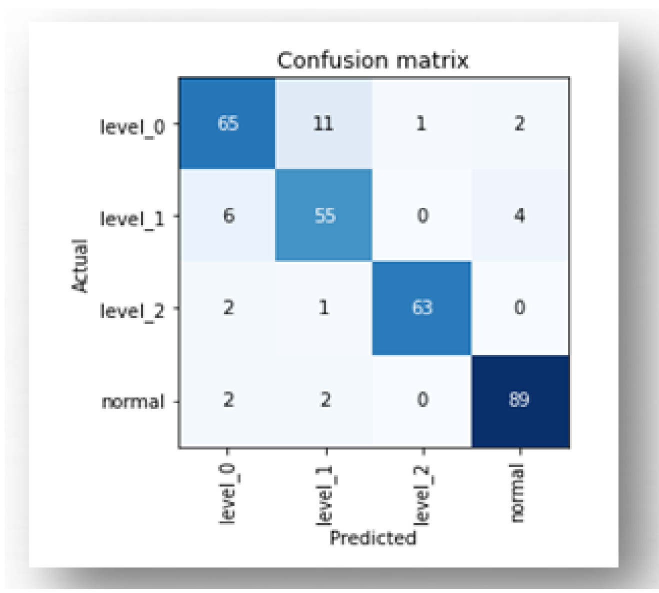

Fig.4.1 Confusion Matrix

The loss function graph in acne detection represents how the model's loss, a measure of the difference between predicted and actual values, changes over the course of training. The loss function is a crucial component in the optimization process, guiding the model to minimize errors and improve its predictive capabilities. Typically, the loss decreases as the model learns from the training data. Figure 4.3 and 4.4represents the loss function graph on the used dataset and model.

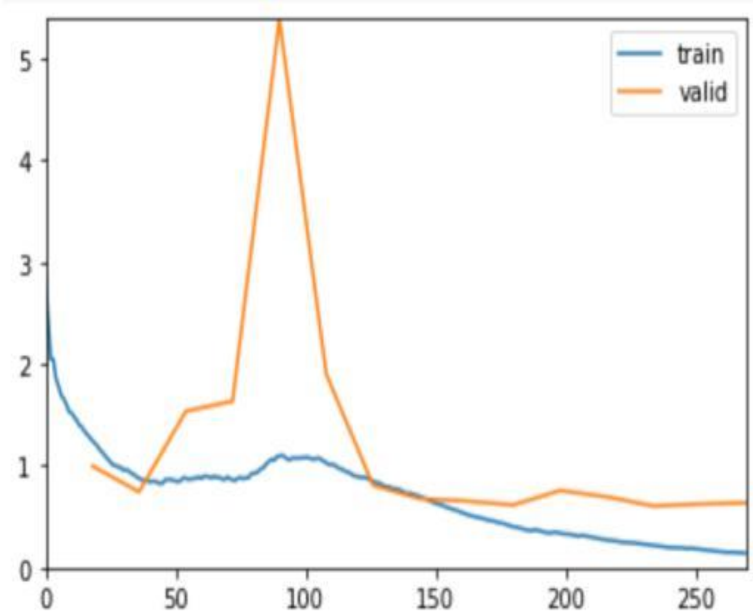

Fig. 4.2 Loss Function Graph

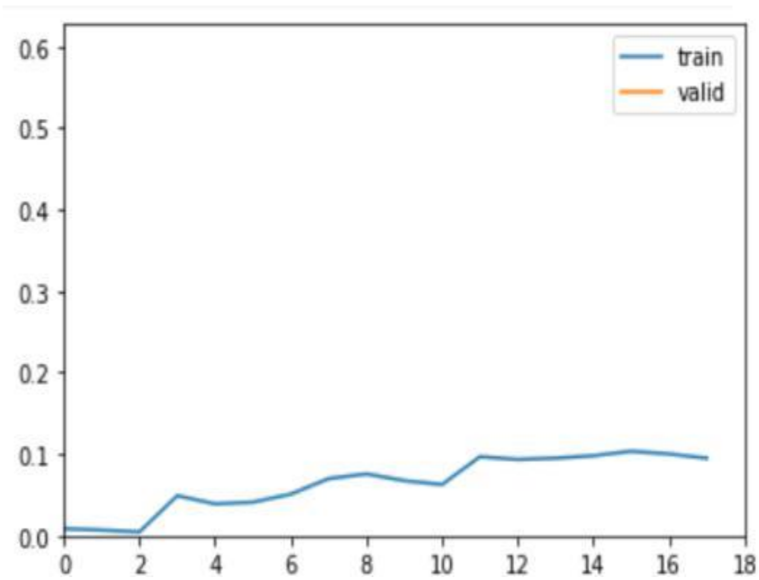

Fig. 4.3 Loss Function Graph

4.3 Performance analysis of acne detection model

In the realm of acne lesion detection, CenterNet asserts its clinical utility through the lens of rigorous quantitative measures. Against the backdrop of established models, CenterNet emerges with a kappa statistic of 0.833, denoting a substantial concordance with clinical diagnosis, surpassing the 0.642 of Faster RCNN. While Faster RCNN demonstrates high accuracy, particularly with nodules at 91.4%, its F1 scores for pustules at 60.3% and nodules at 30.3% reveal a diminished precision-recall balance, hinting at the model's nuanced challenges in delineating complex lesion types. RetinaNet offers a consistent detection capability across lesion types, yet its performance does not eclipse that of CenterNet, which achieves a more harmonious accuracy-recall equilibrium, particularly reflected in a superior F1 score for nodules at 33.9% compared to RetinaNet's 26.5%. Although YOLOV3 achieved 90.8% accuracy for nodules, it ran into obstacles in terms of clinical consistency, with a kappa statistic of 0.608, which did not meet the benchmark set by CenterNet. Similarly, YOLOX parallels Faster RCNN's accuracy for comedones but falls short of CenterNet's consistency, highlighted by a kappa statistic equal to Faster RCNN's at 0.64. EfficientDet competes closely in terms of accuracy, but a kappa statistic of 0.602 indicates a potential for enhancement in its clinical correlation. Moreover, the accuracy of CenterNet for comedones, at 83.8%, is slightly higher than that of Ret-Net at 81.2%. And the kappa statistic demonstrates a significant advancement, indicating that CenterNet is more finely tuned to the intricacies of clinical diagnosis. These comparative findings not only validate the robust diagnostic capabilities of CenterNet but also highlight its potential for seamless integration into clinical workflows. The data underscores the necessity for adaptive and precise detection methodologies, positioning CenterNet as a frontrunner in terms of diagnostic accuracy and alignment with clinical standards. CenterNet's prowess in automated acne lesion detection is characterized by its high accuracy and precision. In categorizing comedones, CenterNet achieved a max_recall of 0.985 and an AP of 0.625, outperforming the second best model's max_recall of 0.833 by a notable margin. Its superior performance extends to the identification of papules and pustules, with max_recall values exceeding 0.9, demonstrating its proficiency in discerning lesions with variable shapes and pigmentation. The model's adeptness in differentiating between acne types is corroborated by F1 scores of 0.888 for comedones and 0.858 for papules. These scores not only stand out in the context of classification categories but also signify the highest performance against competing models. For pustules and nodules, CenterNet's F1 scores, while not the highest across all types, represent the peak within this specific model comparison, emphasizing its potential and identifying areas for targeted refinement in the center point detection algorithm, especially for smaller or less defined lesions. The robustness of CenterNet is evident in its handling of pustules and nodules. It surpasses competing models, achieving an F1 score of 0.659 for pustules—significantly exceeding the average F1 score of 0.60 recorded by other models. This superior detection capability is consistent across varying sample sizes and is reinforced by steadfast max_recall rates for the more commonly presented acne types, affirming its clinical applicability,

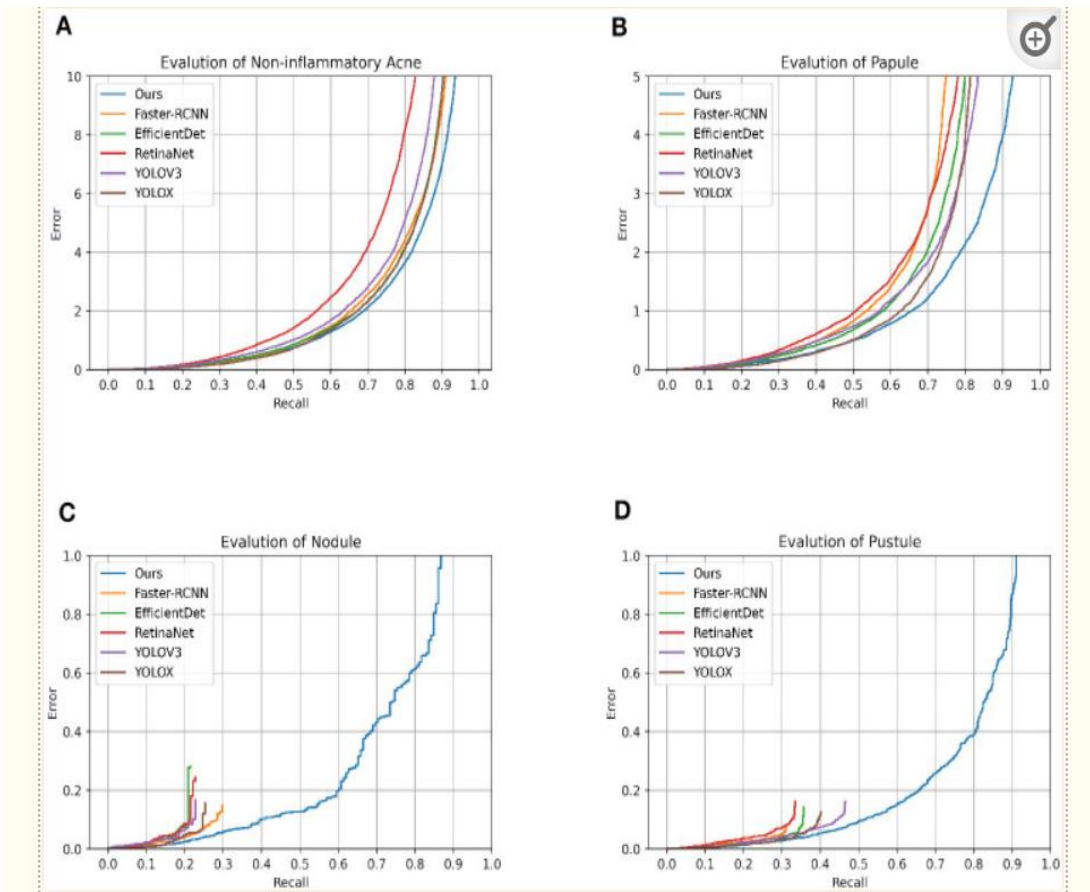

Fig. 4.4 Model error_recall graph. This is the error_recall plot of the various models on different classifications.

Table 4.2 Overall sample image lesion situation table.

Avg acne per picture	Comedones	papule	pustule	Nodule	Cyst	Scar
Test set	3.70(46.27%)	1.37(17.134%)	0.16(1.99%)	0.03(0.35%)	0.27(3.39%)	2.47(30.86%)
Validation set	4.89(37.04%)	2.74(20.764%)	0.35(2.69%)	0.09(0.68%)	1.03(7.84%)	4.09(31.01%)
Training set	3.56(40.18%)	2.42(27.321%)	0.14(1.63%)	0.10(1.10%)	0.23(2.62%)	0.23(2.613%)

While there is an opportunity to enhance the model's precision for certain lesion types, CenterNet's overall functionality exhibits an advanced level of clinical alignment. In this comprehensive study, we rigorously evaluated the performance of our advanced acne detection model. The dataset, consisting of 150,219 training images, 2,322 validation images, and 642 test images, offered a robust platform for analysis. Our focus was on the model's capability to accurately detect and classify various acne types, leveraging state-of-the-art statistical methodologies for a thorough evaluation. The data distribution of lesions in the overall sample of our images is shown in Table 4.2. The data set in this study was designed to reflect the clinical incidence and diversity of acne lesions. The distribution of lesions in the training set was characterized by a high prevalence of comedones, papule and scar (40.18, 27.31, and 27.16%, respectively, in the dataset), which was consistent with the commonality of diseases in the clinical environment. The incidence of pustules, nodules, and cysts is low, but the incidence of this type of acne is low in the general patient population. The validation set reflected the distribution of the training set, with slightly higher incidences of cysts and scars, which accounted for 7.84 and 31.01% of cases, respectively. This adjustment ensures that the validation of the model is robust for a wider range of lesion types. In contrast, the test set presented a different Acne distribution, with a greater proportion of comedones (46.27%) and a reduced prevalence of nodules and pustules. This variance is instrumental in assessing the model's adaptability and performance across different clinical settings. The composition of the test set encompasses the multifaceted nature of acne and validates the breadth of manifestations that acne detection models may encounter in real-world clinical Settings. In summary, the composition of these data sets fully considers the various situations that acne detection models may encounter in practical clinical applications, ensuring the generalization ability and accuracy of the models.

4.4 Discussion

This study proposes and implements an acne detection and grading system based on machine learning. The system is specifically designed to parse facial images taken by smartphones and provide physicians with an accurate assessment of the number of acne cases and their severity level. This method performs well in reducing the human error inherent in traditional manual counting, providing an efficient and more accurate solution for acne grading. Compared with previous diagnostic methods that rely on intuitive judgment, our model significantly improves the quantification and objectivity of diagnosis. In the design of the algorithm, we paid special attention to transforming the diagnostic process of the “black box” model into a system with high transparency and interpretability.

The model not only outputs results, but more importantly, it provides a visual explanation of the decision-making process, ensuring that the physician can clearly understand the reasoning logic of the model. This transformation allows physicians to accurately determine the nature and severity of the lesion, effectively track the evolution of the lesion during treatment, and adjust the treatment plan at the appropriate time. In this study, compared with data collection methods that rely on professional cameras or pre-built databases (13, 25), data collected by smart phones can provide more real-time and diversified images of clinical cases. The innovation of this approach is that it ADAPTS to the variability that is common in everyday clinical Settings, increasing the model's ability to process real-world data. Second, we designed the image quality inspection module to set high standards for data preparation, ensuring that the model is trained using high-quality data.

This step is critical to improving the performance of the model, as in complex clinical image processing, image sharpness and lighting conditions greatly affect the final result. In terms of target detection, the CenterNet model adopted in this study showed higher accuracy than the traditional model in identifying irregular lesions, especially in pixel-level segmentation. By predicting the central point of an object and generating a heat map for a specific category, CenterNet is able to efficiently locate acne of varying sizes. This technology breaks through the limitation of traditional models such as Faster RCNN and RetinaNet, which rely on candidate box generation strategy to identify the approximate location of the target, and provides a more sensitive and accurate detection method for irregular targets (26, 27). Therefore, the model can well introduce segmentation branches to distinguish between common acne types and irregular acne types.

The results show that our model achieves 0.76 accuracy on average, compared to 0.67 accuracy in existing studies such as Ziying Vanessa and her team (5). Finally, in terms of acne grading accuracy, the model showed a high degree of agreement with senior physician ratings, especially in the identification of grade III and IV acne, which reduced the possibility of misjudgment caused by the subjective experience of the physician. This study not only advances the state of the art in acne detection and grading, but also highlights the feasibility of using non-specialist camera equipment in clinical practice. This innovative research method and technology application is of great significance for the future development of the field of medical image analysis, and is expected to provide auxiliary tools in daily clinical diagnosis and improve the accuracy and efficiency of disease diagnosis. We expect that this system can be further improved and widely used in clinical practice in the future. In this study, we demonstrate the potential of a CenterNet-based acne detection model. While some progress has been made, several key limitations remain to be noted. First, current methods do not take into account the differences in the importance of acne in different areas of the face, which may have an impact on the accuracy of treatment decisions and condition assessments. Second, the model has not been extended to the diagnosis of acne in the trunk of the body, an area that is equally important in clinical practice.

Finally, although the acne grading criteria adopted provide a basic framework for the experiment, there is still room for further improvement and optimization given the diversity of acne types and the complexity of clinical practice. Future studies should explore these limitations to more fully evaluate the potential of AI in acne diagnosis and treatment. In future studies, a number of innovative measures will be taken to enhance our acne detection system. Recognizing that our current model, based on feature extraction from single images, may not suffice for all grading standards, we plan to refine this approach. This improvement will focus on adapting the model to accommodate a broader range of diagnostic criteria, ensuring a more comprehensive and accurate assessment of acne severity from multiple image perspectives. Secondly, when analyzing the experimental results, it was noted that nodular and pustular acne had a small sample size in the existing dataset. In order to solve this limitation, the study is expected to adopt advanced data enhancement techniques, such as rotation, flip, scaling, etc., to artificially expand the dataset of rare acne types, in order to enhance the model's learning and recognition ability of these acne types.

In addition, considering that the ruptured and unruptured status of acne has an important impact on patient treatment choice and clinical outcome, a new classification dimension will be introduced to improve the fineness of the classification. Further, given that acne's ulceration status has a decisive impact on condition assessment and treatment options, the team will work to introduce new categorical dimensions aimed at more precisely grading acne to provide patients with more refined diagnostic information. Considering the potential of GAN (SLA-StyleGAN) (28) and whole-body photography (TBP) (29) technologies to improve model performance, future research will focus on evaluating the practical application value of these innovative technologies to further refine our acne detection system.

From the previous parameters studies, we find that the localization module shows relatively poor performance on the prediction of acne number, although the module could detect the acne in the facial image. Considering that the classification module based on ResNet50 could calculate the acne severity and number precisely after training with Kullback–Leibler divergence loss, we combine the classification and localization modules into the ensemble model to enhance the precision of detecting acne. As shown in Figure 4.5, the output of the Linear 2 block in the classification module is connected to the input of the detect block in the localization module. Instead of the preset confidence, we utilize acne numbers to control the output of detection boxes. Figure 4.6 shows several examples of the ensemble model. The top, middle and bottom panels correspond to the mild, moderate and severe classes, respectively. In each panel, the upper and lower rows represent the predicted and true results of each class. We find that the predicted results agree well with the real results and the acne severity, number and position can be achieved simultaneously. We also compare the effect of different loss functions on acne detection.

Fig. 4.5 Representative examples of the true results and prediction images generated by the ensemble model.

As shown in Figure 4.5, the right three columns are the prediction result of the models trained by cross-entropy loss, focal loss and Kullback–Leibler divergence loss, corresponding to the cases (i.e., case 2, case 3 and case 2) with the lowest RMSE , respectively. We find that the model trained by cross-entropy loss and focal loss show a large error in predicting the distribution of acne during inference. The main reason is that the Kullback–Leibler divergence loss could force the model to learn the probability distribution of the acne numbers instead of the category index, greatly improving the model's capability of detecting facial acne. It is worth mentioning that when the distribution density (e.g., >50 per image) of acne in the face is very high, the model here would show a poor peormance in assessing the acne number and locations.

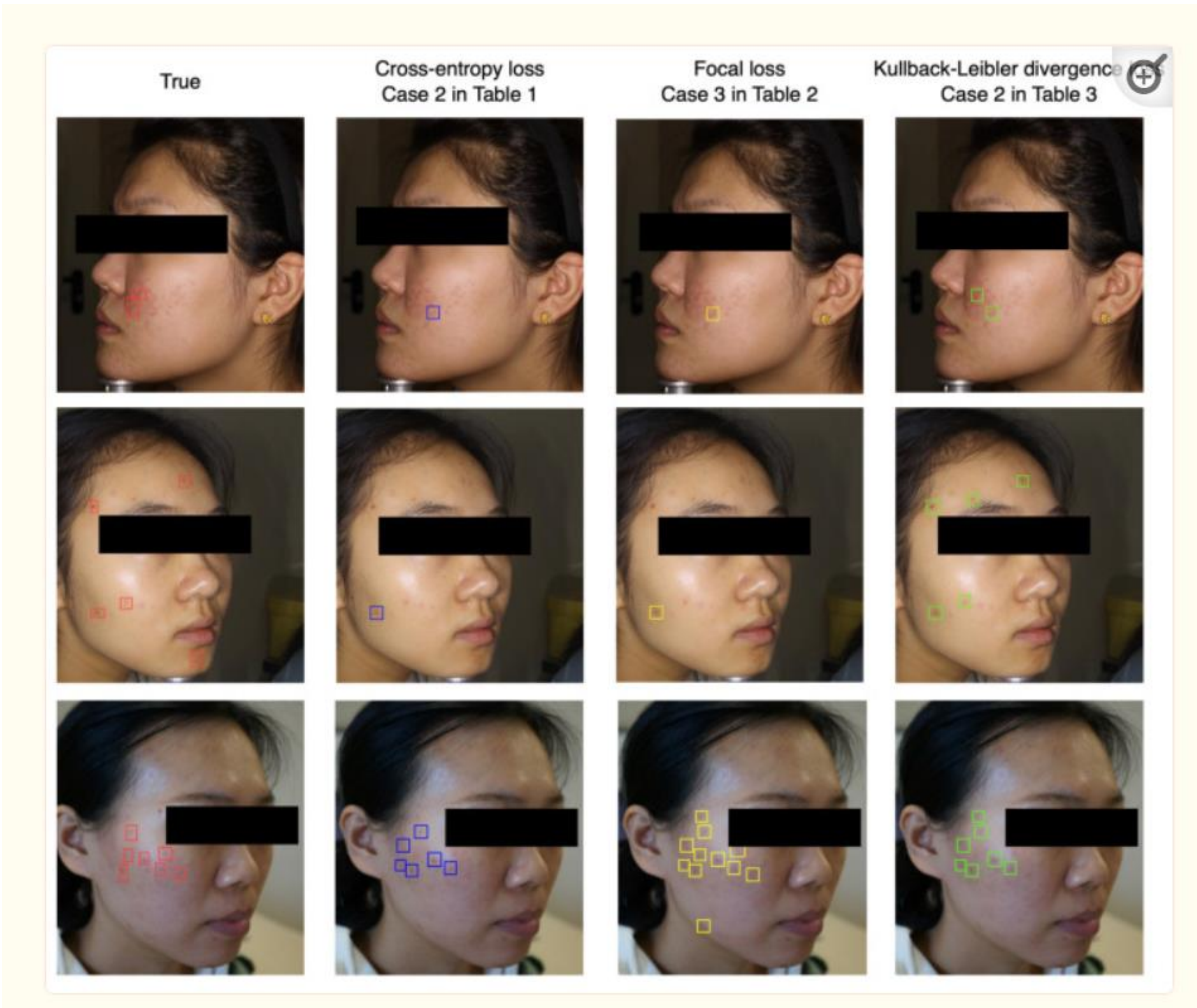

Fig. 4.6 The effect of different loss functions (such as the cross-entropy loss, focal loss and Kullback–Leibler divergence loss) on acne detection.

4.5 Comparison of classification abilities between dermatologists and AI

In this clinical study, confusion matrix data were analyzed to evaluate the diagnostic accuracy of an AI model compared to dermatologists at varying levels of experience in grading acne. The analysis revealed that the AI model achieved an overall accuracy rate of 76%, outperforming both intermediate (65.3%) and junior dermatologists (50.3%). Specificity values further underscored this difference, with junior dermatologists averaging 0.75, intermediates 0.85, and the AI model at 0.91, highlighting its consistent ability to accurately identify true acne cases. The AI model demonstrated a tendency to downgrade severe acne cases, with 70.59% of its misdiagnoses categorized as milder conditions. In contrast, junior and intermediate dermatologists showed more instability classification, with downgrade misdiagnoses at 58.49 and 54.79%, respectively. Cross-grade misdiagnosis was most frequent among junior dermatologists (18.26%), nearly double that of the AI model (9.35%), and intermediate dermatologists exhibited a rate of 13.83%. Both junior and intermediate dermatologists displayed instability in their diagnostic outcomes, especially evident in their uniform misdiagnosis distribution across Grades 2 and 3. Their lower sensitivity for these grades (junior: 0.48 and 0.49; intermediate: 0.60 and 0.63; AI: 0.74 and 0.78) indicated challenges in accurately diagnosing intermediate stages of acne. For Grade 4 acne, junior dermatologists demonstrated a sensitivity of 0.56 and specificity of 0.75, posing a 44% risk of missing actual cases. This was compounded by their tendency to misclassify severe acne as milder, such as Grade 1 .

Table no. 4.3 Comparing the Acne Classifier with Contemporary Alternative Options

Acne classifier	**Dermatology**	**Facial Treatment**
Free	$221	$100
5 Seconds	2 Hours	1.5 Hours
FollowUp Anytime	Appointment Needed	Appointment Needed
Recommends Best Skin Care Solution(Proposed)	Recommends Best Skin Care Products & Solution	Recommends Skin Care Products to Gain Profits
24/7 Support	Working Hours Only	Working Hours Only
Virtual Interaction	Real Life Interaction	Real Life Interaction

In contrast, the AI model showed high sensitivity (0.77) and specificity (0.93) in diagnosing Grade IV acne, with its potential in assisting junior and intermediate dermatologists. This study further introduced Kappa coefficient as an index to measure diagnostic consistency and considered the possibility of random consistency. The AI model is highly consistent with the acne grading standard (kappa value 0.648), and has high accuracy and reliability in the identification and classification of different acne grades. Dermatologists with different levels of experience showed significant differences in consistency. Compared with junior dermatologists (two junior dermatologists with kappa values of 0.243 and 0.366, respectively), intermediate dermatologists (three intermediate dermatologists with kappa values of 0.520, 0.376, and 0.605, respectively) showed some improvement. This observed instability or grading ambiguity among human dermatologists suggests a lack of consistent diagnostic approach in categorizing acne severity, pointing to a broader range of uncertainty in their clinical judgment. The AI models have demonstrated greater stability and accuracy in several instances, yielding superior results in challenging diagnostic scenarios Best option shown in table no. 4.3 ,With all this glaring and concrete information available, no one can hide from the fact that our **Acne Classifier** is the **most viable option** when compared to current plausible alternatives.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This work advances the area of dermatology by utilizing ResNet18’s acne disease detection capabilities. The imple-mentation of an acne detection system using ResNet-18 ar-chitecture represents a significant stride towards leveraging advanced deep learning techniques in the field of dermatol-ogy. The ResNet-18 model, renowned for its depth and skip connections, has proven to be a robust choice for effectively identifying and classifying acne lesions.The utilization of ResNet-18 not only enhances the accuracy of acne detection but also provides a scalable and efficient solution for address-ing the intricacies of diverse skin conditions. The model’s ability to capture nuanced features in facial images, especially concerning different types of acne, showcases its potential for contributing to comprehensive skincare diagnostics.To sum up, the acne classifier is able to classify level of serious-ness into 4 classes, which are normal, level 0, level 1, and level 2 up to 90% accuracy.The journey towards effective acne detection using ResNet-18 marks a significant milestone, laying the foundation for more sophisticated and accessible tools in dermatological diagnostics. This approach not only contributes to the advancement of technology in skincare but also underscores the importance of combining expertise in machine learning with domain-specific knowledge to address real-world challenges in healthcare and well-being.

5.2 Future Work

Our goal is to establish a comprehensive skincare product discussion platform where users may rate and review goods based on their personal experiences. Acknowledging the ex-isting scarcity of resources that enable us to categorize acne mainly among Asians, our goal is to broaden our scope by integrating samples from different regions. Working together with dermatologists will be a crucial component that will allow users to ask the platform directly for individualized guidance and insights regarding their particular skin conditions. We intend to convert our acne classifier into a user-friendly smart-phone app in order to improve accessibility. With the ability to take unfiltered photos straight within the mobile application, this app will enable users to easily evaluate their acne status at any time and from any location. Furthermore, as part of our ongoing commitment to development, we are fine-tuning the acne classifier to identify more specific acne issues, such blackheads, giving customers a more comprehensive picture of their skin difficulties. We understand the value of accuracy and the existing restrictions brought about by a lack of resources. Therefore, by investigating methods to improve our model's capabilities and utilizing advances in processing power and technology, we tried to elevate the efficiency of model. To tackle the issue of insufficient facial coverage in our existing acne classifier, we suggest using an object detection model. In order to provide a more comprehensive evaluation, this model will create bounding boxes around any acne that is seen on the entire face. The website aims to provide comprehensive skincare help by not just identifying acne but also providing insightful information. The model would offer consumers basic treatment recommendations after assessing the severity of their acne, giving them some initial direction before seeking professional dermatological aid. The goal of this multipronged strategy is to develop a strong, user-focused skincare platform that addresses a range of requirements and issues related to skincare.

5.3 Possible Improvements

- A Platform to Discuss about Skin Care Products - Individuals who have tried certain skin care products are able to review and give comments or rating through the platform.
- Cross geographical samples- One of the limitations now is we have limited resources and we can only classify acne for Asians.
- Collaboration with Dermatologists- Individuals can contact dermatologists through this platform to know more details about their skin conditions.
- Make into a Smartphone App – By developing the Acne Classifier into a smartphone app, individuals can check their acne condition anytime, anywhere! Individuals can take picture with no filters directly from the mobile app.
- More detailed classifier- Develop the acne classifier to classify detailed acne problems such as blackhead.

- Higher Accuracy - Due to lacking resources and computational power, we can only achieve optimum accuracy. However, higher accuracy can be obtained by enhancing our model.

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Appendix

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(TRENDS AND FUTURE DIRECTIONS)

CERTIFICATE OF PARTICIPATION

This is to certify that Prof./Dr./Ms./Mr. **Aashika jain ,Rohit yadav** of **Dr A.P.J Abdul Kalam Technical University** has participated and presented paper titled **Acne Detection and Care System using Deep Learning** during the **IEEE 11th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO 2024)** organised by Amity Institute of Information Technology from March 14-15, 2024 at Amity University Uttar Pradesh, India.

Rekha.

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Prof. (Dr.) K.M. Soni
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Acne Detection Care System using Deep Learning

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***Abstract*—Millions of people worldwide suffer from acne, a common dermatological ailment that frequently causes both physical and psychological discomfort. The prevalence of acne, a common skin condition, poses a significant challenge to derma-tologists and individuals seeking effective skincare solutions. This research introduces 'Acne Care', an innovative system that leverages deep learning techniques and Reset18 application for the detection and personalized care of acne. This model analyse various skin abnormalities and make a severity detection system based on the classification using deep learning algorithms. This ensemble model could accurately predict the number, location, and severity of acne at the same time. It might also be a useful tool for the patient to self-test and help the doctor diagnose them.This paper presents the development, methodology, and potential impact of this model, addressing the growing need for more efficient and effective acne management. The findings of this research paper contribute to the development and advancement of deep learning based regression models to assess the severity level of acne lesions from selfie images and their management.**

***Index Terms*—Acne Detection, Deep Learning, Dermatologist, Pimples, Severity**

I. INTRODUCTION

Acne vulgaris, as it is technically called, is a condition where oil and dead skin cells clog pores[3]. This results in whiteheads, blackheads, and red pimples as the inflamma-tion gets greater. Without a doubt, most of the human face acne's problems. This widespread skin condition, which affects more than 85% of teenagers, is characterized by clogged pores, pimples, and occasionally hard, deep lumps on the face, neck and upper arms. Based on the statistic by the American Academy of Dermatology Association, it is known that approximately 85% of people between 12 and 24 experience at least minor acne. Moreover, acne occur in adult is up to 15% of women [1]. Figure 1 shows the different types of acne.

Acne manifests in various types, each characterized by distinct features and severity levels. Whiteheads, for instance, are small, raised bumps with a white or flesh-colored center, resulting from the blockage of hair follicles by a combination of oil and dead skin cells. Conversely, blackheads share similarities with whiteheads but have an open pore, and their dark appearance is attributed to the oxidation of the exposed clogged material when in contact with air [2].Papules, on the other hand, present as small, red, inflamed bumps without a visible center and can be tender to the touch, often stemming from bacterial activity and inflammation. Pustules, similar to papules, contain pus at their tips, giving them a distinctive appearance of white or yellowish bumps with a red base. Nodules represent a more severe form of ance, severe form of acne, characterized by large, painful, and solid lumps located beneath the skin's surface. These deep-rooted nodules often require medical intervention due to their prolonged healing time and potential for com-plications. Understanding the unique characteristics of each type of acne is crucial for effective diagnosis and tailored treatment approaches, especially in the case of nodular acne, where medical attention is frequently necessary for proper management.

Fig. 1. Types of Acne

Understanding one's skin's functioning is necessary to comprehend acne. Oil glands can be found in skin pores. Androgens, the sex hormones, are released in greater amounts when a person reaches puberty. One's oil glands grow, become hyperactive, and generate excessive amounts of oil, or sebum, as a result of having too many hormones. Skin cells clog pores and hair follicles when sebum production is excessive. Additionally, as oil levels rise, Cutibacterium acnes germs proliferate. Acne, which is characterized by a raised red spot with a white center, is caused by infection or inflammation of blocked pores. A whitehead is present if the pore becomes clogged, shuts, and then bulges. When a pore clogs, remains open, and the top turns black from oxidation or air exposure, this is known as a blackhead. A pustule, or red, inflammatory pimple, may develop when bacteria multiply in the clogged pore. Cysts develop when there are big, painful lumps beneath the skin's surface due to deep-seated pore blockage and inflammation. Acne can be brought on by hormonal changes brought on by birth control medications, menstruation, and pregnancy. Hair dyes, oily hair ointment, and thick face creams and cosmetics are some other external acne causes that can clog pores. Wearing clothing that scrapes against the skin can exacerbate acne, particularly on the chest and back. As might excessive perspiration while exercising in hot, muggy weather [6]. Since stress has been linked to an increase in oil production, many teenagers get a fresh round of pimples right before or on the first day of school.

Dermatologists evaluate the severity of acne in a clinical setting traditionally. Dermatologists administer prescribed treatments, or depending on the severity, over-the-counter skin care items are suggested. Due to the prevalence of the condition, there is a greater demand from acne sufferers to have their acne severity professionally evaluated on a regular basis than there are dermatologists available to do so [4]. Patients with acne are thought to have to wait an average of more than 32 days to see a dermatologist. For acne sufferers, this poses a significant obstacle and source of irritation as it postpones advice regarding food, lifestyle, and skin care products.

Deep learning and computer vision developments recently opened the door for quick and automated illness diagnosis systems. This paper focuses on the application of ResNet-18, a neural network architecture that was introduced to address the challenges of training very deep neural networks. ResNet introduces the concept of residual learning, which involves using shortcut connections to skip one or more layers and assists in detection of acne severity at a deeper level. ResNet-18 consists of 18 layers (hence the name), organized into several blocks. These blocks include convolutional layers, batch normalization, rectified linear unit (ReLU) activations, and residual connections. Utilizing ResNet-18 in acne detection involves leveraging the capabilities of this deep convolutional neural network architecture for image classification tasks. This architecture has been widely used and adapted for various computer vision tasks, including image classification, object detection, and segmentation. Researchers often use pre-trained versions of ResNet-18 on large datasets, like Image Net, for transfer learning in specific applications, including medical image analysis such as acne detection. ResNet-18, along with its deeper variants like ResNet-50, has become a foundational architecture in the field of acne detection using deep learning algorithms [5]. The aim of an acne detection model is to combine techno-logical advancements with dermatological expertise to enhance early detection, provide personalized skincare guidance, and contribute to the overall well-being of individuals by fostering awareness and accessibility in the realm of skincare.

II. LITERATURE REVIEW

Numerous algorithms for the analysis of skin images have been created, including ones for the analysis of acne. However, techniques based on traditional image processing frequently fail to produce satisfactory results due to the intricacy of skin lesions. The advent of deep learning techniques, particularly the convolutional neural network (CNN), has revolutionized the field of computer vision in general and skin image analysis in particular [5].In 2018, a CNN-based approach to automat-ically identify face acne was presented by Xiaolei Shen et al.The process allowed for the distinction of seven groups of acne lesions: modules, cysts, blackheads, whiteheads, papules, pustules, and normal skin. The accuracy of any class 81% was shown in the results. However, the study by Xiaolei Shen et al. used nonsmartphone facial pictures [6]. In 2019, Junayed et al. used the AcneNet model which is based on a deep residual neural network to classify five different types of acne lesions: cystic, open comedo, keloidalis, closed comedo, and pustular.1800 photos in total were split equally across the classes,360 pictures for every class. With an accuracy of 99.44% for the Keloidalis class, the accuracy was over 94%. But the pictures utilized in the research by Junayed et al. were also not from smartphones [7].Seite et al. published a deep learning-based artificial intelligence method for facial acne analysis using smartphone photos at the end of 2019. The method can evaluate the severity of facial acne using the Global Evaluation Acne (GEA) scale and differentiate between multiple types of acne lesions, including comedonal lesion, inflammatory lesion, and post-inflammatory hyperpigmentation[8]. The approach made use of a dataset consisting of 5972 photos that were gathered from 1072 acne sufferers using both iOS and Android cellphones. However, the method's accuracy in evaluating the severity of acne was just 68% [9].Yin Yang et al. created a new acne assessment system in 2021 that graded the severity of face acne based on Chinese guidelines by utilizing deep learning [10]. Using Fujifilm and Canon cameras, 5871 clinical photos of 1957 patients were gathered to create a dataset. The method consisted of three steps: preprocessing the image data to remove interference from the eyes, nose, and mouth; second, identifying the acne lesions using an Inception-V3 network; and finally, evaluating the model's effectiveness in acne vulgaris patients[11]. The findings revealed that the deep learning model had an average F1 score of 0.8 and a Kappa coefficient of 0.791,it quantifies the level of association between dermatologists and the deep learning model[12].

III. RESEARCH METHODOLOGY

As part of our effort to develop a customized acne detec-tion algorithm, we carefully selected a Kaggle dataset that only included people with fair skin. With 999 photos in all, the dataset includes a wide variety of viewpoints and face expressions to guarantee a thorough portrayal of real-world situations. We found three unique classes in our carefully selected dataset, each of which captured a unique facet of acne manifestation. The careful selection of images allows us to address the complexities associated with acne detection, particularly in individuals with light skin tones. By including a variety of skin conditions and acne manifestations, our dataset aims to enhance the robustness and generalization capabilities of the acne detection model. The diversity within the dataset not only reflects the natural variability in skin conditions but also accommodates the potential nuances associated with different acne types. The model used in the acne classifier is pre- trained Resnet-18 model.ResNet-18, short for Residual Network with 18 layers, represents a convolutional neural network (CNN) architecture renowned for its depth and effectiveness in image recognition tasks. ResNet 18 has 18 layers with a 7 X 7 kernel as 1st layer. It has four layers of ConvNets that are identical. Each layer consists of two residual blocks .Each residual block consists of two convolutional layers and introduces a shortcut or skip connection that bypasses one or more layers. This skip connection facilitates the direct flow of information from the input to the output, enabling the model to learn residual mappings. Figure 2 provides a visual representation of the architecture, showcasing the intricate design of ResNet-18.

Implementing ResNet-18 for acne detection involves several steps, including data preparation, model creation, training, and evaluation. In our pursuit of creating a specialized acne detection model, we meticulously curated a dataset from Kaggle, focusing specifically on individuals with a light skin complexion. The dataset, comprising a total of 999 images, encompasses a diverse range of facial expressions and angles to ensure a comprehensive representation of real-world scenarios . Within this curated dataset, we identified three distinct classes, each capturing different aspects of acne presentation.

In the subsequent phase of our project, we undertook the crucial task of data annotation by categorizing the acquired dataset into distinct classes that reflect varying levels of acne severity. The annotated classes include ”Normal,”

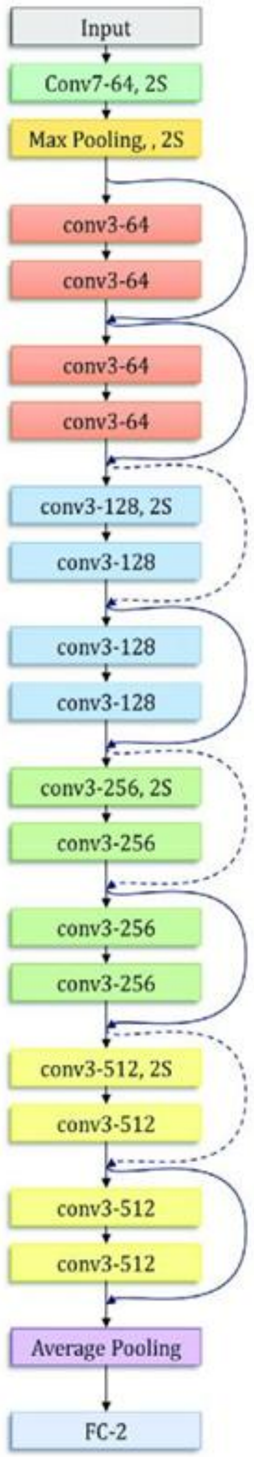

Fig. 2. Architecture of ResNet-18

representing skin in its natural, acne-free state; ”Level 0,” indicating a very minor amount of acne that may be considered negligible; ”Level 1,” denoting the presence of a few visible acne lesions on the face, requiring treatment; and ”Level 2,” representing a severe acne condition necessitating the expertise of a der-matologist. This meticulous classification provides a nuanced understanding of the diverse skin conditions within the dataset, essential for training our acne detection model. The flowchart is depicted by Fig 3.

Data pre-processing plays a pivotal role in optimizing model accuracy during training and testing phases.To address the limitation of available open source,we employ various data augmentation techniques to diversify the dataset.

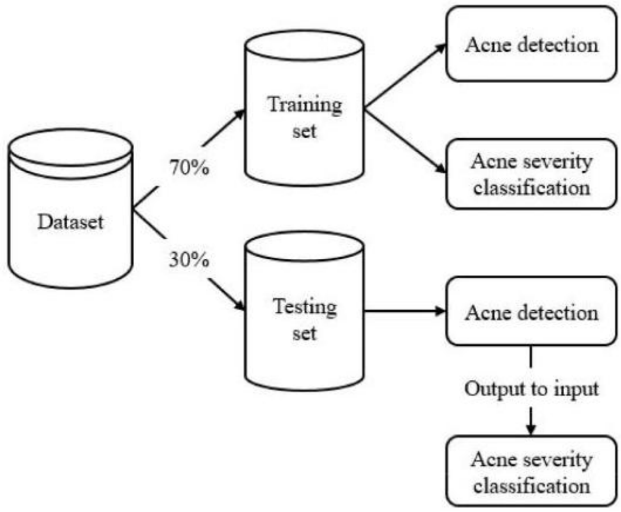

Fig. 3. Flow Chart

The types of data pre-processing methods applied, includes horizontal and vertical flips, 90° rotations (clockwise, counter-clockwise, and upside down), cropping with minimum zoom (0%) to maximum zoom (50%), rotation within a range of -15° to +15°, blur effects up to 10 pixels, and a fixed rotation of 30 degrees. These techniques contribute to the augmentation of the dataset, effectively increasing its size and introducing variability that aids in robust model training.

In the domain of data architecture and modeling for the acne classifier, we adopted the ResNet-18 architecture. ResNet-18 is often pre-trained on large-scale image datasets, such as ImageNet, before being fine-tuned for specific tasks like acne detection. Its ability to capture intricate features in facial images makes it well-suited for the task of acne detection, contributing to the overall efficacy and accuracy of the model in identifying and classifying different levels of acne severity

IV. RESULT AND DISCUSSSION

The results of using the ResNet-18 architecture for acne detection can be evaluated based on various performance metrics. The specific outcomes will depend on factors such as the dataset used for training and testing, the preprocessing techniques applied, and the overall model configuration. In evaluating the performance of an acne detection model, several key metrics are considered. Accuracy, a fundamental measure, reflects the overall correctness of the model’s predictions by calculating the ratio of correctly classified samples to the total number of samples. This indicates the percentage of correctly classified cases among all instances, providing a general measure of the model's effectiveness. Figure 4 represents the accuracy on the used dataset and model. By using ResNet-18 pretrained model, we optimize the model to our custom dataset and achieve an accuracy up to 90%.

epoch	train_loss	valid_loss	accuracy	time
0	1.275670	0.998097	0.765677	00:08
1	0.892795	0.743409	0.811881	00:08
2	0.880464	1.535807	0.821782	00:07
3	0.871721	1.634758	0.808581	00:07
4	1.088481	5.388702	0.656766	00:07
5	1.044595	1.901320	0.762376	00:07
6	0.863624	0.809342	0.858086	00:07
7	0.710001	0.676677	0.894389	00:07
8	0.532709	0.652870	0.897690	00:07
9	0.408114	0.615403	0.894389	00:07
10	0.343163	0.756864	0.854786	00:07
11	0.276528	0.694668	0.894389	00:08
12	0.217420	0.604474	0.897690	00:07
13	0.181705	0.625304	0.900990	00:07
14	0.141823	0.635878	0.900990	00:07

Fig. 4. Accuracy over epochs for Acne Classification.

The Confusion Matrix offers a detailed breakdown of the model's predictions, distinguishing true positives, true negatives, false positives, and false negatives. This matrix provides valuable insights into the specific types of errors the model is making, aiding in the identification of areas for improvement. The confusion matrix is typically represented in a matrix format, with the rows representing the actual classes (presence or absence of acne) and the columns representing the predicted classes by the mode.

Figure 5 represents the confusion matrix on the used dataset and model. The loss function graph in acne detection represents how the model's loss, a measure of the difference between predicted and actual values, changes over the course of training. The loss function is a crucial component in the optimization process, guiding the model to minimize errors and improve its predictive capabilities. Typically, the loss decreases as the model learns from the training data.Fig.6 represents the loss function graph on the used dataset and model.

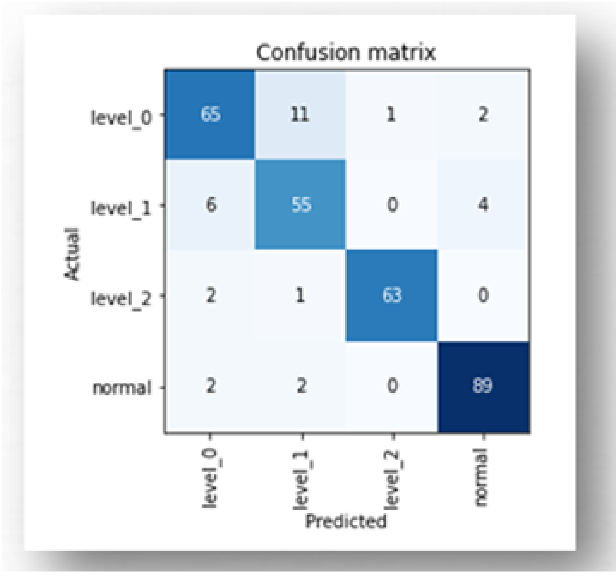

Fig. 5. Confusion Matrix.

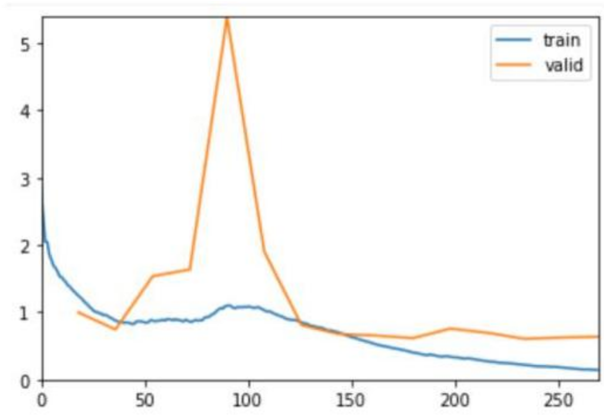

Fig. 6. Loss Function Graph

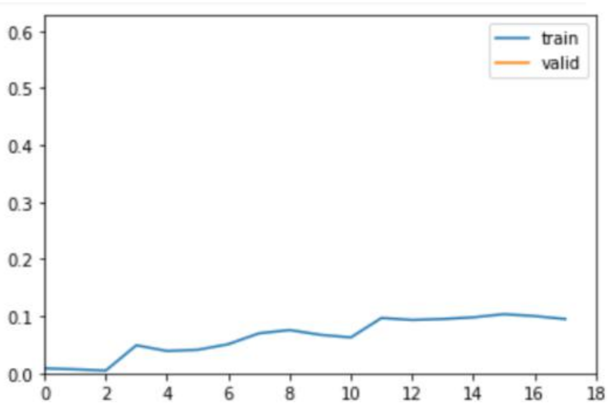

Fig. 7. Loss function Graph

Together, these metrics contribute to a holistic evaluation of the acne detection model's performance. Accuracy speaks to the overall correctness, the Confusion Matrix delves into specific prediction outcomes, and the loss function curve provides a nuanced understanding of the model's ability to improve its predictive capabilities. These assessments collectively guide the refinement and optimization of the model, ensuring its effectiveness in the challenging task of acne detection.

V. FUTURE WORKS

Our goal is to establish a comprehensive skincare product discussion platform where users may rate and review goods based on their personal experiences. Acknowledging the existing scarcity of resources that enable us to categorize acne mainly among Asians, our goal is to broaden our scope by integrating samples from different regions. Working together with dermatologists will be a crucial component that will allow users to ask the platform directly for individualized guidance and insights regarding their particular skin conditions. We intend to convert our acne classifier into a user-friendly smart-phone app in order to improve accessibility. With the ability to take unfiltered photos straight within the mobile application, this app will enable users to easily evaluate their acne status at any time and from any location. Furthermore, as part of our ongoing commitment to development, we are fine-tuning the acne classifier to identify more specific acne issues, such blackheads, giving customers a more comprehensive picture of their skin difficulties. We understand the value of accuracy and the existing restrictions brought about by a lack of resources. Therefore, by investigating methods to improve our model's capabilities and utilizing advances in processing power and technology, we tried to elevate the efficiency of model. To tackle the issue of insufficient facial coverage in our existing acne classifier, we suggest using an object detection model. In order to provide a more comprehensive evaluation, this model will create bounding boxes around any acne that is seen on the entire face. The website aims to provide comprehensive skincare help by not just identifying acne but also providing insightful information. The model would offer consumers basic treatment recommendations after assessing the severity of their acne, giving them some initial direction before seeking professional dermatological aid. The goal of this multipronged strategy is to develop a strong, user-focused skincare platform that addresses a range of requirements and issues related to skincare.

VI. CONCLUSION

This work advances the area of dermatology by utilizing ResNet18's acne disease detection capabilities. The implementation of an acne detection system using ResNet-18 architecture represents a significant stride towards leveraging advanced deep learning techniques in the field of dermatology. The ResNet-18 model, renowned for its depth and skip connections, has proven to be a robust choice for effectively identifying and classifying acne lesions. The utilization of ResNet-18 not only enhances the accuracy of acne detection but also provides a scalable and efficient solution for addressing the intricacies of diverse skin conditions. The model's ability to capture nuanced features in facial images, especially concerning different types of acne, showcases its potential for contributing to comprehensive skincare diagnostics. To sum up, the acne classifier is able to classify level of seriousness into 4 classes, which are normal, level 0, level 1, and level 2 up to 90% accuracy. The journey towards effective acne detection using ResNet-18 marks a significant milestone, laying the foundation for more sophisticated and accessible tools in dermatological diagnostics. This approach not only contributes to the advancement of technology in skincare but also underscores the importance of combining expertise in machine learning with domain-specific knowledge to address real-world challenges in healthcare and well-being.

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Acne Detection and Care System using Deep Learning

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Acne Detection and Care System using Deep Learning

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***Abstract*—Acne is a prevalent dermatological condition that affects millions of individuals worldwide, often leading to physical and psychological distress.The prevalence of acne, a common skin condition, poses a significant challenge to dermatologists and individuals seeking effective skincare solutions.This research introduces 'Acne Care', an innovative system that leverages deep learning techniques and Reset18 application for the detection and personalized care of acne.This model analyse various skin abnormalities and make a severity detection system based on the classification using deep learning algorithms.This ensemble model could precisely predict the acne severity, number, and position simultaneously, and could be an effective tool to help the patient self test and assist the doctor in diagnosis.This paper presents the development, methodology, and potential impact of this model, addressing the growing need for more efficient and effective acne management.The findings of this research paper contribute to the development and advancement of deep learning based regression models to assess the severity level of acne lesions from selfie images and their management.**

***Index Terms*—Acne Detection, Deep Learning, Dermatologist, Pimples, Severity**

I. Introduction

Acne, medically known as acne vulgaris, occurs when pores become clogged with dead skin cells and oil[3]. This creates blackheads, whiteheads and as inflammation worsens, red pimples.Without a doubt, most of the human face acne's problems. More then 85% of teenagers have this common skin problem, which is marked by clogged pores, painful pimples, and sometimes, hard,deep lumps on the face, neck, shoulders,chest,back and upper arms. Based on the statistic by the American Academy of Dermatology Association, it is known that approximately 85% of people between 12 and 24 experience at least minor acne. Moreover, acne occur in adult is upto 15% of women [1]. Figure 1 shows the different types of acne.

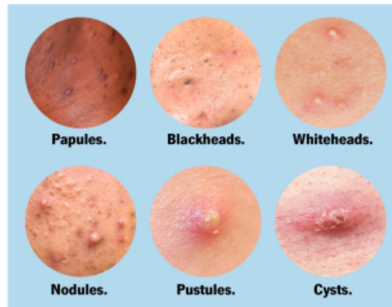


Fig. 1. Types of Acne

Acne manifests in various types, each characterized by distinct features and severity levels. Whiteheads, for instance, are small, raised bumps with a white or flesh-colored center, resulting from the blockage of hair follicles by a combination of oil and dead skin cells. Conversely, blackheads share similarities with whiteheads but have an open pore, and their dark appearance is attributed to the oxidation of the exposed clogged material when in contact with air [2].Papules, on the other hand, present as small, red, inflamed bumps without a visible center and can be tender to the touch, often stemming from bacterial activity and inflammation. Pustules, similar to papules, contain pus at their tips, giving them a distinctive appearance of white or yellowish bumps with a red base.Nodules represent a more severe form of acne, characterized by large, painful, and solid lumps located beneath the skin's surface. These deep-rooted nodules often require medical intervention due to their prolonged healing time and potential for complications. Understanding the unique characteristics of each type of acne is crucial for effective diagnosis and tailored treatment approaches, especially in the case of nodular acne, where medical attention is frequently necessary for proper management.

To understand acne, one needs to know how one's skin works. The pores in one's skin contain oil glands. When one hits puberty, there's an increase in sex hormones called androgens. The excess hormones cause one's oil glands to become overactive, enlarge, and produce too much oil, or sebum. When there's too much sebum, the pores or hair follicles become blocked with skin cells. The increase in oil also results in an overgrowth of bacteria called Cutibacteriumacnes. If blocked pores become infected or inflamed, a pimple – a raised red spot with a white centre - forms. If the pore clogs, closes, and then bulges, one has a whitehead.A blackhead occurs when the pore clogs, stays open, and the top has a blackish appearance due to oxidation or exposure to air. When bacteria grow in the blocked pore, a pustule may appear, meaning the pimple becomes red and inflamed. Cysts form when the blockage and inflammation deep inside pores produce large, painful lumps beneath the skin's surface.Hormonal changes related to birth control pills, menstrual periods, and pregnancy can trigger acne. Other external acne triggers include heavy face creams and cosmetics, hair dyes, and greasy hair ointment – all of which can increase blockage of pores. Clothing that rubs one's skin may also worsen acne, especially on the back and chest. So can heavy sweating during exercise, and hot, humid climates [6]. Stress is known to trigger increased oil production, which is why many teens have a new crop of pimples on the first day of school or just before that big date.

Dermatologists evaluate the severity of acne in a clinical setting traditionally. Dermatologists administer prescribed treatments, or depending on the severity, over-the-counter skin care items are suggested. Due to the prevalence of the condition, there is a greater demand from acne sufferers to have their acne severity professionally evaluated on a regular basis than there are dermatologists available to do so [4]. Patients with acne are thought to have to wait an average of more than 32 days to see a dermatologist. For acne sufferers, this poses a significant obstacle and source of irritation as it postpones advice regarding food, lifestyle, and skin care products.

Deep learning and computer vision developments recently opened the door for quick and automated illness diagnosis systems.This paper focuses on the application of ResNet-18, a neural network architecture that was introduced to address the challenges of training very deep neural networks. ResNet introduces the concept of residual learning, which involves using shortcut connections to skip one or more layers and assists in detection of acne severity at a deeper level. ResNet-18 consists of 18 layers (hence the name), organized into several blocks. These blocks include convolutional layers, batch normalization, rectified linear unit (ReLU) activations, and residual connections.Utilizing ResNet-18 in acne detection involves leveraging the capabilities of this deep convolutional neural network architecture for image classification tasks.This architecture has been widely used and adapted for various computer vision tasks, including image classification, object detection, and segmentation. Researchers often use pre-trained versions of ResNet-18 on large datasets, like ImageNet, for transfer learning in specific applications, including medical image analysis such as acne detection. ResNet-18, along with its deeper variants like ResNet-50, has become a foundational architecture in the field of acne detection using deep learning algorithms [5].

The aim of an acne detection model is to combine technological advancements with dermatological expertise to enhance early detection, provide personalized skincare guidance, and contribute to the overall well-being of individuals by fostering awareness and accessibility in the realm of skincare.

II. LITERATURE REVIEW

Numerous algorithms for the analysis of skin images have been created, including ones for the analysis of acne. However, techniques based on traditional image processing frequently fail to produce satisfactory results due to the intricacy of skin lesions. The science of computer vision in general and skin image analysis in particular have seen a revolution with the introduction of deep learning techniques, especially the convolutional neural network (CNN) [5].In 2018, a CNN-based approach to automatically identify face acne was presented by Xiaolei Shen et al. Seven classes of acne lesions (blackheads, whiteheads, papules, pustules, modules, cysts, and normal skin) could be distinguished by the procedure. The accuracy of any class 81% was shown in the results. Xiaolei Shen et al.'s study, however, employed non-smartphone facial photos [6].In 2019, Junayed et al. classified five kinds of acne lesions (Closed Comedo, Cystic, Keloidalis, Open Comedo, and Pustular) using the AcneNet model, which is built on a deep residual neural network. 1800 photos in total were split equally across the classes,360 pictures for every class. With an accuracy of 99.44% for the Keloidalis class, the accuracy was over 94%. But the pictures utilized in the research by Junayed et al. were also not from smartphones [7].Seite et al. published a deep learning-based artificial intelligence method for facial acne analysis using smartphone photos at the end of 2019. The technique can distinguish between several forms of acne lesions (comedonal lesion, inflammatory lesion, and post-inflammatory hyperpigmentation) and assess the severity of face acne using the Global Evaluation Acne (GEA) scale [8]. The approach made use of a dataset consisting of 5972 photos that were gathered from 1072 acne sufferers using both iOS and Android cellphones. However, the method's accuracy in evaluating the severity of acne was just 68% [9].Yin Yang et al. created a new acne assessment system in 2021 that graded the severity of face acne based on Chinese guidelines by utilizing deep learning [10]. Using Fujifilm and Canon cameras, 5871 clinical photos of 1957 patients were gathered to create a dataset. Three phases made up the method: first, preprocessing the picture data to exclude interference from the mouth, nose, and eyes; second, using an Inception-v3 network to identify the acne lesions; and third, assessing the model's performance in patients with acne vulgaris [11]. The findings revealed that the deep learning model had an average F1 score of 0.8 and a Kappa coefficient of 0.791, which measures the degree of correlation between the deep learning model and the dermatologists[12].

III. RESEARCH METHODOLOGY

As part of our effort to develop a customized acne detection algorithm, we carefully selected a Kaggle dataset that only included people with fair skin. With 999 photos in all, the dataset includes a wide variety of viewpoints and face expressions to guarantee a thorough portrayal of real-world situations. We found three unique classes in our carefully selected dataset, each of which captured a unique facet of acne manifestation.The careful selection of images allows us to address the complexities associated with acne detection, particularly in individuals with light skin tones. By including a variety of skin conditions and acne manifestations, our dataset aims to enhance the robustness and generalization capabilities of the acne detection model. The diversity within the dataset not only reflects the natural variability in skin conditions but also accommodates the potential nuances associated with different acne types.

The model used in the acne classifier is pre- trained Resnet-18 model.ResNet-18, short for Residual Network with 18 layers, represents a convolutional neural network (CNN) architecture renowned for its depth and effectiveness in image recognition tasks.ResNet 18 has 18 layers with a 7 X 7 kernel as 1st layer. It has four layers of ConvNets that are identical. Each layer consists of two residual blocks. Each residual block consists of two convolutional layers and introduces a shortcut or skip connection that bypasses one or more layers. This skip connection facilitates the direct flow of information from the input to the output, enabling the model to learn residual mappings. Figure 2 provides a visual representation of the architecture, showcasing the intricate design of ResNet-18.

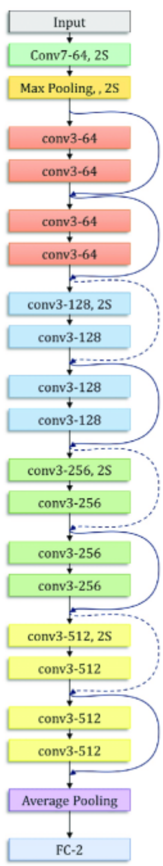


Fig. 2. Architecture of ResNet-18.

Implementing ResNet-18 for acne detection involves several steps, including data preparation, model creation, training, and evaluation.In our pursuit of creating a specialized acne detection model, we meticulously curated a dataset from Kaggle, focusing specifically on individuals with a light skin complexion. The dataset, comprising a total of 999 images, encompasses a diverse range of facial expressions and angles to ensure a comprehensive representation of real-world scenarios. Within this curated dataset, we identified three distinct classes, each capturing different aspects of acne presentation.

In the subsequent phase of our project, we undertook the crucial task of data annotation by categorizing the acquired dataset into distinct classes that reflect varying levels of acne severity. The annotated classes include "Normal," representing skin in its natural, acne-free state; "Level 0," indicating a very minor amount of acne that may be considered negligible; "Level 1," denoting the presence of a few visible acne lesions on the face, requiring treatment; and "Level 2," representing a severe acne condition necessitating the expertise of a dermatologist. This meticulous classification provides a nuanced understanding of the diverse skin conditions within the dataset, essential for training our acne detection model.The flowchart is depicted by Fig 3.

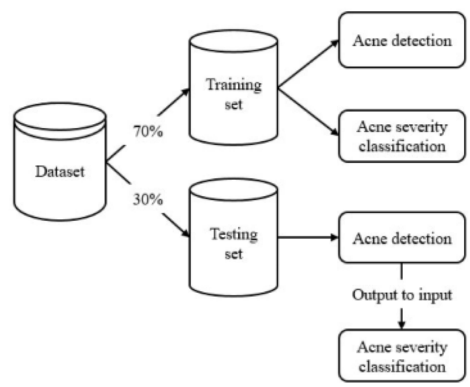


Fig. 3. Flowchart

Data pre-processing plays a pivotal role in optimizing model accuracy during training and testing phases.To address the limitation of available open-source data, we employ various data augmentation techniques to diversify the dataset. The types of data pre-processing methods applied, includes horizontal and vertical flips, 90° rotations (clockwise, counter-clockwise, and upside down), cropping with minimum zoom (0%) to maximum zoom (50%), rotation within a range of -15° to +15°, blur effects up to 10 pixels, and a fixed rotation of 30 degrees. These techniques contribute to the augmentation of the dataset, effectively increasing its size and introducing variability that aids in robust model training.

In the domain of data architecture and modeling for the acne classifier, we adopted the ResNet-18 architecture. ResNet-18 is often pre-trained on large-scale image datasets, such as ImageNet, before being fine-tuned for specific tasks like acne detection.Its ability to capture intricate features in facial images makes it well-suited for the task of acne detection, contributing to the overall efficacy and accuracy of the model in identifying and classifying different levels of acne severity.

IV. RESULT AND DISCUSSSION

The results of using the ResNet-18 architecture for acne detection can be evaluated based on various performance metrics. The specific outcomes will depend on factors such as the dataset used for training and testing, the preprocessing techniques applied, and the overall model configuration.In evaluating the performance of an acne detection model, several key metrics are considered. Accuracy, a fundamental measure, reflects the overall correctness of the model's predictions by calculating the ratio of correctly classified samples to the total number of samples.This indicates the percentage of correctly classified cases among all instances, providing a general measure of the model's effectiveness. Figure 4 represents the accuracy on the used dataset and model.By using ResNet-18 pretrained model, we optimize the model to our custom dataset and achieve an accuracy up to 90%.

epoch	train_loss	valid_loss	accuracy	time
0	1.275670	0.998097	0.765677	00:08
1	0.892795	0.743409	0.811881	00:08
2	0.880464	1.535807	0.821782	00:07
3	0.871721	1.634758	0.808581	00:07
4	1.088481	5.388702	0.656766	00:07
5	1.044595	1.901320	0.762376	00:07
6	0.863624	0.809342	0.858086	00:07
7	0.710001	0.676677	0.894389	00:07
8	0.532709	0.652870	0.897690	00:07
9	0.408114	0.615403	0.894389	00:07
10	0.343163	0.756864	0.854786	00:07
11	0.276528	0.694668	0.894389	00:08
12	0.217420	0.604474	0.897690	00:07
13	0.181705	0.625304	0.900990	00:07
14	0.141823	0.635878	0.900990	00:07

Fig. 4. Accuracy over epochs for Acne Classification.

The Confusion Matrix offers a detailed breakdown of the model's predictions, distinguishing true positives, true negatives, false positives, and false negatives. This matrix provides valuable insights into the specific types of errors the model is making, aiding in the identification of areas for improvement.The confusion matrix is typically represented in a matrix format, with the rows representing the actual classes (presence or absence of acne) and the columns representing the predicted classes by the model. Figure 5 represents the confusion matrix on the used dataset and model.

The loss function graph in acne detection represents how the model's loss, a measure of the difference between predicted and actual values, changes over the course of training. The loss function is a crucial component in the optimization process, guiding the model to minimize errors and improve its predictive capabilities. Typically, the loss decreases as the

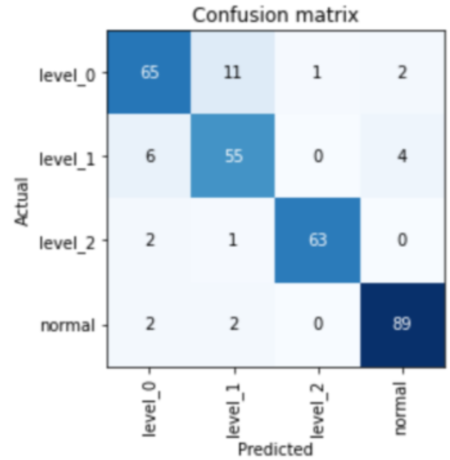


Fig. 5. Confusion Matrix

model learns from the training data. Figure 6 represents the loss function graph on the used dataset and model.

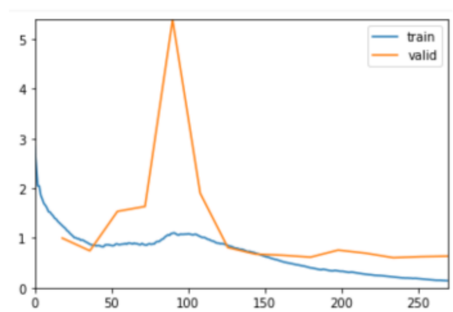
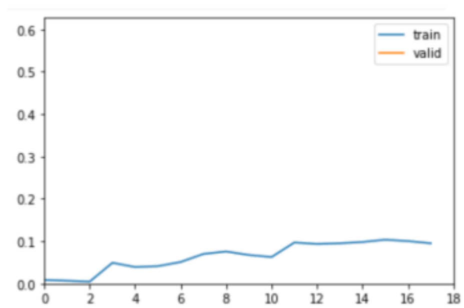


Fig. 6. Loss Function Graph



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