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Full Paper

Optimizing Acne Severity Detection: A Deep Learning Approach with Electronic Medical Record System Integration and Diverse Image Data

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Abstract

Acne vulgaris is the 8th most common skin ailment in the world. Although there are many studies in European countries to predict the severity level of acne, there is a significant gap in predicting South Asian skin texture, which is different due to inherent biological differences such as the thickness of the dermis, complexion, and frequency of skin sensitivity. Therefore, the study aims to address this gap with a deep learning (DL) algorithm based on images from different nationalities with different skin colours and features who have low-resolution images and often contain more than one acne lesions. The modal was deployed as a Progressive Web Application (PWA) and embedded in an Electronic Medical Record (EMR). 1,148 training images and 100 testing images were acquired from several resources and labelled into five main categories: from 1 (Clear) to 5 (Severe). A transfer learning approach was implemented by extracting image features using a ResNet-152 pre-trained model, then a fully connected layer was added and trained to learn the target severity level from labelled images. OpenCV (Facial landmark and One-Eye modal) is used to find facial landmarks and extract key skin patches from the images. To address the spatial sensitivity of CNN models, an existing image rolling augmentation approach was used to help the trained CNN model to generalise better on testing data. Theoretically, it causes acne lesions to appear in more locations in the training images and improves the generalisation of the CNN model on test images. Finally, the model's performance was evaluated on 100 test images using RMSE concerning a consensus among experts. In this research, we obtained a lower RMSE value (0.37) compared to the previous studies, and severity levels are categorised into five alphabetical values.

Keywords: Acne severity detection, OpenCV, image augmentation, ResNet-152, convolutional neural network

Introduction

Acne vulgaris affects 85% of the population, making it the eighth-most common disease worldwide [1, 2]. Traditionally, dermatologists evaluate acne type and severity level, counting the number of acne lesions through visual inspection or scanning acquired images of the patient's skin manually [1]. These methods are time-consuming and require excessive effort by the physician. This research was conducted based on information obtained from the Department of Dermatology, National Hospital of Sri Lanka. A survey was conducted among 200 local adolescents aged 20 to 35. Several interviews were carried out with a few dermatologists regarding the novel methods and the current situation relevant to acne treatment processes.

During the requirement-gathering process, it was observed that many Sri Lankans were channeling skincare and cosmetic dermatologist consultants from different medical institutes and hospitals for treatments. Traditional diagnosis methods such as manual observation and counting acne are used in Sri Lanka. According to statistics obtained during interviews with dermatologist consultants, it is estimated that acne patients must wait for an average of over 28-30 days for an appointment with their dermatologist. Since the diagnosis results depend on the dermatologist's experience and ability, these manual methods are labour-intensive, time-consuming, subjective, and may result in inter-observer and intra-observer variations [3].

It is a challenge for dermatologists to manage a massive amount of appointments from patients having various categories of acne lesions at different levels of severity. Though there are many applications developed by European countries to predict the severity level of acne, the literature review and the focused group discussion revealed that a proper prediction and detection system, mainly focusing on Sri Lankan skin texture, is not yet available. Rawlings (2006) defined that many inherent underlying biological differences exist between European and Asian skin such as the thickness of the dermis, complexion and frequency of skin sensitivity [4].

The body of research surrounding the automatic diagnosis of facial acne using machine learning and image processing techniques has expanded significantly in recent years. Notably, Malik *et al.,* (2014) proposed a severity detection method that utilizes the CIE La*b* color space to segment skin colors, employing an automated modified K-means clustering algorithm alongside a Support Vector Machines (SVM) classifier to classify acne into categories such as mild, moderate, severe, and very severe based on color and diameter features [5]. Similarly, Ramli *et al*., (2012) provided an overview of acne analysis and computational assessment methods, highlighting the effectiveness of k-means clustering with color features, achieving high sensitivity and specificity in their segmentation results [6]. These foundational studies underscore the potential of machine learning approaches in enhancing acne assessment.

Recent advancements have further leveraged deep learning techniques to improve acne severity detection. of Zhao *et al.,* (2019), developed a convolutional neural network (CNN)-based transfer learning regression model that assesses acne severity from selfie images, marking a significant step forward as the first deep learning solution for acne assessment using low-resolution images from diverse populations [7]. This approach is particularly relevant given the challenges posed by varying skin colors and features, which complicate traditional high-resolution assessments. In research, dropout techniques and data augmentation methods have been employed in several studies to mitigate overfitting, ensuring that models remain robust across different datasets [8-11]. Han *et al*., (2018) also demonstrated that deep learning algorithms could achieve accuracy comparable to dermatologists in diagnosing other skin conditions, further emphasizing the potential for similar applications in acne detection [12].

The main objective of this study is to address this gap with a deep learning (DL) algorithm based on images from different nationalities with different skin colours and features who have low-resolution images and often contain more than one acne lesions. Further study aims to develop a Progressive Web Application

(PWA) powered by a deep learning model embedded within an Electronic Medical Record (EMR) system. This application serves as a supportive tool for dermatologists, allowing them to diagnose acne by processing images taken from various angles, such as frontal and profile views of the face. Such a system would enable dermatologists to evaluate acne's severity efficiently and manage patients' recovery progress against prescribed treatments. The automated process allows patients to autonomously track the evolution of their acne, providing valuable data and regular reports on the state of their lesions for their physicians. Electronic health record software helps streamline several functions essential for running a practice and improving revenues [13].

Comprehensive and accurate documentation of a patient's medical history, tests, diagnosis, and treatment in EMRs is crucial for ensuring appropriate care throughout a provider's clinic. Implementing an EMR as a web-based application can effectively maintain standardized clinical and medical information in electronic format. The use of electronic health record software not only streamlines essential functions for running a practice but also contributes to improved revenue management [3]. Despite the advancements in automated acne assessment tools, there remains a notable gap in the literature regarding integrating these automated methods into clinical practice. While deep learning algorithms have shown promise in diagnosing other dermatological conditions with accuracy comparable to specialists, the specific application of these methodologies to acne prediction and severity detection requires further exploration.

Additionally, the existing tools for acne assessment, as discussed by Alsulaimani *et al.*, (2020) lack standardization, complicating inter-observer agreement and clinical applicability [3]. Thus, future research should focus on developing standardized, robust, and technologically advanced methods for acne severity assessment that can be validated across diverse populations and clinical scenarios, ultimately bridging the gap between technological innovation and clinical practice.

Materials and Methods

A PWA application was developed for capturing images of acne and detecting acne severity levels. With this app, the user is able to use a mobile camera to capture acne images; at the same time, they can upload any image collected from a mobile image library or any image downloaded from other sources. Upon uploading an image, each image is validated and saved to the image database, which is linked to the algorithm implemented for image processing and deep learning. Each image added by the users will be saved to the dataset as a newly added image, helping us to improve prediction accuracy. This PWA was designed using frontend technologies such as React Native, Js & Jquery.

The UI of the application was designed using Material UI & Bootstrap according to UX methodologies. This application uses Rest API in the backend to handle image processing, severity level detection, and uploading newly added images to the database. The following flow chart (Figure 1) demonstrates the steps followed by image processing and deep learning techniques that were used in order to implement the proposed system.

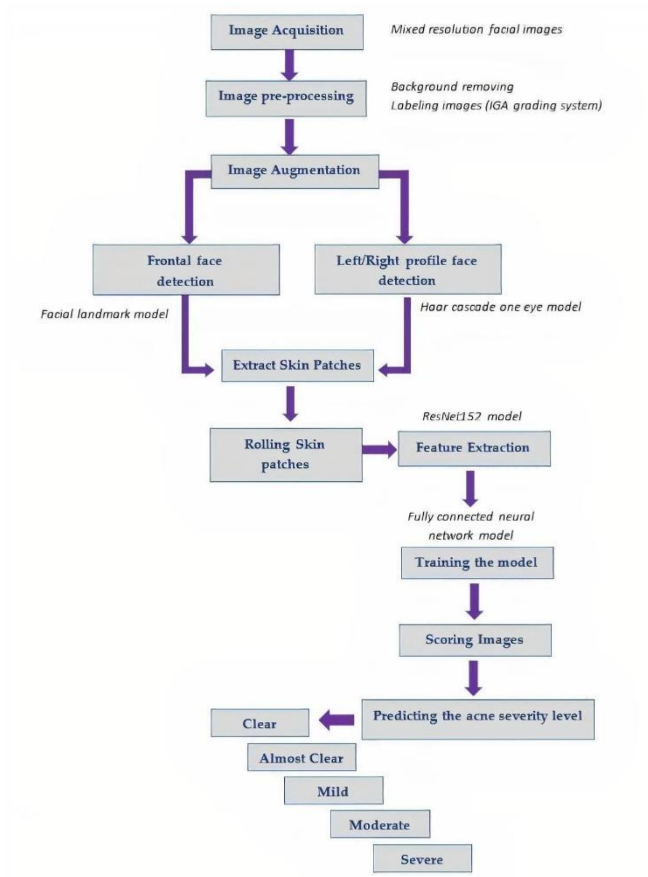

Figure 1. Acne severity detection proposed methodology

Image Acquisition

The dataset acquired for the training process consisted of 1,148 selfie images of different people from different nationalities (European and South Asian), skin colors and features of mixed resolutions (high and low resolution) containing more than one acne lesion all over the face. The initial resources for the dataset were found on kaggle.com, DermNet NZ acne image sets [14, 15] used as the training dataset, and 100 test images were obtained to serve as a 'golden set' for model evaluation from Flicker Faces HQ Dataset [16]. In order to improve the performance of the model, more pictures from the Asian skin type were analysed and added to the initial dataset.

Image Pre-Processing

The image background was removed to eliminate any unnecessary items in images so that any other objects are not confused with acne lesions by the algorithm. The acquired dataset contained images that are different in size, which are not applicable to the selected models and blurry images with low quality that are hard to distinguish from other categories. This preprocessing step improved the generalisation performance of the testing images. To train and evaluate CNN models, every image in the training and testing sets has to be labelled. The training images were randomly split into two groups and labelled accordingly. Although acne severity levels are categorical, using ordinary numerical values as labels makes identifying users easier. The obtained images were labelled into five main groups, 0 - Not Acne, 1 - Clear, 2 - Almost Clear, 3 - Mild, 4 - Moderate, and 5 - Severe according to the IGA (Investor's Global Assessment) acne grading system [17]. We could find noise in the labelling process, and the dataset was reanalyzed after identifying the confusing and conflicting images.

Detect Facial Landmarks

Acne vulgaris may occur in any area of the face. However, the dominant areas can be identified as the forehead, cheeks, and chin. Two pre-trained models from the OpenCV library have been used to identify the most acne-occurring parts of a face, minimising the effects of irrelevant parts of the image. The facial landmark model [18] and the haar cascade one-eye model [19] were used to detect facial features when a pre-processed image (eyes) is provided and then automatically identify dominant areas from the facial images. A facial landmark model was applied to extract the skin patches of each image when both eyes are open and visible in the image, which means the images that have been taken from the front angle. Whenever the landmark model fails to detect both eyes, the haar cascade one-eye model is used to extract skin patches inside angle images, detecting at least one eye from the image. If any of these models cannot detect the facial features and fail to extract them, the original file will be stored in the destination folder. The Region Identification process is illustrated in Figures 2 (a) and 2 (b).

Figure 2. (a) Detect facial landmarks and (b) Facial skin patches (Forehead, Left Chin, Right Chin and Chin)

Image Augmentation

The extracted skin patches from the above step are processed under an image augmentation technique called "rolling". This method has been introduced by of Zhao *et al.,* (2019) to augment the images so that the trained CNN models could generalise efficiently on the golden set images (The set of testing images abstracted from the main dataset). Rolling the skin patches support CNN models generalise well on the validation and golden set images. In CNN models, the features extracted from a particular area will be projected onto a specific neuron in the feature space. Mostly, the CNN model will not be able to identify the acne lesion well if the acne lesion on the testing image appears in new locations that the CNN model had never recorded previously. As an ailment, the acne severity is not reliant on location; instead, the volume and severity of acne lesions on the patient's face [7]. The rolling step size for this function is decided by the size of the dimension that the rolling is on with the number of rolling times as shown in the following equation. The forehead patch has been rolled from left to right and the cheeks patches from bottom to top.

Step size = int (rolling dimension size) / (num_rolling_times+1) **Equation 1.** The rolling step size

After the rolling step those image patches are stored in separate subdirectories relevant to their level of acne severity as 0-Not Acne, 1-Clear, 2-Almost Clear, 3-Mild, 4-Moderate and 5-Severe. During this saving process a random number generating method has been used to decide whether each of these images belongs to the training set or testing set. Figure 3 contains the skin patches belonging to one image after processed under the rolling technique.

Figure 3. Image rolling

Converting Classification to the Regression Model

During the organisation of the image samples, it was discovered that multiple identical or similar images were in the training image set, all of which had been labeled differently by both medical professionals, making training the classification model challenging. To mitigate the impact of label noise on the implemented model, a regression model was used instead of building an image classification model. Ordinary numerical values were assigned to five acne severity levels in the regression CNN model as given in Table 1.

Feature Extraction (Transfer Learning Model)

CNN being a leading approach for computer vision and providing advanced accuracy for classification models, the ResNet-152 (a residual neural network), which is regularly used in the field as a powerful backbone model was selected for this research [20]. A pre-trained deep learning model in Microsoft Cognitive Toolkit (CNTK), ResNet-152 was used to extract features from the training image skin patches and then trained a fully-connected neural network model on these features to make the entire deep learning model precise to the acne severity classification domain. A pre-trained ResNet-152 model was used to extract features from the last max-pooling layer. The trained fully connected neural network was then kept for the future scoring pipeline. The features of the training image patches were used to train the fully-connected neural network with three hidden layers, each with 1024, 512, and 256 hidden neurons. The trained CNN model was then saved and used to predict the input image labels. The defined method used to train the fcnn model is given below.

```
from sklearn.neural_network import MLPRegressor
clf_regr = MLPRegressor(hidden_layer_sizes=(1024, 512, 256), activation='relu',randomstate=randomseed)
clf_regr.fit(train_dataset, train_labels) #Start training the regression model
```

Scoring the Severity

- Get the skin patches for each image.
- Score each image patch according to the detected severity using the fully connected neural network model developed. Prediction labels are given in Table 1.
- Get the average value of skin patches and predict the severity of the whole image

For the scoring process, we used the following numerical values from the study of Zhao *et al.,* (2019) . The below list of boundaries was used to discretize the ground truth and the predicted severity levels into categorical severity levels, with the severity label < 1.5 labelled as 1 (Clear), and severity labels in the range of 1.6–2.5 labelled as 2 (Almost Clear) and so on.

Table 1. Scoring the severity

Value	Label
0.5 - 1.5	Clear
1.6 - 2.5	Almost clear
2.6 - 3.5	Mild
3.6 - 4.5	Moderate
4.6 - 5.5	Severe

Lastly, the trained CNN model, together with the image augmentation steps, has been operationalized as a Python Flask web service API using Azure Container Service (ACS) and Azure Kubernetes Service (AKS), enabling patients to submit selfie images and get acne severity labels from the web service API.

Progressive Web Application (PWA) Development

The name given for the first version of the PWA is Aceno 1.0. The deep learning model for Aceno was developed in Python, utilizing the Anaconda environment, and incorporated four distinct pre-trained models. The first model detects facial landmarks, ensuring precise localization of key facial features. The second model assesses the angle of the user's image, whether it's taken from a side or full view. The remaining two models focus on detecting various facial features, crucial for accurately identifying acne severity.

The application itself was constructed as a progressive web app. PWA Builder was employed to convert the desktop application into a mobile-friendly version seamlessly. On the front end, Bootstrap and React were used to create a responsive and dynamic interface. For the backend, PHP was utilized alongside Flask for endpoint management. Data was stored in a MySQL database, which was hosted via C Panel. To ensure continuous integration and delivery, the final deployment was orchestrated using a CI/CD pipeline in Azure, optimizing the delivery and updates of the application for users.

Results and Discussion

Initial model training without the augmentation procedure resulted in a high error value (RMSE value 0.48) due to the lack of a sufficient number of images covering all acne-prone areas and the noisy data. The dataset had to be re-analyzed and processed to remove background noise and low-resolution images. Later, the accuracy was increased when the model was trained with an augmentation rolling step (RMSE value 0.37). The severity levels were decided based on the IGA (investor's global assessment) measuring procedure.

In the scoring step, the severity is predicted as numerical values since the predictions are done by a fully connected neural network. These numerical values were converted into class labels given in Table 1, and saved in the output CSV file. Afterwards, the result was redirected to the mobile application's results interface. Moreover, the output file provides the most severe skin patch in each image to provide a more detailed understanding of the patient's condition. The initial accuracy of the fully connected neural network was 62% due to the noise in the image labelling process. After re-analyzing the dataset by removing the confusing and low-resolution images and re-labelling some of the images the model achieved a 75.7% accuracy in severity prediction. The RMSE value of 0.37 was obtained in the final training process. The CNN-based regression model performs well for the moderate (89%) and severe (100%) classes, as illustrated in the confusion matrix (Figure 4). In contrast, the Almost Clear and Mild classes scored 86% and 78%, respectively, which is a bit low in comparison to the most accurate predicting classes. The model shows poor performance for predicting Clear class images being confused with Almost Clear. This can be further improved by re-analyzing the dataset of Clear and Almost Clear images so that the model accurately distinguishes these two severity classes.

Predicted values \ Actual values	1	2	3	4	5
1	**5**	0	0	0	0
2	11	**20**	2	0	0
3	1	3	**22**	2	0
4	0	0	4	**25**	0
5	0	0	0	1	**3**

Figure 4. Confusion matrix

Accordingly, the precision values for the 5 classes are; Clear: 100%, almost clear: 86%, mild: 78%, moderate: 89%, and severe: 100%.

Comparative Analysis

The results of this study align with, yet extend beyond, existing research on acne diagnosis and severity prediction. As reported in the literature, acne vulgaris can still be diagnosed with traditional methods such as manual observation and lesion counting [1]. To address these inefficiencies of manual methods, we developed a CNN-based system based on these insights, which was tailored for South Asian skin textures to address subjectivity, time consumption, and observer variation.

The challenges faced during this research are consistent with prior studies on acne detection systems. For instance, Malik *et al.,* (2014) and Ramli *et al.,* (2012) used machine learning techniques (i.e. K-means clustering and SVM classifiers), but their methods were focused on high-resolution images and specific skin types, which do not fully represent the variety in real-world data [5, 6]. In our results, we observed that initial model training on a dataset containing low-resolution and noisy images resulted in poor accuracy (62%) and a high error value (RMSE of 0.48). After applying an augmentation process and cleaning the dataset by removing low-quality images, we were able to improve the accuracy to 75.7% with an RMSE of 0.37. It showed the significance of using clean and diverse data sets in the selection of as well as in the training of the model.

Results in Table 2 present a relative comparison of various acne detection and severity prediction models in order to assess the performance of the CNN-based approach against more established machine learning techniques, such as Bayesian algorithms, Binary Threshold, and Fuzzy C-Means clustering techniques.

Table 2. Comparative Analysis of Acne Detection and Severity Prediction Models

Method	Accuracy	Sensitivity	Precision
CNN (ResNet-152) (Clear)	62,00%	83.30%	100%
CNN (ResNet-152 (Almost Clear)	75.70%	86.95%	86.95 %
CNN (ResNet-152) (Mild)	75.70%	78.57%	78.57%
CNN (ResNet-152) (Moderate)	89.00%	86.21%	86.21%
CNN (ResNet-152) (Severe)	100%	100%	100%
Bayesian Classification	70.65%	83.17%	81.13%
Binary Threshold Method	70.00%	86.37%	80.00%
Fuzzy C-means Clustering	92.63%	89.67%	93.19%

Note: The above CNN (ResNet-152) values are based on the current study.

The CNN model possesses great variability within its class-wise performance. In the cases of Severe acne, the sensitivity, precision, and accuracy of the CNN model were perfect, with 100% values, which justifies the strength of the model in identifying instances of severe acne. This finding is supported by previous studies such as Zhao *et al.*, (2019), since deep learning models showed good performance in more obvious severe conditions. For instance, in the case of Moderate acne, it showed an accuracy of 89%, a sensitivity of 92.59%, and a precision of 86.21% for CNN. This reflects that this model is effective for distinguishing more pronounced categories of acne; hence, further improvement of diagnosis accuracy, especially for those cases that might need immediate medical attention.

However, the performance is slightly lower for the Clear, Almost Clear, and Mild categories, as compared to the other categories. As a result of minute variations in skin texture and appearance of lesions and a variation in datasets, the CNN model's values are relatively low. The specificity in the case of Clear was 62.00% and the sensitivity was reduced to 83.33%, whereas having a high level of accuracy of 100%. This can be due to the fact that it correctly categorizes images which are predicted as Clear but it cannot distinguish enough of the real Clear images, thus resulting in wrong classification with Almost Clear images. Sensitivity and precision values for all almost clear and mild categories were less than the other categories with sensitivity and precision of 64.00%. The sensitivity for Almost Clear was at 52.00% while that of Moderate was at 78%. It is seen that the overall accuracy is 57.00% for the Mild category, which again underlines the need for making the system even more discriminative to avoid including images from one category into another.

Compared to the other machine learning techniques, CNN outperforms traditional methods in some areas but shows room for improvement in specific categories. For example, the Bayesian algorithm produced 83.17% in sensitivity and 81.13% in precision [21] which had a relatively lower accuracy of 70.65%, showing a higher possibility of false positives. On the one hand, the Binary Threshold method gave an accuracy of 70.00% [22] but had poor performance concerning noise in the images and false positive cases. These are shown with sensitivities of 86.37% and precision of 80.00%, respectively. On the other hand, Fuzzy C-Means clustering gives very high accuracy, 92.63%, sensitivity, and precision, 89.67% and 93.19%, [23] respectively, proving to be more robust concerning difficult conditions such as non-uniform illumination of the face. However, it is important to note that their study was based on only 50 color images of acne patients from Hospital Kuala Lumpur, Malaysia. Only two components were discovered that could separate lesions from the skin and showed robustness against non-uniform illumination. The dataset was comparatively much simpler than that used in our study.

The Binary Threshold Method performed similarly with an accuracy of 70.00%, but it struggled with noise in images and false positives, yielding 86.37% sensitivity and 80.00% precision. On the other hand, the Fuzzy C-Means clustering technique excelled in lesion segmentation tasks, achieving high accuracy (92.63%), sensitivity (89.67%), and precision (93.19%), showing robustness in detecting acne under challenging conditions like non-uniform illumination.

The technical contributions of this study significantly enhance the field of acne diagnosis and severity prediction by developing a convolutional neural network (CNN) specifically tailored for South Asian skin textures. This approach addresses the limitations of traditional methods, such as manual observation and lesion counting, which have been shown to be inefficient and subjective [1]. By leveraging insights from existing literature, we aimed to reduce observer variation and improve diagnostic accuracy. Our research identified challenges consistent with prior studies, where earlier machine learning techniques, such as K-means clustering and SVM classifiers, were limited by their focus on high-resolution images and specific skin types, failing to represent the diversity found in real-world data [12]. Overall, this research not only confirms the efficacy of CNNs in acne detection but also emphasizes the necessity for tailored approaches that consider the unique characteristics of diverse skin types. Additionally, the integration of this model into a Progressive Web Application (PWA) within an Electronic Medical Record (EMR) system aims to provide dermatologists with a robust tool for diagnosing acne and tracking patient progress, ultimately addressing existing gaps in acne management systems [1]. In summary, while the CNN model demonstrates strong performance for more severe acne cases, it underperforms for mild and clear cases, suggesting the need for more refined algorithms to handle subtle variations in skin texture. Future work should focus on improving the dataset by increasing the number of high-resolution images for mild acne categories and employing techniques like class rebalancing and fine-tuning of the CNN architecture to enhance sensitivity across all classes.

Progressive Web Application

The Aceno project has been implemented as a progressive web application, enabling seamless access as a practical consumer mobile application. Figure 5 illustrates key interfaces: the home page (Figure 5a) allows users to register or log in to the Aceno platform (Figure 5b). This page also links the "About" and "Contact" sections. Once logged in, users can either upload an image from their gallery or capture one using the camera to submit for acne severity analysis (Figure 5c). Additionally, users must input their unique ID number before the image and ID are uploaded to the database via the upload button (Figure 5d).

After submission, the machine learning model processes the image and predicts the severity of acne. By clicking the “Check Severity” button, the user is redirected to a results screen (Figure 5e), where the predicted severity is displayed. This screen also shows the user’s ID and the result’s generated date, ensuring that users can track their diagnosis history easily and efficiently.

The main audience of our research project is acne patients between the age of 20 to 30 years. This study would be beneficial not only to acne patients but also to dermatologists, who spend hours managing patient details. However, this research never recommends replacing a dermatologist visit but speeds up the diagnosis process by assisting dermatologists. The final decision on the diagnosis should always be made under the supervision of dermatologists. Further PWA development was carried out in alignment with evolving future changes and standard practices in software development and maintenance [11, 24, 25]. Furthermore, the application development has encountered issues and challenges similar to those in previous studies [10, 26].

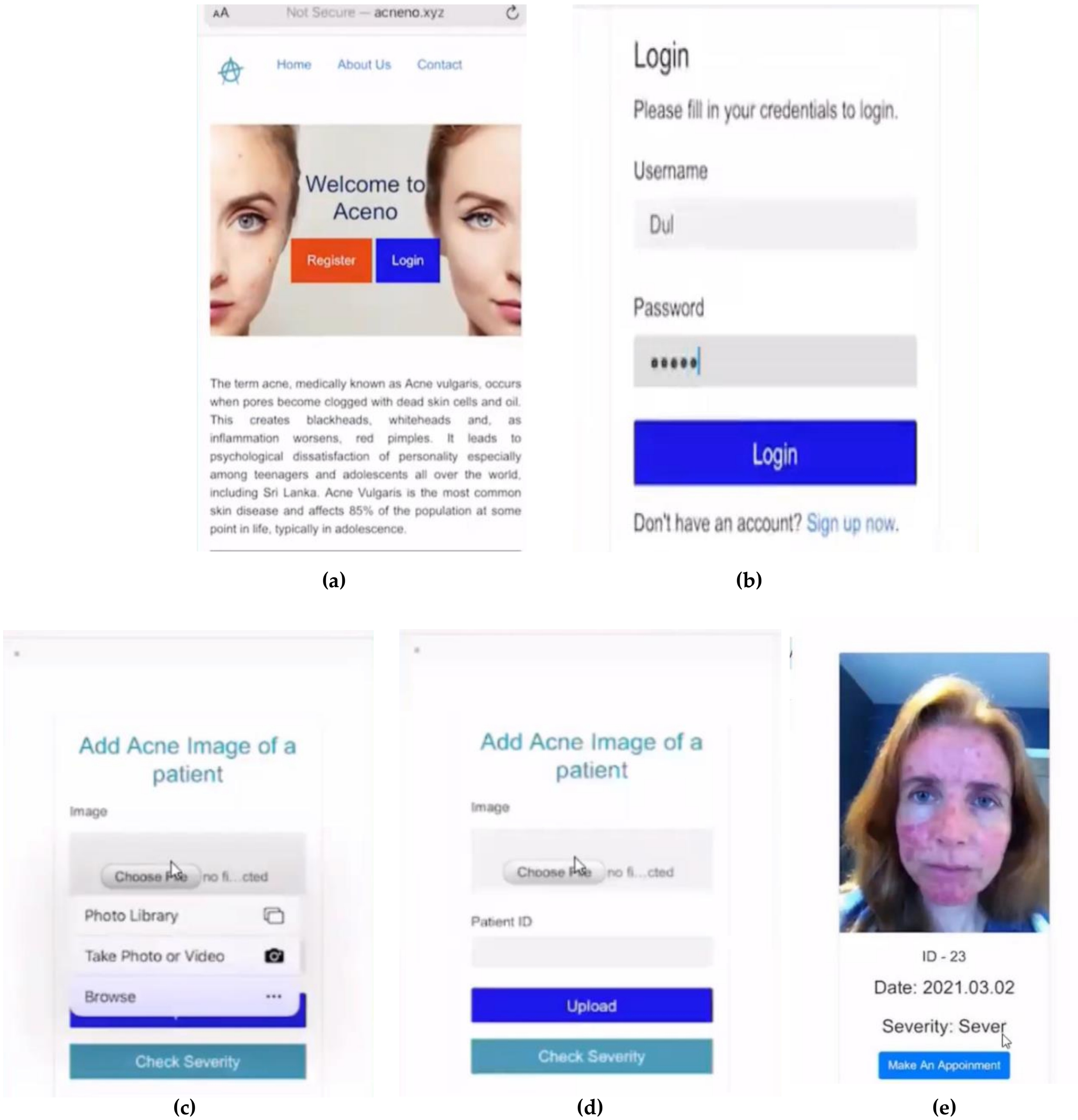

Figure 5. Key interfaces of the mobile application (a) the home page, (b) register or log in view, (c) add acne image, (d) upload an acne image, and (e) results screen.

This paper explains that the severity level of facial acne can be successfully detected with deep learning techniques. The current situation that both patients and dermatologists must deal with has made it necessary to develop computerised and automated acne severity level detection methods. The necessity of computerised and automated acne severity level detection came into the topic with the current situation that both patients and dermatologists had to face. Since the diagnosis results depend on the dermatologist's experience and abilities, these manual methods are labour-intensive, time-consuming and subjective [12]. It is challenging, even for dermatologists, to manage a large number of appointments from acne patients of different levels and categories. It is a challenge even for dermatologists to manage a massive number of appointments from patients with different levels of acne lesions in various categories. In general, assessing acne lesions, choosing products, and monitoring progress are difficult for people suffering from the condition. It is not feasible or desirable for all patients to seek treatment from qualified dermatologists. As mentioned, most of the previous work detected the skin lesion with high resolution. However, in this provided application, images used were from different sources of people from different nations, skin colour and features with low resolution and contained more than one acne lesion, which has made this work more specific compared to other studies.

Limitations and Future Work

One of the key limitations of this study is that the current model primarily focuses on South Asian skin textures, which may limit its generalizability when applied to individuals from other regions or cultural backgrounds. Acne presentation can vary across different ethnicities and environmental conditions, which may impact the system's accuracy for diverse populations. To address this, future work should aim to test and enhance the web application's accuracy across a broader demographic by allowing users to select their country or region during login. This data could help fine-tune the model's parameters for specific skin types and environmental factors, improving performance in different geographical regions.

In terms of performance, while the CNN model demonstrates strong results for moderate and severe acne cases, it faces challenges in accurately distinguishing between Clear and Almost Clear cases. This is likely due to class imbalances and the subtle differences in skin features that are harder to detect. The inclusion of noisy and low-resolution images in the dataset before preprocessing also impacted the model's initial accuracy. Additionally, the lack of diverse images representing different skin types, lighting conditions, and acne variations further limits the model's ability to generalize to wider populations.

Aceno 1.0, the first version of the application, does not currently include patient registration functionality, which is planned for future iterations. Despite these limitations, Aceno 1.0 marks a significant advancement in detecting facial acne types, and the application has the potential to be expanded into a comprehensive diagnostic tool for dermatologists.

Future work will focus on addressing these limitations by expanding the dataset to include a wider range of skin tones, conditions, and acne severity levels. Techniques like transfer learning, attention mechanisms, and class rebalancing will be explored to improve accuracy, particularly for the more challenging Clear and Almost Clear classifications. Additionally, incorporating a multi-task learning approach could enable the model to predict other acne-related attributes, further enhancing its diagnostic capabilities. To ensure the system's robustness in clinical settings, the model should be deployed in real-world environments where continuous feedback can be gathered. This will provide valuable insights for ongoing refinement and adaptation, helping to improve its effectiveness in practical applications. In summary, while Aceno 1.0 lays a solid foundation for acne severity assessment, future iterations will focus on overcoming current limitations, expanding the dataset, and improving algorithmic precision to create a more versatile and globally applicable solution.

Conclusion

In conclusion, this study successfully addressed the initial research objective by developing a deep learning (DL) algorithm that utilizes images from individuals of different nationalities, with varying skin tones and features, who often have low-resolution images containing multiple acne lesions. Furthermore, the research resulted in creating a Progressive Web Application (PWA) and an Electronic Medical Record (EMR) System, which enable dermatologists to efficiently assess acne severity and manage patients' recovery progress based on the prescribed treatments for the identified facial acne types. The technical contributions of this study significantly enhance the field of acne diagnosis and severity prediction by developing a convolutional neural network (CNN) specifically tailored for South Asian skin textures. A deep learning model was deployed as a Progressive Web Application (PWA) and embedded in an Electronic Medical Record (EMR) system to provide dermatologists with an easy way to evaluate the acne severity and record and manage the patient's recovery progress. In the absence of dermatologists, this provided application can predict 5 Acne severity levels, with accuracy surpassing that of general practitioners in many cases. We have also highlighted our choice to adopt a particular architecture for further development. There has been some previous work that detected skin lesions with high resolution, but this application uses images obtained from different sources of people from different nations with low-resolution skin colour and features and contains more than one acne lesion, which has led to this work being more specific when compared to previous work.

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