Mobile Application Based on Convolutional Neural Networks for the Initial Evaluation of Cutaneous Melanoma

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***Abstract*—Cutaneous melanoma is a dermatological disease that affects a large portion of the world's population and is characterized by its high capacity for dissemination and aggressiveness, especially when not detected early. Given this need, the objective was to develop a mobile application based on convolutional neural networks for the initial assessment of this condition. Therefore, the percentage increase in sensitivity, specificity, and accuracy was evaluated. The research employed a quantitative approach and a pre-experimental design. The study variable was the initial assessment of cutaneous melanoma. The sample consisted of 120 images: 60 images from patients with melanoma-positive and 60 images from patients with melanoma-negative. The results of the implementation showed an increase in sensitivity of 0.729%, specificity of 3.626%, and accuracy of 2.631%. In conclusion, the adoption of the mobile application based on convolutional neural networks strengthens the initial assessment of cutaneous melanoma by optimizing these indicators.**

***Keywords*—Melanoma; skin disease; convolutional neural networks; mobile app**

I. Introduction

Cutaneous melanoma presents one of the greatest challenges in the field of dermatology, particularly regarding its early and accurate identification. These difficulties are largely due to its visual resemblance to moles, leading to delayed diagnoses and, in many cases, fatal consequences. In response to this situation, a mobile application using AI and convolutional neural networks (CNNs) has been developed, demonstrating its potential as a preliminary detection method through images.

Melanoma originates from the melanocytes of the skin [1]. It is one of the few cancerous tumors with an increasing incidence; however, its mortality rate has decreased dramatically with effective systemic therapy [2]. The most common type of melanoma develops in the skin [3]. It is associated with skin pigmentation factors. Some people have atypical melanocytes that act as a genetic initiator of malignant mutations, and the sun is a frequent trigger [4].

The morphological and histopathological characteristics of this condition allow us to classify it into four main types: superficial spreading melanoma, nodular melanoma, acral lentiginous melanoma, and lentigo maligna [5]. If detected early, it can be effectively treated through a local incision. However, for some specialists, the accurate identification of melanoma from skin lesions can be challenging. The most commonly used techniques are visual inspection, medical history, dermatoscopic analysis, biopsy, and histological evolution [6]. Furthermore, metastatic melanomas exhibit a wide variety of clinical and morphological characteristics [7].

Regarding age distribution, the epidemiological data indicate that cutaneous melanoma has a significantly lower incidence in the adolescent and young adult population, specifically between 15 and 39 years of age. On the other hand, the highest concentration is found in individuals over 50 years of age [8].

The rising incidence of skin melanoma and the need for accessible early detection are driving the development of efficient technological solutions. In this context, we propose a mobile application based on convolutional neural networks for the initial assessment of melanoma using skin images. Unlike traditional approaches, this work explicitly addresses the challenges of implementing artificial intelligence models on mobile devices, including reducing inference latency, optimizing computational resource consumption, and preserving user privacy through local data processing. The system is based on the automatic recognition of visual patterns associated with melanoma and has been designed with a focus on key metrics such as sensitivity, specificity, and accuracy. Thus, the proposal not only contributes to the field of assisted diagnosis but also introduces a viable and efficient solution for deployment in real-world mobile environments.

The research is organized as follows: Part II presents related works, Part III applies the methodology, Part IV presents the results, Part V presents the discussion, and Part VI presents the study's conclusions.

II. Related Works

A study was conducted [9]on the development and evaluation of a convolutional neural network for detecting invasive cutaneous melanoma in histological slide images, using tumor morphology as a key criterion. After training their model with 1068 slide images of this condition, the results showed high efficiency in locating conventional invasive melanoma tissue, achieving a sensitivity of 97.59% and a specificity of 99.86%. Furthermore, [10] they conducted a pilot study to determine the accuracy of a convolutional neural network, previously trained on Swedish data records, in predicting the risk of invasive cutaneous melanoma over 5 years. This algorithm was evaluated in a cohort of 36,866 individuals and was structured in two stages: the first stage involved low-level feature extraction using CRN, while the second stage involved high-level feature extraction. This approach resulted in an accuracy of 97.92% and

98.86% in the first and second stages, respectively, demonstrating the significant potential of machine learning.

To mitigate the problem of data imbalance in dermatological image sets, [11] they implemented the MSLP-MR method, which is based on MASK R-CNN for the synthetic generation of images of various skin lesions. This procedure used MASK R-CNN to integrate mask segmentation and enhance expected learning. ISIC data was used, and the method proved to be effective and viable, achieving an accuracy of 90.61%, a sensitivity of 78.00%, and a specificity of 93.43%. These results establish a level of performance comparable to the visual diagnosis performed by medical specialists. The successful implementation of an artificial intelligence (AI)-based imaging system requires, according to [reference missing] [12], a robust structure that does not compromise the diagnosis in the face of image variations. The central objective of their research was to quantify the degree to which small image perturbations impact the performance of convolutional neural networks applied to lesions and to propose possible strategies to mitigate this effect.

Given the increasing integration of AI into clinical practice, [13] the authors highlight the need for further research aimed at streamlining the process, improving efficiency, and increasing the accuracy of lymph node (LN) detection for cutaneous melanoma. To facilitate this process, test data were stored on a cloud platform specifically designed for AI-assisted pathology. This research developed and trained an AI-powered model to detect metastases directly from images and classify tumor deposits according to their size. The results indicated that the AI algorithm demonstrated high accuracy in detecting LN metastases in melanoma patients, effectively identifying and classifying tumor deposits with high specificity.

Additionally, [14] they proposed the design and development of a mobile application based on Convolutional Neural Networks (CNNs) to provide an initial assessment of cutaneous melanoma. The use of images captured directly by the user makes this solution particularly valuable for facilitating early detection in the general population or in vulnerable groups with limited access to healthcare services. Despite its user-focused design, the research demonstrated the effectiveness of CNNs in detecting cutaneous melanoma with an accuracy comparable to that observed in specialized clinical settings.

Convolutional neural networks (CNNs) constitute a paradigm for processing complex data whose architecture is inspired by the biological functionality of neurons and human senses [15]. A distinctive feature of CNNs is their wide application in diverse fields, including image classification, object recognition, and the development of computer-aided diagnostics [16].

On the other hand, [17] a research project was undertaken to address the need for early detection. The main objective was to develop a mobile application based on convolutional neural networks to optimize the initial assessment of rosacea, achieving results of 94% sensitivity, 98% specificity, and 96% accuracy. A mobile application is defined as a type of software specifically designed to run on smartphones and other mobile devices [18]. Currently, there is a marked need to develop intelligent applications due to the growing user demand for advanced functionalities. [19]In the healthcare context, the integration of these applications is advantageous due to their potential for easy scalability, meaning they are simple to use and have low maintenance and staff training costs [20].

III. Methodology

The methodology applied in this research was a quantitative approach with a pre-experimental design, focusing on the application of existing AI techniques in the development of a mobile application for the initial diagnosis of cutaneous melanoma. The pre-experimental design aimed to demonstrate that the dependent variable (a mobile application based on convolutional neural networks) can generate an initial diagnosis of cutaneous melanoma. The study population consisted of images obtained from free repositories such as PAD-UFES-20 and ISIC. For sampling and subsequent evaluation, images of patients with and without a diagnosis of cutaneous melanoma were included. Data collection was carried out through observation, while data analysis was based on the calculation of key metrics such as sensitivity, specificity, and accuracy. Additionally, the Receiver Operating Characteristic (ROC) curve was used to evaluate the overall performance of the system, illustrating the relationship between the true positive rate and the false positive rate at different decision thresholds.

A. Case Development

The Mobile-D methodology was chosen, an optimal and agile framework specifically designed for the creation and/or development of mobile applications. This framework allowed us to address the main needs of this study by integrating best practices with software engineering principles. The test set consisted of 120 images: 60 positive and 60 negative. The phases of this Mobile-D methodology are specified below.

B. Phase 1: Exploration

This initial stage focused on research, in-depth knowledge, and strategic formulation to establish the essential characteristics of the project, which translates to capturing the requirements. [21] priority was given to understanding the core problem in order to clearly define the specific functionalities that a mobile application should incorporate to perform the preliminary detection of cutaneous melanoma.

1) Definition: Develop a mobile application with convolutional neural networks for the initial evaluation of cutaneous melanoma.

2) Set of functional requirements: The key functional requirements that will define the core capabilities of our application are identified. (See Table I)

TABLE. I. Functional Requirements

Requirements	Description of requirements
RF01	The system must allow user registration and authentication.
RF02	The application should provide truthful information about cutaneous melanoma and offer suggestions.
RF03	The application should display instructions for taking photos clearly and correctly.
RF04	The user will be able to take a photo or upload images from their mobile gallery for analysis.

RF05	The result of the analysis should be visualized clearly and concisely with the probability of the evaluation.
RF06	The application must generate reports that show the results of the evaluated images.
RF07	The application must display metrics and indicators through reports.
RF08	The system should have a tab or section that shows information about the application, who created it, its purpose, and context.

C. Phase 2: Initialization

In this stage, the development team focuses on identifying the system architecture, creating the initial design, and preparing the necessary technological resources, as well as assigning roles and structuring the team [22]. The primary objective of this phase is to generate a basic, functional version of the application that allows for early validation of the initial hypothesis against user expectations and requirements.

1) Hardware environment configuration: Intel i5 11th generation laptop, an i5 13th generation laptop, and a mobile device (cell phone)

Software: Android Studio IDE, Visual Code, Firebase and TensorFlow.

2) Flowchart of the CNN-based application process: Fig. 1 shows the flowchart of the mobile application based on convolutional neural networks (CNNs) for the initial detection of cutaneous melanoma. This process begins with image capture, which can be taken with the phone's camera or uploaded from the gallery. These images undergo an in-depth process of identifying cutaneous melanoma characteristics and are then fitted to the validation set. This is followed by evaluation by the architecture using the test set. Once implemented and optimized, the model is integrated into the app, classifies the images, and stores the results, providing a preliminary diagnosis.

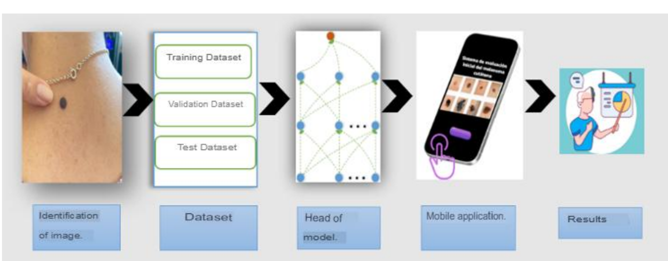

Fig. 1. MelanoCheck application workflow diagram based on CNN.

a) Application architecture diagram: The mobile application was developed using Android Studio software, working in conjunction with TensorFlow for image segmentation and classification, and Firebase as the database engine. Training was performed using Google Colab and Python, along with model tuning for classification. Java handled the logic in the mobile application. (See Fig. 2).

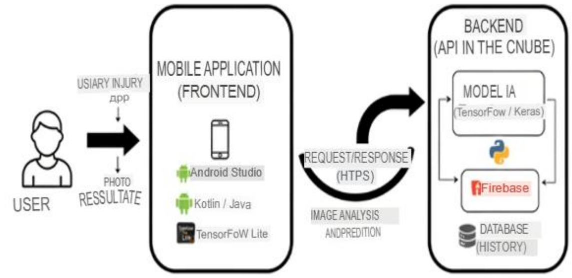

Fig. 2. Mobile application architecture diagram.

3) Project structure: The project structure in Android Studio follows a hierarchical structure to facilitate code management. It begins with the application configuration file, followed by the source code directory containing the logic, then the folders responsible for resource storage, and finally the deep learning file in TensorFlow format. (See Fig. 3).

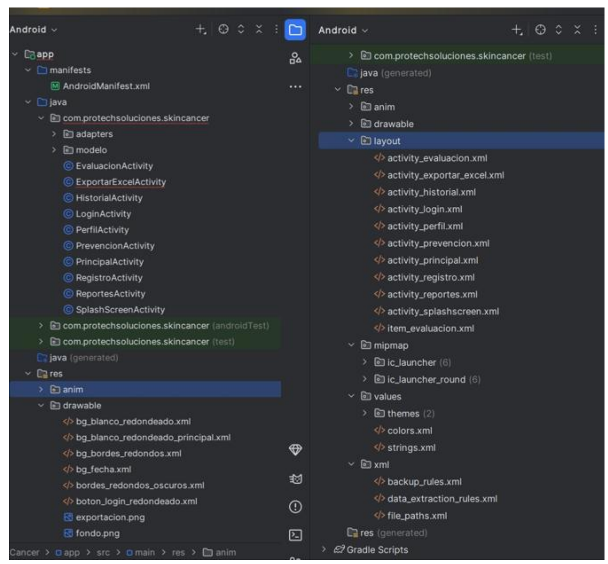

Fig. 3. Project structure in Android.

D. Phase 3: Production

During this phase, the development team works with an incremental and iterative approach, aiming to implement all features in the progressive delivery of mobile application versions. This ensures the software's evolution and allows for testing and adjustments (see Table II).

TABLE. II. MODULE

Module	Code	Process	Request
User Account Management Module	M01	"Registration" and "Login" process, allowing you to log in and save your data.	RF01, RF02, RF03 Y RF04
Information module in the user profile	M02	Process where the user should be able to view their profile data (Names, Email, Cell Phone, etc.)	RF05, RF06 Y RF07

Assessment Module	M03	Process where the system must allow the user to start an evaluation where the results of the analysis must be displayed	RF08, RF09, RF10, RF11, RF12 Y RF13
Information and prevention module on cutaneous melanoma	M04	Process where information on the prevention of cutaneous melanoma is displayed.	RF1 Y RF15
Reporting Module	M05	Process of filtering evaluation history by a date range	RF16, RF17 Y RF18
Assessment History Module	M06	The system must show the user a chronological list of all the evaluations they have performed.	RF19 Y RF20
Export Generation Module	M07	Process of exporting the evaluation history.	RF21

E. Stabilization

Tests were carried out, and errors were corrected, optimizing performance and guaranteeing the quality of the application before its launch.

1) Recommendations for mobile devices: It is recommended to use a mobile device with sufficient storage space and a good internet connection to maintain communication and synchronization with data in the cloud (see Table III).

TABLE. III. RECOMMENDATIONS FOR THE USE OF MOBILE DEVICES

HARDWARE	Characteristics
RAM Memory:	A minimum of 4 GB of RAM is recommended for smooth operation.
Camera:	The device must have a functional camera (rear or front) to use the Evaluation module.
SOFTWARE	Characteristics
Operating System:	Android 8.0 or higher.
Internet connection	Network: 4G

F. Tests

This phase involves the final validation of the mobile application under real-world usage conditions. A detailed inspection is performed to ensure functionality and compliance with the requirements established during the exploration phase.

1) Unit Test 03: Assessment module: The unit test is displayed in the assessment module (See Table IV).

TABLE. IV. TEST RESULTS DISPLAY

CODE	DESCRIPTION
M03	Assessment module
AIM	The application allows verification of the complete evaluation flow, including capture, analysis of the CNN model, and presentation of results.
STEPS	• Go to the "Evaluation" module. • Select an image from the gallery to take a photo • The application evaluates and displays the result
RESULTS OBTAINED	The user receives the result correctly; if the evaluation is "POSITIVE", with a probability of >= 45.99, the application will display the message: "...GO TO A SPECIALIZED CENTER". Otherwise, if it is negative, the message " ... (NEGATIVE)" will be displayed.

IV. RESULTS

This research focuses on evaluating the extent to which a mobile application, using convolutional neural networks, increases the effectiveness and accuracy of the initial diagnosis of cutaneous melanoma.

A. Calculation of Indicators

The results of validation tests, performed to evaluate the system's sensitivity, specificity, and accuracy indicators, are presented. For this analysis, a controlled set of 120 images was used, selected to analyze the mobile application's accuracy and behavior under standardized conditions. Specifically, the calculation and analysis of the indicators were performed on a balanced test set of 120 images, evenly divided into 60 positive images (malignant diagnosis) and 60 negative images (benign diagnosis) for the CNN model's binary classification task (see Table V).

TABLE. V. CONFUSION MATRIX

	CNN MODEL TEST			
	SENSITIVITY	SPECIFICITY	TOTALS	PILOT TEST
	RESULTS. PEOPLE WITH MELANOMA	RESULT. PEOPLE WITHOUT MELANOMA		
+ MALIGNANT	58	1	59	0.9667
NEGATIVE BENIGNO	2	59	61	0.9833
TOTALS	**60**	**60**	**120**	
PILOT TEST	0.97	0.98		0.97

The following results were obtained from the confusion matrix analysis:

Sensitivity = 97%

Specificity = 98%

Accuracy = 97%

1) Analysis of the ROC curve and the area under the curve (AUC): Fig. 4 shows the Receiver Operating Characteristic (ROC) curve of the CNN model, which was generated by evaluating a test set of 120 images. This graph is a standard tool for evaluating the performance of a binary classifier because it visualizes the balance between the sensitivity and specificity of the trained model.

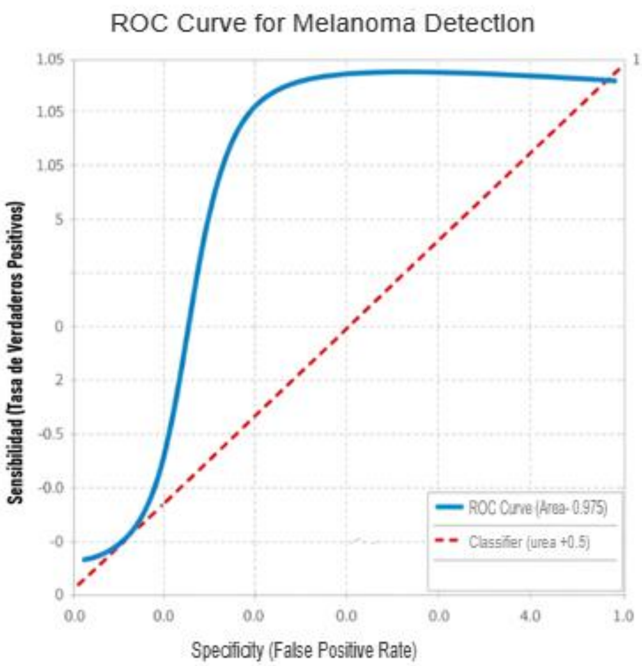

Fig. 4. ROC curve.

The AUC value is 0.975, indicating that the application has a 97.5% accuracy in correctly classifying positive (melanoma) and negative (benign) cases. This value, so close to 1.0, validates that the model is an excellent and robust classifier. (See Table VI)

TABLE. VI. AREA UNDER THE CURVE

Area	Error Deviation	Asymptotic significance	95% asymptotic confidence interval	
			lower limit	upper limit
,985	,013	,000	,960	1,000

B. Analysis of the Pre-Experimental Design

1) Pre-test: The accuracy, sensitivity, and specificity values of the EfficientNet-b4 model for various dermatological diseases were compared with the values for melanocytic nevus from the respective mobile application model [23] (see Table VII).

TABLE. VII. PRE-TEST RESULTS

MODEL	**Pink (%)**	**VW (%)**	**EAD (%)**	**SD(%)**	**SK (%)**	**MN (%)**	**Pso (%)**	**BCC (%)**
Sensitivity	92.00	92.00	84.00	48.00	76.00	**96.00**	92.00	88.00
Specificity	92.57	95.43	88.57	91.43	96.00	**94.86**	94.29	99.43
Accuracy	92.50	95.00	88.00	86.00	93.50	**95.00**	94.00	98.00

2) Post-test: In this case, the post-test was carried out with Images from the dataset, from which the detailed report was obtained by the mobile application. Table VIII shows the percentages of the indicators.

TABLE. VIII. INDICATOR RESULTS

TOTAL	**VP**	**VN**	**FN**	**FP**	**% SENSITIVITY**	**% SPECIFICITY**	**% ACCURACY**
120	58	59	2	1	97%	98%	97%

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

TABLE. IX. COMPARISON OF RESULTS

INDICATOR	**EFFICIENTNET-B4**	**APPLICATION NEURAL NETWORK**
SENSITIVITY	96.00%	97.00%
SPECIFICITY	94.86%	98.00%
ACCURACY	95.00%	97.00%

C. Hypothesis Testing

1) Specific Hypothesis HE1

HE 1(0): A mobile application using convolutional neural networks failed to increase sensitivity in the initial assessment of cutaneous melanoma.

HE1(1): A mobile application using convolutional neural networks succeeded in increasing sensitivity in the initial assessment of cutaneous melanoma.

% Sensitivity variation = (96.7-96) / 96 X 100 = 0.729 %

An increase in sensitivity was found in the percentage variant, obtaining a positive result of 0.729%; therefore, the alternative hypothesis is accepted, and the null hypothesis is discarded.

2) Specific Hypothesis HE2:

HE2(0): A mobile application using convolutional neural networks failed to increase specificity in the initial assessment of cutaneous melanoma.

HE2(1): A mobile application using convolutional neural networks succeeded in increasing the specificity in the initial assessment of cutaneous melanoma.

% Variation in specificity = (98.3-94.86) / 94.86 X 100 = 3.626 %

An increase in specificity was found in the percentage variant, obtaining a positive result of 3.626%; therefore, the alternative hypothesis is accepted, and the null hypothesis is discarded.

3) Specific Hypothesis HES3:

HE3(0): A mobile application using convolutional neural networks failed to increase accuracy in the initial assessment of cutaneous melanoma.

HE3(1): A mobile application using convolutional neural networks succeeded in increasing the accuracy in the initial assessment of cutaneous melanoma.

% Accuracy variation = (97.5-95) / 95 X 100 = 2.631 %

An increase in accuracy was found in the percentage variant, yielding a positive result of 2.631%. Therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

D. Results of the Indicator Increases

Table X shows the percentage increase per indicator (positive numbers) at which the null hypothesis is rejected, and the alternative hypothesis is accepted.

TABLE. X. RESULTS OF INCREASES BY INDICATOR

INCREASED SENSITIVITY	INCREASED SPECIFICITY	INCREASED ACCURACY
0.73%	3.63%	2.63%

E. General Hypothesis

HG (0): A mobile application using convolutional neural networks does not improve diagnosis in the initial evaluation of cutaneous melanoma.

HG(1): A mobile application using convolutional neural networks improves diagnosis in the initial evaluation of cutaneous melanoma.

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

V. DISCUSSION

This section is dedicated to a detailed and in-depth interpretation of the mobile application validation results. The analysis seeks to determine the efficiency of the proposed approach, based on convolutional neural networks, for the initial diagnosis of cutaneous melanoma using technological tools. The discussion focuses on the performance of key indicators (sensitivity, specificity, and accuracy). Furthermore, a critical interpretation of our previous findings in the scientific literature is presented, allowing us to situate the contribution of this research.

The first specific objective was to evaluate the extent to which a mobile application based on convolutional neural networks increases the sensitivity of the initial assessment of cutaneous melanoma. The results show 97% sensitivity, attributed to the use of modern and robust CNN architectures, allowing for accurate feature extraction. This result is slightly lower than the 97.59% obtained by [9] who used a patch-based architecture for invasive melanoma recognition.

Regarding the second specific objective, to evaluate the extent to which a mobile application based on convolutional neural networks increases specificity, a specificity of 98% was obtained, showing an increase of 3.63%. This significant increase is attributed to image processing techniques and the increase in data, significantly improving the model's ability to reduce false positives. The performance exceeds the 93.43% achieved by [11]; this difference is attributed to the learning concept, methodology, and data used.

On the other hand, the third specific objective was to evaluate the extent to which a mobile application based on convolutional neural networks increases the initial accuracy of cutaneous melanoma diagnosis. This result, derived from optimized model training, surpasses the 90.61% achieved by [11]. The superiority of our approach stems from the limitations of [11], whose MASK R-CNN method was affected by image variability. However, the result obtained is slightly lower than that of [10], who reported 97.92% and 98.86% accuracy, as they applied two phases using five years of Swedish data, whose images included 23,866 individuals, applying both low- and high-level features.

Regarding the research of [17], it also used the same convolutional neural network model to be able to preliminarily evaluate rosacea, obtaining a sensitivity of 94%, a specificity of 98% and an accuracy of 96%, results very close to the mobile application developed, but it did not manage to surpass our results, but it does not show the efficiency and confirms that the use of the CNN achieves technological advances on a large scale.

The main objective is to evaluate how a mobile application based on convolutional neural networks (CNNs) improves the initial assessment of cutaneous melanoma. The increase in sensitivity, specificity, and accuracy (post-test) validates the application's effectiveness. This aligns with several studies demonstrating how CNNs enhance dermatological diagnosis. In fact, [24] it reaffirms the importance of image processing, demonstrating the significance of CNNs in the development of medical diagnostics.

VI. CONCLUSION

The mobile application developed, based on convolutional neural networks, shows promising results for the initial assessment of cutaneous melanoma, with a sensitivity of 97%, a specificity of 98%, and an overall accuracy of 97%. These results suggest that the model is capable of adequately distinguishing between positive and negative cases in the evaluated dataset, which could contribute to reducing false negatives and enabling more efficient preliminary detection. The performance achieved can be attributed to the model’s architecture and the use of data augmentation techniques during training.

However, these findings should be interpreted with caution, as the evaluation was conducted under specific conditions and with a limited dataset, which may affect the model’s generalizability in real-world clinical settings. Furthermore, the study did not incorporate additional metrics such as the F1 score or inference time assessments, which are relevant for a more comprehensive comparison with other approaches.

Among the system's limitations is the absence of user feedback mechanisms, which hinders the model's continuous improvement based on its use in real-world scenarios. Consequently, future work should consider validation with more diverse datasets, the incorporation of additional evaluation metrics, and the analysis of real-time performance on mobile devices, to strengthen the system's practical applicability.

As future work, we propose expanding the validation of the model using more diverse datasets to improve its generalization. We also suggest incorporating additional metrics such as the F1 score, along with an analysis of inference time and resource consumption on mobile devices. We also propose exploring hybrid approaches that integrate multiple architectures to increase the system's robustness, as well as optimizing the model using compression techniques that reduce latency and energy consumption. Finally, we consider incorporating user feedback mechanisms and multilingual support to improve usability and adoption.

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