Mobile Application Using Convolutional Neural Networks for Preliminary Diagnosis of Rosacea

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***Abstract*—Rosacea is a chronic skin disease affecting millions of people worldwide, characterized by redness and inflammatory lesions on the face. Given the need to improve early detection, this research aims to develop a mobile application using convolutional neural networks to improve the preliminary diagnosis of rosacea. For this purpose, increases in sensitivity, specificity and accuracy percentages were evaluated. The study was applied, with a quantitative approach and an experimental design, specifically pre-experimental. The study variable was the preliminary diagnosis of rosacea, and the sample consisted of 100 images: 50 from rosacea patients and 50 from healthy people. The technique used for data collection was observation. The results of the implementation of the mobile application showed an increase in sensitivity of 2.7%, specificity of 1.97% and accuracy of 0.10%. In conclusion, the use of the mobile application with convolutional neural networks improves the preliminary diagnosis of rosacea by optimizing the indicators evaluated.**

Keywords*—Convolutional neural networks; mobile application; rosacea; preliminary diagnosis; sensitivity; specificity

I. Introduction

In dermatology, the initial and correct detection of rosacea is considered a challenge. This may be because the symptoms are very different and can even be confused with other skin diseases. Thus, the development of a mobile application using convolutional neural networks is proposed to reach a better preliminary detection and thus increase the rates of sensitivity, specificity and accuracy in the diagnosis.

Rosacea is a chronic, non-cancerous dermatological disease affecting the patient's face [1]. The symptoms that appear can be mild, such as spontaneous facial flushing, to more severe cases, such as persistent inflammatory lesions, visibly dilated blood vessels and thickening of the nasal and ocular skin [2].

Rosacea is a skin problem; although the exact cause is unknown, it results from a combination of environmental factors, heredity and specific triggers [3]. Genetic susceptibility, constant intense exposure to ultraviolet (UV) radiation, climate and stress are also some of the main factors contributing to this condition [4]. In addition, certain foods and drinks, such as spicy foods, alcohol and dairy products, can cause rosacea flare-ups in people with sensitive skin [5].

This disease impacts approximately 5.5% of people in the world [6]. Although it affects both genders, it is more common in women and occurs between the ages of 20 and 50 in women but is usually more severe in men and can occur at any age, including childhood [7]. Individuals with rosacea often suffer from anxiety, depression and embarrassment, which affect their quality of life and disrupt their relationships [8]. In terms of physical discomfort, it can be debilitating, but the effect on self-perception and social interaction can be equally stifling [9].

Diagnosing rosacea often presents challenges due to the variability of its symptoms, because it can often be confused with other skin diseases such as seborrheic dermatitis or acne [10]. In addition, rosacea can vary from person to person, and its symptoms can evolve over time, especially in the early stages, complicating the accurate identification of rosacea.

Although dermatological medicine has progressed, there are still major challenges in the early and correct diagnosis of rosacea [11]. Furthermore, the subjectivity of clinical assessment, the diversity in the clinical symptoms of rosacea and the absence of standardized diagnostic standards are just some of the challenges faced by practitioners in their efforts to diagnose and treat rosacea appropriately [12]. Therefore, it is crucial that emerging technologies are used to support the diagnosis of dermatological diseases [13].

For this reason, a mobile application using convolutional neural networks was proposed as a solution to enable more effective picture-based diagnosis of rosacea. This application was developed using convolutional neural networks, which identify characteristics of rosacea. The aim was to increase sensitivity to detect positive cases, increase specificity to minimize false positives and improve accuracy. In this way, this tool provides a technological solution to patients and dermatologists for the effective detection of the disease.

This study is organized as follows: Section II presents the related works. In Section III, the methodology is applied. Section IV presents the results. Section V, the discussion of results and in Section VI, the conclusions of the research is presented.

II. Related Works

In [14], the authors studied deep learning frameworks to establish skin lesions from dermatological images. The study tested the use of convolutional neural networks to detect and categorize diseases at different levels. Some of the findings included efficacy in determining the presence of diseases and their type, with potential breakthroughs that would help individualize treatments for each patient. These results highlighted that the tool is potentially powerful and efficient for dermatological diagnosis in clinical settings.

In [15], the authors conducted a study to optimize the effectiveness of deep learning model training in detecting rosacea lesions from facial images. They performed further tests and observed that their technique not only trained the model faster (up to 25.6 times faster) but also maintained equivalent accuracy. Finally, they indicated that this method is a fairly accurate and efficient method for detecting rosacea, which could prove to be of great value in the future for clinical uses.

Also in [16], a study to classify skin lesions using images through a customized deep learning framework designed with fewer convolution layers was explored in India for comparison with the previously trained VGG16, ResNet50 and InceptionV3 models. The study focused on collecting dermatoscopic images of patients with various skin conditions using the new customized framework. The main tools included the use of advanced image processing techniques and optimized algorithms to handle complicated visual data. Results were reduced by 95%, 85% and 84% against VGG16-TrL, ResNet50-TrL and InceptionV3-TrL, respectively, highlighting the accuracy of skin lesion classification against conventional methods.

On the other hand, [17] the current applications and results of implementing deep learning algorithms in dermatology were extensively examined. The study population covered a wide range of clinical and research dermatological applications using deep learning algorithms for multiple skin conditions. The tools examined were mainly convolutional neural networks, predicting in the image category. The main features highlighted in this case indicated that, although deep learning provides a noticeable increase in diagnostic accuracy compared to conventional methods, it also involves risks such as the need for large amounts of recorded data and model interpretation.

In addition, [18] investigated the effectiveness of collaboration between dermatologists and artificial intelligence in skin cancer identification, including a large set of dermatological images related to the disease. The techniques used for image processing were multiclass regression and content-based image retrieval (CBIR) to identify patterns in skin cancer. Primary results showed that the fusion of human- and computer-generated analysis not only produces more accurate diagnostic results than conventional methods but also reduces assessment time, suggesting a potential model for future use in routine dermatology.

Also in [19], the authors detected brain tumors by using deep learning and transfer learning. A database of MRI scans from a medical center with a random sample of patients was used. Advanced convolutional neural networks, including VGG, ResNet, MobileNet and DenseNet, were used for this dataset of MRI images that were trained and provided. The research showed that the implementation of the transfer learning technique in the proposed models improved brain tumor detection with an accuracy result of 99.75% for MobileNetv3.

On the other hand, [20] implemented an artificial intelligence model to detect and discern between actinic keratosis and seborrheic keratosis. They used a dataset of 2000 images, with training, validation and test subsets. The AI model was developed using deep learning techniques and implemented using the Python programming language and frameworks such as TensorFlow and PyTorch. Furthermore, taking advantage of the Google Collaboration Platform, the model was efficiently trained in two hours and thirteen minutes, using the computing resources provided by the platform. The model study showed a high ability to distinguish between images of both diseases, with high levels of accuracy, precision and specificity.

III. Methodology

This section describes the methodology used in this research, which was applied because it focused on the use of existing artificial intelligence techniques with the aim of developing a mobile application for the preliminary diagnosis of rosacea. The approach was quantitative and a pre-experimental design because it sought to demonstrate that the independent variable: mobile application using neural networks can provide a preliminary diagnosis of rosacea, this being the dependent variable. The population consisted of images obtained from the free repositories Dermatology Atlas, Fitzpatrick 17k and Flickr-Faces-HQ Dataset (FFHQ). For the sampling, images of people with and without a diagnosis of rosacea were considered for further evaluation. Observation was used to collect data. For data analysis, formulae were applied to calculate sensitivity, specificity and accuracy, respectively. Additionally, the Receiver Operating Characteristic (ROC) curve was used to evaluate the test performance. The ROC curve illustrates the connection between the true positive rate and the false positive rate across different thresholds.

A. Case Development

The methodology that was implemented is Mobile-D, which has an agile approach adapted specifically for mobile application development, combining agile and software engineering practices to address the needs of this type of project [23]. Regarding the population, a total of 600 images were considered, and for the distribution of images in the dataset, 450 images were used for training, a total of 30 images for validation and 20 images as a test set. Finally, for the post-test, 100 images were used. Thus, the sample consisted of 100 images selected from the described population, of which 50 were images of people diagnosed with rosacea and the other 50 were images of healthy people. The phases of the Mobile-D methodology are specified below.

B. Phase 1: Exploration

The product is defined, and customer requirements are understood, an initial plan is drawn up, and potential risks are identified and mitigated [21]. In this initial phase, priority is given to understanding the problem and clearly defining the essential functionalities of the rosacea detection application.

1) Outreach. Develop a mobile application using convolutional neural networks for the preliminary detection of rosacea.

2) Set of functional requirements. Key functional requirements are identified that will define the core capabilities of the application (see Table I).

TABLE I FUNCTIONAL REQUIREMENTS

Requirement	Description of the Requirement
RF01	• The system should allow users to register and authenticate themselves.
RF02	• The app should provide reliable information about rosacea and provide links to additional resources.

RF03	• The app should offer clear instructions to ensure that photos are taken correctly.
RF04	• The user should be able to select images from the gallery or take a picture from the camera to be analyzed.
RF05	• The results of the analysis should be clearly displayed, including the probability of each diagnosis.
RF06	• The system should generate reports summarizing the results of the analyzed images.
RF07	• The system should display the results and generate reports on metrics and indicators.
RF08	• The system should include an 'about the mobile application' section, mentioning that it is a university project, detailing its purpose and context.

C. Phase 2: Initialization

The development environment is established, the architecture and initial design are defined, and teams and their roles are formed [21]. The objective is to have a basic functional version of the mobile application that allows validating the first hypotheses and adjusting it to the user's expectations.

1) Configuration of the environment. Hardware: HP AMD Ryzen 3 laptop and mobile device (mobile phone).

Software: Android Studio IDE Koala 2024, Java, Firebase, Google Colab and Tensor Flow.

2) CNN-based application workflow diagram. Fig. 1 presents the workflow diagram of the convolutional neural network (CNN)-based application for rosacea detection that starts with the acquisition and augmentation of images resized to 224x224 pixels, which are divided into training, validation and test sets. The deep learning model is trained to identify rosacea features, tuned with the validation set, and the Application architecture diagram is evaluated with the test set. Once optimized, the model is integrated into the mobile app, which classifies the images and saves the results, providing a preliminary diagnosis.

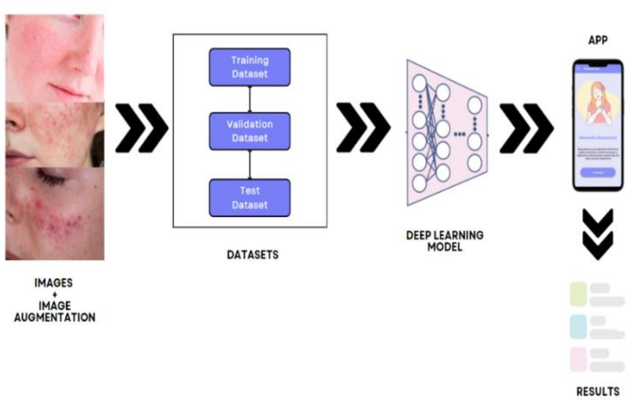

Fig. 1. Workflow diagram of the CNN-based application

a) Application architecture diagram: The mobile application was developed using Android Studio, with integration of TensorFlow for image classification and Firebase as a real-time database. Python and Google Colab were used for training and tuning the classification model, while Java was used for implementing the business logic in the mobile application (see Fig. 2).

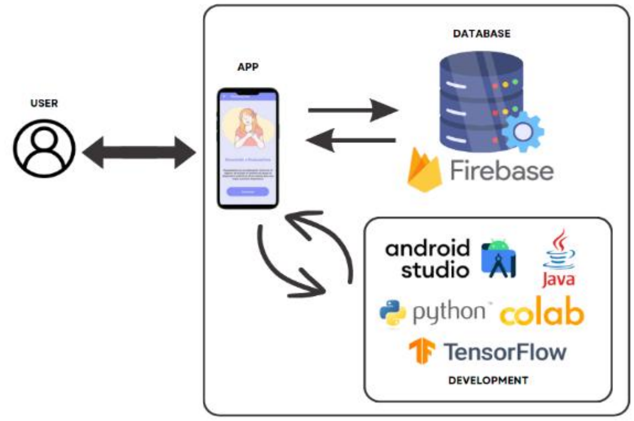

Fig. 2. Application architecture diagram

3) Android project structure. The project structure in Android Studio is organized hierarchically for easy code management and maintenance. The project includes a manifest.xml file that contains application settings and metadata. The source code (Java) directory contains Java files that implement the application logic. The res folder is where the resources of the application are stored. Within res, there are subfolders such as drawable for images, layout for XML files that define the user interface, mipmap for application icons and values for resources such as text strings and colors. The menu folder contains XML files that define the application's menus, such as nav_menu.xml, which specifies the navigation menu items. Finally, the model.tflite file in the assets folder is the deep learning model in TensorFlow Lite format.

D. Phase 3: Production

Work is underway to deliver incremental versions of the application, adding features such as detection, visualization of results, and integration of intuitive interfaces (see Table II).

TABLE II MODULE PLAN

Module	Code	Process	Requirement
User Authentication Module	M01	User authentication process, allowing the user to log in and save their diagnostic data.	RF01
Rosacea Information Module	M02	Process of presenting information about the disease rosacea, including symptoms, causes and recommended treatments.	RF02
Instructions Module	M03	Process of presenting instructions and recommendations on how to take pictures of your face properly.	RF03
Image Upload Module	M04	Process of classifying images using a machine learning model, which determines whether rosacea is present or not.	RF04
Results Viewing Module	M05	Process of visualization of the classification results. Displays diagnostic probabilities and conclusion (positive/negative).	RF05

Report Generation Module	M06	Report generation and visualization process, showing diagnostic results in tabular form, including probabilities and diagnosis.	RF06
Performance Metrics Module	M07	Application performance metrics visualization and report generation process.	RF07
About the Application Module	M08	Process of presenting information about the application, including its purpose, functionalities.	RF08

E. Stabilization

Extensive testing and bug fixes, optimizing performance and ensuring product quality prior to release [21]. The objective is to ensure that the application is ready to be used by end-users without critical problems.

1) Recommendations for mobile equipment. It is recommended to use a mobile device with sufficient storage space, and it is suggested that the device has access to a stable internet connection to perform the analysis in the cloud and synchronize the results with the database (see Table III).

TABLE III RECOMMENDATION FOR THE MOBILE PHONE

Hardware	**Software**
• RAM: 4GB or more. • Display: HD resolution (720x1280).	• Operating system: Android 8.0 or higher. • Network: 4G

F. Testing

The testing phase involves the final validation of the application under real conditions of use. A detailed review is carried out to ensure that all implemented functionalities meet the requirements established during the exploration phase. Continuous support is provided, and the product is updated with enhancements and new functionalities based on user feedback, version management and post-release problem solving.

1) Unit test 05. Results Display Module: The unit test on the results display module is shown (see Table IV).

TABLE IV TEST RESULT DISPLAY TEST

Code	**Name**
M05	• Results Display Module
Target	• The application displays the results of the image classification to the user.
Steps	• Access the results module after classification. • Review probabilities and diagnosis. • View analysis details for each loaded image.
Results achieved	• Classification results are clearly displayed to the user. • Probabilities and diagnosis are displayed correctly. • Information is presented without errors or interruptions.

IV. RESULTS

The aim of this research is to determine whether a mobile application using convolutional neural networks improves the preliminary diagnosis of rosacea.

A. Calculation of Indicators

Table V shows a confusion matrix showing the performance of the application with 100 images. Of 50 images of people with rosacea, 47 were correctly classified as positive, while 3 were incorrectly classified as negative. Of 50 images of people without rosacea, 49 were correctly identified as negative, and 1 was incorrectly classified as positive. With a sensitivity of 94% and a specificity of 98%, the model shows an accuracy of 96%. The matrix was developed using SPSS software to analyze the results of the application and evaluate the ability of the classification model on a controlled set of images, this analysis allowed the effectiveness of the model to be determined.

TABLE V CONFUSION MATRIX

	Prediction					
		Sensitivity Person with rosacea	Specificity Person without rosacea	Total	**Function test**	
Current	Positive	**47**	**1**	48	0.9791666667	Rosacea
	Negative	**3**	**49**	52	0.9423076923	Without rosacea
	Total	50	50	**100**		
	Laboratory test	0.94	0.98		0.96	

From the confusion matrix analysis, the following results were obtained:

% Sensitivity = 94%

% Specificity = 98%

% Accuracy = 96%

1) Analysis of the ROC curve and the area under the curve (AUC). The ROC curve, represented in blue, is shown in Fig. 3, which shows outstanding performance, characterized by high sensitivity and a low false positive rate. In contrast, the red diagonal line represents a random classifier with an AUC of 0.5, equivalent to making random predictions. The blue curve, located above this line, confirms significantly superior performance, highlighting the model's ability to make accurate classifications during testing.

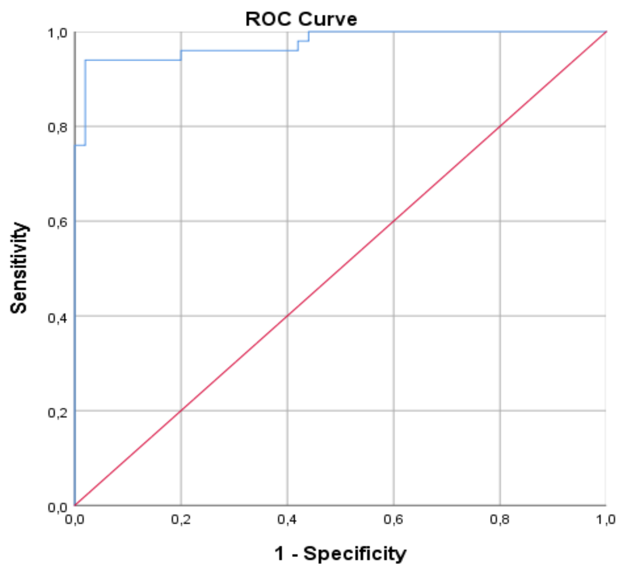

Fig. 3. ROV curve.

The AUC value is 0.975, indicating that the app has a 97.5% ability to correctly classify between positive and negative cases of rosacea (see Table VI).

TABLE VI AREA UNDER THE CURVE

Area	Std. Error	Asymptotic significance	95% asymptotic confidence interval	
			Lower limit	Upper limit
,975	,014	,000	,948	1,000

B. Analysis of the Pre-Experimental Design

a) Pre-test: Table VII shows the accuracy, sensitivity and specificity values of the EfficientNet-b4 model for different dermatological diseases; to verify the increase in percentages in the indicators, it was compared with the rosacea values of the model with the proposed mobile application [22].

TABLE VII PRE-TEST VALUES RESULTS

Disease category	Accuracy	Sensitivity	Specificity
Overall	0.948	0.934	0.950
Lichen planus	0.969	0.873	0.975
Rosacea	0.959	0.920	0.961
Viral warts	0.932	0.944	0.930
Acne vulgaris	0.935	0.974	0.927
Keloid and hypertrophic scar	0.969	0.934	0.970
Eczema/dermatitis	0.877	0.924	0.866
Dermatofibroma	0.987	1.000	0.987
Seborrheic dermatitis	0.926	0.811	0.933
Seborrheic keratosis	0.953	0.858	0.957
Melanocytic nevus	0.960	0.961	0.960
Hemangioma	0.984	0.975	0.984
Psoriasis	0.886	0.920	0.882
Port wine stain	0.963	0.989	0.961
Basal cell carcinoma	0.979	0.971	0.979

b) Post-test: The post-test was performed with 100 images from the dataset, the results of which were obtained with the report generated from the mobile application. Table VIII shows the metrics and percentages of the indicators, indicating sensitivity of 94%, specificity of 98% and accuracy of 96%.

TABLE VIII RESULTS OF THE INDICATORS FOR THE POST-TEST

Quantity	VP	VN	FN	FP	Sensitivity	Specificity	Accuracy
100	47	49	3	1	94%	98%	96%

Table IX shows the comparison between the percentages of sensitivity, specificity and accuracy indicators between the EfficientNet-b4 model and the mobile application.

TABLE IX COMPARISON OF RESULTS

Indicator	Efficientnet-B4	Mobile application
Sensitivity	92%	94%
Specificity	96.1%	98%
Accuracy	95.9%	96%

C. Hypothesis Testing

a) Specific scenario HE1: HE10: A mobile application using convolutional neural networks does not increase sensitivity in the preliminary diagnosis of rosacea.

HE11: A mobile app using convolutional neural networks increases sensitivity in the preliminary diagnosis of rosacea.

% Sensitivity variation = (94-92) / 92 X 100 = 2.17%

An increase in sensitivity was found in the percentage variation, obtaining a positive result of 2.17%; therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

b) Specific scenario HE2: HE20: A mobile app using convolutional neural networks does not increase specificity in the preliminary diagnosis of rosacea.

HE21: A mobile app using convolutional neural networks increases specificity in the preliminary diagnosis of rosacea.

% Change in specificity = (98-96.1) / 96.1 X 100 = 1.97%

An increase in specificity was found in the percentage variation, giving a positive result of 1.97%; therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

c) Specific scenario HE3: HE30: A mobile app using convolutional neural networks does not increase accuracy in the preliminary diagnosis of rosacea.

HE31: A mobile app using convolutional neural networks increases the accuracy in the preliminary diagnosis of rosacea.

% Variation in accuracy = (96-95.9) / 95.9 X 100 = 0.10%

An increase in accuracy was found in the percentage variation, giving a positive result of 0.10%; therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

D. Results of Indicator Increments

Table X shows the percentage increments for each indicator, a positive number is the reason for acceptance of the hypothesis and a negative number is the reason for the increase for each indicator.

TABLE X RESULTS OF THE INCREMENTS FOR EACH INDICATOR

Increased sensitivity	Increased specificity	Increased accuracy
2.17%	1.97%	0.10%

E. General Hypothesis

HG0: A mobile application using convolutional neural networks does not improve the preliminary diagnosis of rosacea.

HG1: A mobile application using convolutional neural networks improves the preliminary diagnosis of rosacea.

By verifying the specific hypotheses HE1, HE2, and HE3, the general hypothesis is accepted.

V. DISCUSSION

The results showed a sensitivity of 94%, resulting in an increase of 2.17%, due to the use of advanced convolutional neural network architectures, which allowed accurate extraction of rosacea-related features. This result is lower than that obtained by [18], who achieved a sensitivity of 95.2% in skin cancer recognition, possibly because they used the ResNet34 architecture previously trained with ImageNet, together with the cross-entropy loss function and the Adam optimizer. Also, the results of this study are lower than those obtained by [20], which was 99.01% in the detection of actinic and seborrheic keratosis; this difference was possibly due to the use of a larger dataset consisting of 2000 high-resolution images. This shows that, although an increase in sensitivity for rosacea diagnosis was achieved, performance depends on factors such as network architecture, dataset size and preprocessing techniques.

In addition, 98% specificity and an increase of 1.97% were obtained because of image preprocessing and data enhancement techniques, which improved the model's ability to differentiate patterns, contributing significantly to the reduction of false positives in diagnosis. This outperformed the result of [18], which only scored 59.2% when detecting skin cancer. This could be attributed to class imbalance in the HAM10000 dataset, with some classes underrepresented. When compared to the study of [20], which obtained 100% specificity and with a higher value than this research, is an outstanding result due to factors such as a balanced and high-quality dataset, as well as distinctive visual patterns that facilitate the differentiation between actinic and seborrheic keratosis in high quality dermatological images. Based on the above, it is evident that image preprocessing and data augmentation contribute to the creation of more robust models with greater specificity.

On the other hand, the results revealed an accuracy of 96%, resulting in an increase of 0.10%, attributed to the training of the model with a carefully labeled high-resolution dataset, which shows its ability to identify relevant features of the dermatological condition. This result is superior to that obtained by [23], where the accuracy was 88-90% in detecting rosacea, this may be because the original images have a high resolution (4608 × 3072 pixels), but were divided into patches of different sizes (64 × 64, 128 × 128, etc.), which may have limited the ability of the model to capture global features. However, the accuracy achieved in this work is lower than that reported by [19], who achieved an accuracy of 99.75% in the detection of brain tumors, as a possible result of the use of fine-tuning and the large number of images used. Taken together, these findings demonstrate that accuracy is strongly influenced by factors such as the quality and resolution of the images used in the model. Skin diseases pose a major global health challenge, and emerging digital tools show promise in enhancing their diagnosis and treatment [24]. Finally, the results confirmed that the application significantly increased the key diagnostic indicators on the basis that in the post-test, there was a marked improvement in the sensitivity, specificity and accuracy of the results.

VI. CONCLUSION

The developed mobile application, based on convolutional neural networks, represents a significant advance in the preliminary diagnosis of rosacea, by considerably improving the sensitivity, specificity and accuracy of the model. A sensitivity of 94% with a variance of 2.7% was achieved, indicating a high ability to minimize false negatives and ensure that affected patients are correctly identified. This is attributed to the innovative implementation of the network architecture, advanced data augmentation techniques and the diversity of the training set, which contributed to better generalization of the model. Likewise, specificity reached 98% with a variation of 1.97%, reflecting a higher accuracy in the identification of negative cases, a result positively influenced by a rigorous image preprocessing and data enhancement process. Finally, the overall accuracy of the model was 96% with a variation of 0.10%, evidencing a substantial improvement in predictive capacity, is supported by using a high-quality data set and rigorous labeling. This study not only provides scientific value by demonstrating the effectiveness of convolutional neural networks applied on mobile devices for dermatological diagnosis but also offers an accessible and practical approach that can facilitate early diagnosis and improve clinical management of rosacea, especially in settings with limited access to specialists.

Among the main limitations of the system is the need to improve diagnostic accuracy, especially in complex cases or with low-quality images, which could affect reliability in diverse clinical settings. In addition, the model currently does not include additional evaluation parameters, such as F1-score or processing time, which would allow a more comprehensive and objective comparison with other existing methodologies. Another relevant limitation is the absence of user feedback mechanisms, which hinders the early identification of errors and the continuous incorporation of improvements based on real experience.

To overcome these limitations, future research should consider implementing ensemble models that combine different architectures to reduce individual errors and increase diagnostic robustness. It is also advisable to extend the evaluation parameters to include metrics such as F1-score, accuracy, recall, and runtime analysis to facilitate comprehensive comparisons with other approaches. It is also suggested to develop a direct feedback module for users to report bugs or suggestions, thus driving continuous improvement of the application. Finally, the incorporation of multilingual support will favor the accessibility and global adoption of the system, adapting it to different cultural and linguistic contexts.

REFERENCES

[1] D. Piccolo, I. Fusco, T. Zingoni, and C. Conforti, "Effective Treatment of Rosacea and Other Vascular Lesions Using Intense Pulsed Light System Emitting Vascular Chromophore-Specific Wavelengths: A Clinical and Dermoscopical Analysis," J Clin Med, vol. 13, no. 6, p. 1646, Mar. 2024, doi: 10.3390/jcm13061646.

[2] G. Galluccio et al., "Advances in the Pathogenesis and Treatment of Rosacea: A Phenotype-Based Therapeutic Approach," Cosmetics, vol. 11, no. 1, p. 11, Feb. 2024, doi: 10.3390/cosmetics11010011.

[3] P. Abdi, Z. Haq, M. J. Diaz, and H. I. Maibach, "Psychiatric comorbidities associated with rosacea: a propensity score-matched case–control study in the All of Us database," Clin Exp Dermatol, vol. 49, no. 4, pp. 400–403, Apr. 2024, doi: 10.1093/ced/llad417.

[4] Z. Yang et al., "Quality of life, sleep and anxiety status among patients with rosacea in the Yunnan plateau region: A 2-year retrospective study," Skin Research and Technology, vol. 30, no. 3, p. e13616, Mar. 2024, doi: 10.1111/srt.13616.

[5] K. Zujko-Kowalska, J. Masłowska, M. Knaś-Dawidziuk, J. Hamulka, and M. E. Zujko, "Dietary Antioxidants May Support Cosmetic Treatment in Patients with Rosacea," Antioxidants, vol. 13, no. 3, p. 381, Mar. 2024, doi: 10.3390/antiox13030381.

[6] Y. Pan, K. Jia, S. Yan, and X. Jiang, "Effectiveness of VISIA system in evaluating the severity of rosacea," Skin Research and Technology, vol. 28, no. 5, p. 740, Sep. 2022, doi: 10.1111/SRT.13194.

[7] Z. Qi, F. Wang, Y. Huang, and P. Wang, "Analysis of the correlation between skin barrier function and age in rosacea patients in Qinghai region," J Cosmet Dermatol, vol. 23, no. 3, pp. 999–1003, Mar. 2024, doi: 10.1111/jocd.16041.

[8] P. V. Chernyshov et al., "Bullying in persons with skin diseases," Journal of the European Academy of Dermatology and Venereology, vol. 38, no. 4, pp. 752–760, Apr. 2024, doi: 10.1111/jdv.19683.

[9] L. Montali and S. Garnieri, "Feeling uncomfortable in your own skin: a qualitative study of problematic skin picking in Italian women," Current Psychology, vol. 43, no. 14, pp. 12870–12881, Apr. 2024, doi: 10.1007/s12144-023-05377-4.

[10] L. Ji and X. Hongfu, "How to avoid misdiagnosis of rosacea[如何避免玫瑰痤疮的误诊]," Chinese Journal of Dermatology, vol. 57, no. 2, pp. 119–122, Feb. 2024, doi: 10.35541/cjd.20230419.

[11] Y. Peng et al., "Clinical characteristics of the well-defined upper eyelid vascular network pattern in patients with rosacea," Int J Dermatol, vol. 63, no. 3, pp. 337–344, Mar. 2024, doi: 10.1111/ijd.16946.

[12] Y. R. Woo and H. S. Kim, "Deciphering Childhood Rosacea: A Comprehensive Review," J Clin Med, vol. 13, no. 4, p. 1126, Feb. 2024, doi: 10.3390/jcm13041126.

[13] R. O. Flores-Castañeda, S. Olaya-Cotera, M. López-Porras, E. Tarmeño-Juscamaita, and O. Iparraguirre-Villanueva, "Technological advances and trends in the mining industry: a systematic review," Mineral Economics, pp. 1–16, Jul. 2024, doi: 10.1007/S13563-024-00455-W/METRICS.

[14] S. S. Noronha, M. A. Mehta, D. Garg, K. Kotecha, and A. Abraham, "Deep Learning-Based Dermatological Condition Detection: A Systematic Review With Recent Methods, Datasets, Challenges, and Future Directions," IEEE Access, vol. 11, pp. 140348–140381, 2023, doi: 10.1109/ACCESS.2023.3339635.

[15] H. Binol, M. K. K. Niazi, A. Plotner, J. Sopkovich, B. H. Kaffenberger, and M. N. Gurcan, "A multidimensional scaling and sample clustering to obtain a representative subset of training data for transfer learning-based rosacea lesion identification," Progress in Biomedical Optics and Imaging - Proceedings of SPIE, vol. 11314, p. 1131415, Jan. 2020, doi: 10.1117/12.2549392.

[16] S. R. Sahoo, R. Dash, and R. K. Mohapatra, "A customized deep learning framework for skin lesion classification using dermoscopic images," Comput Animat Virtual Worlds, vol. 34, no. 5, p. e2132, Oct. 2023, doi: 10.1002/cav.2132.

[17] H. K. Jeong, C. Park, R. Henao, and M. Kheterpal, "Deep Learning in Dermatology: A Systematic Review of Current Approaches, Outcomes, and Limitations," JID Innov, vol. 3, no. 1, p. 100150, Jan. 2023, doi: 10.1016/J.XJIDI.2022.100150.

[18] P. Tschandl et al., "Human–computer collaboration for skin cancer recognition," Nat Med, vol. 26, no. 8, pp. 1229–1234, Aug. 2020, doi: 10.1038/s41591-020-0942-0.

[19] S. K. Mathivanan, S. Sonaimuthu, S. Murugesan, H. Rajadurai, B. D. Shivahare, and M. A. Shah, "Employing deep learning and transfer learning for accurate brain tumor detection," Sci Rep, vol. 14, no. 1, p. 7232, Dec. 2024, doi: 10.1038/s41598-024-57970-7.

[20] S. Reddy, D. Giri, and R. Patel, "Artificial Intelligence-Based Distinction of Actinic Keratosis and Seborrheic Keratosis," Cureus, vol. 16, no. 4, p. e58692, Apr. 2024, doi: 10.7759/CUREUS.58692.

[21] Y. D. Balaguera Amaya, "Metodologías ágiles en el desarrollo de aplicaciones para dispositivos móviles. Estado actual," Revista de Tecnología, ISSN 1692-1399, Vol. 12, No. 2, 2013 (Ejemplar dedicado a: Transportes sustentables), págs. 111-123, vol. 12, no. 2, pp. 111–123, 2013, Accessed: Jun. 26, 2024. [Online]. Available: https://dialnet.unirioja.es/servlet/articulo?codigo=6041502&info=resumen&idioma=SPA

[22] C. Y. Zhu et al., "A Deep Learning Based Framework for Diagnosing Multiple Skin Diseases in a Clinical Environment," Front Med (Lausanne), vol. 8, p. 626369, Apr. 2021, doi: 10.3389/FMED.2021.626369/BIBTEX.

[23] H. Binol, A. Plotner, J. Sopkovich, B. Kaffenberger, M. K. K. Niazi, and M. N. Gurcan, "Ros-NET: A deep convolutional neural network for automatic identification of rosacea lesions," Skin Research and Technology, vol. 26, no. 3, pp. 413–421, 2020, doi: 10.1111/srt.12817.

[24] A. F. Sapaico-Alberto, S. Olaya-Cotera, and R. O. Flores-Castañeda, "Analysis of the use of digital technologies in the preliminary diagnosis of dermatological diseases: a systematic review," Arch Dermatol Res, vol. 317, no. 1, pp. 1–11, Dec. 2025, doi: 10.1007/S00403-024-03650-5/METRICS.