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Classification Model of Skin Cancer Using Convolutional Neural Network

Hugo Vega-Huerta[1], Manuel Rivera-Obregón[1], Gisella Luisa Elena Maquen-Niño[2*], Percy De-la-Cruz-VdV[1], Juan Carlos Lázaro-Guillermo[3], Jorge Pantoja-Collantes[1], Adegundo Cámara-Figueroa[1]

[1] Department of Computer Science, Universidad Nacional Mayor de San Marcos (UNMSM), Lima 15081, Peru
[2] Department of Electronics and Computing, Universidad Nacional Pedro Ruiz Gallo (UNPRG), Lambayeque 14013, Peru
[3] Department of Basic Sciences, Universidad Nacional Intercultural de la Amazonia (UNIA), Ucayali 25004, Peru

Corresponding Author Email: gmaquenn@unprg.edu.pe

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ABSTRACT

Skin cancer is a major health problem worldwide, with China and India being the most affected, according to the Global Cancer Observatory (GCO). In Peru, skin cancer is the fourth most frequent cancer. Its seriousness underscores the importance of early detection, a key factor in improving survival rates and optimizing treatment outcomes. To address this problem, an innovative method is being applied that leverages artificial intelligence to examine skin-related medical images. The main objective of the model is to identify the presence of cancer and categorize the specific type detected. This study employs a machine learning methodology, centered on the use of CNNs along with data augmentation and transformation techniques. The ISIC - 2019, is the dataset comprising 2357 dermatoscopic images, strategically chosen to bolster performance metrics and strengthen the overall resilience of the model. The result of this innovative approach is a remarkable 94% accuracy rate, accompanied by a test loss of 16%. By leveraging advanced technologies such as CNNs and incorporating extensive data sets, this research not only contributes to the field of medical imaging, but also represents a substantial advance in the field of skin cancer diagnosis.

1. INTRODUCTION

Cancer is a worldwide health problem, not only because of its high incidence and mortality rates, but also because of the high social cost it represents for each country. The General Directorate of Epidemiology (DGE) of Peru has conducted an investigation of the cancer statistics in this country based on the epidemiological surveillance of cancer, finding that in the period 2006 – 2010, with 5975 cases of skin cancer registered, representing 6.6% of all cancers registered. According to this report, skin cancer ranks fourth in frequency at the national level [1].

Furthermore, in the period 2014 - 2018 the most frequent types of cancer globally were those of the cervix (18.6%), stomach (11.1%) and skin (10.8%) [2]. Skin cancer has been increasing in recent decades, mainly due to population aging and exposure to ultraviolet (UV) radiation, changes in human behavior and ozone depletion [3]. According to the International Agency for Research on Cancer (IARC) in 2022 there were more than 1.5 million new cases of cancer and approximately 330,000 cases of melanoma cancer, the most dangerous type of skin cancer [4].

The skin cancer was the most frequently diagnosed cancer in Metropolitan Lima, also in several coastal regions it is the second in frequency [2].

Three categories of skin cancer include “basal cell carcinoma”, “squamous cell carcinoma”, and “melanoma” [5], however, in our article, we classified skin lesions into 9 types, which will be described later.

Traditional methods of skin cancer detection, which include visual inspection and biopsies, have problems with regard to accuracy and accessibility, relying heavily on the expertise of the dermatologist which poses an obstacle to many regions where there is little access to trained specialists. Although machine learning has emerged as an alternative detection method, it faces limitations related to the diversity of data used to train it, as well as acceptance by healthcare professionals and patients [6].

This article outlines the creation and structure of an AI model employing convolutional neural networks for analyzing skin medical images. Its purpose is to identify and classify cancer types among those mentioned based on the detected abnormalities. Deep neural networks demonstrate remarkable capabilities in facilitating efficient planning optimization and proficiently addressing a diverse spectrum of problem-solving scenarios [7-9].

The most important factor for the success of an application is the optimal organization of its data [10-16].

2. RELATED WORKS

Early identification of skin and oral cancers is vital for effective therapy. Increasingly, machine learning technologies are being utilized in computer-aided clinical diagnosis, with evidence suggesting their effectiveness. These technologies encompass models and algorithms capable of learning from data, enabling them to generate predictions for previously unseen data, thereby contributing to improved early detection in the cases of these prevalent cancers [17, 18].

In recent years, the widespread adoption of Information and Communication Technologies (ICT), particularly accelerated during the COVID-19 pandemic, has revolutionized various sectors, including healthcare. A study conducted on university professors in Peru demonstrated a significant increase in the use of ICT tools during the pandemic, highlighting the broader trend of digital migration across disciplines, including medical fields. This shift has fostered advancements in medical imaging and AI, which form the foundation of our work on skin cancer classification using convolutional neural networks (CNNs). Similarly, machine learning techniques have been successfully applied in different domains, such as predicting student dropouts using decision trees [19], underscoring the versatility and potential of AI in predictive and classification tasks.

Studies show AI/ML algorithms can assist clinicians, enhancing clinical decisions and, in certain instances, potentially replacing human judgment [20].

Sophisticated learning techniques demonstrate promise in precisely detecting these cancers using "Computer-Aided Cancer Detection" (CAD) and medical imaging [21].

Table 1 outlines selected research articles. The papers were sourced from Science Direct, Web of Science, and Scholar Google, focusing on skin cancer classification. In refining the search, exclusion and inclusion criteria were applied to enhance precision:

Studies on skin cancer image identification.

Utilizing CNN-based models or key elements within CNN architectures.

Metrics: precision, accuracy, sensitivity, specificity, and/or AUC, to measure the effectiveness in medical diagnosis.

Publications produced between 2019 and 2023.

Publications in English and Spanish.

Table 1. Current overview of skin classification in related works

Art.	Dataset	Architecture	Methods	ACC	AUC
[21]	HAM10000 Oral Cancer Dataset	AlexNet VGGNet ResNet DenseNet	Image Resizing, Normalization, Filtering and Segmentation Data Augmentation Feature Extraction	92.85	-
[22]	ISBI 2016	DenseNet-201 MobileNet	Data Augmentation	88.02	-
[23]	ISIC	VGG16 ResNet InceptionV3	ISR with GAN	91.26	-
[24]	Original (Raman spectra)	Custom CNN	PLS-DA	-	96
[25]	ISIC	Custom-3-layer CNN VGG-16 Inception-V3	Data Augmentation Feature Scaling Min-Max Normalization Re-scaling	81	87.7
[26]	HAM10000	Custom Sequential CNN	Resizing	94.06	-
[27]	HAM10000 ISIC 2019	DenseNet-201 Inception-ResNet-V2 Inception-V3	Data Augmentation	98	-
[28]	ISIC 2019	Custom Sequential CNN	Wiener Filtering Segmentation Feature Extraction	99.9	-
[19]	SIIM-ISIC	Efficient Net B4, B5, B6 Inception V3 ResNet 50, VGG-19	Data Augmentation K-fold	92.85	

In Table 1, the most commonly used datasets in the cited research are HAM10000 (2 studies), ISIC (2 studies), ISIC 2019 (1 study), as well as HAM10000 and ISIC 2019 working together.

Regarding architecture, excluding versions, it is evident that the most utilized transfer learning model architectures are VGG (4 studies) and ResNet (4 studies).

Regarding architecture, excluding versions, it is evident that the most utilized transfer learning model architectures are VGG (4 studies) and ResNet (4 studies).

Concerning the most employed method for image processing, Data Augmentation stands out with 5 studies.

Concerning the accuracy, which is the metric used for evaluating model performance, it can be seen that 6 studies achieved values higher than 0.90, with 2 studies obtaining values surpassing 0.95. One study even reached an accuracy of 0.99. While accuracy indicates the number of correct predictions by the model, it is also essential to consider other metrics such as sensitivity and f1-score to complement the obtained results.

This scientific paper seeks to fill a scientific knowledge gap in multicategorial skin cancer classification through a robust solution using Deep Learning with a personalized convolutional neural network and data preprocessing techniques such as data augmentation, which has brought improvements in the accuracy of multicategorial classification, an area that has been a challenge in previous studies. The use of regularization layers within neural network models is a good practice that has been taken into account in this research and has yielded favorable results [29].

Compared to other research using deep learning algorithms, this study demonstrates excellent performance in the classification of certain categories such as Vascular lesion, Dermatofibroma and Squamous cell carcinoma reaching accuracies of 99 and 100% which represents a key contribution in this field. In previous research, deep learning-based models have been shown to be more effective than traditional machine learning algorithms but still have limitations in melanoma detection and multi-categorical classification [25, 30].

There are also investigations that have used pre-trained models to improve the robustness of the model, but nevertheless the accuracy values are less than 90% [22]. In this sense, the approach of convolutional neural networks, data augmentation and regularization layers have allowed to offer a model with good accuracy for multicategorial classification skin cancer.

3. PROPOSAL DESIGN

3.1 ISIC dataset

The "International Skin Imaging Collaboration" (ISIC) have a public dataset (2019), to comprises dermoscopic images with "normal" and "skin cancer". It was created to gather skin lesion images under Creative Commons licenses, featuring reference diagnoses and additional clinical metadata for comprehensive use [31]. This dataset was used for the SIIM-ISIC 2020 melanoma classification challenge, organized in Kaggle during the summer of 2020.

The Kaggle dataset of 2019 contains 2357 dermoscopic images of different skin lesions classified into 9 types [32]:

"Actinic keratosis" (130 images)
"Basal cell carcinoma" (392 images)
"Dermatofibroma" (111 images)
"Melanoma" (454 images)
"Nevus" (373 images)
"Pigmented benign keratosis" (478 images)
"Seborrheic keratosis" (80 images)
"Squamous cell carcinoma" (197 images)
"Vascular lesion" (142 images)

This dataset presents an imbalance in the number of samples per class, which may bias the model towards those classes with more images, such as "Pigmented benign keratosis" or "Basal cell carcinoma", and affect the performance in less represented classes, such as "Seborrheic keratosis" or "Dermatofibroma". To mitigate this problem, it was deemed necessary to apply data augmentation techniques, which generate new instances and balance the distribution of classes. This improves the ability of the model to generalize and correctly recognize lesions across categories [33]. Then, the size of the images was then set to 180×180 pixels, as this is large enough to capture important details, but not so large that the training would be too slow.

3.2 Pre-processing

The ISIC dataset provides a diverse collection of dermatoscopic images, classifying skin lesions into nine distinct types. Each type represents a specific pathology, allowing for a comprehensive analysis of various dermatologic conditions.

To improve the performance of the model in the classification of these images, it was considered necessary to apply data augmentation techniques. These techniques are essential when working with reduced data sets, since they allow the generation of new samples from the original images, thus increasing the volume of available data. In this way, the distribution of classes is balanced, thus improving the accuracy and robustness of the model [33].

In this project, rotations, cropping and scaling were implemented as key transformations to increase image variability. Image rotation allows the model to learn to recognize skin lesions in different orientations, which is critical in medical image analysis where lesions can appear in various positions. Cropping helps the model to recognize key features of lesions, even when they are not perfectly centered or when parts of the image are not visible. On the other hand, scaling allows the model to identify lesions of different sizes, simulating variations in distance or field of view, which is particularly useful when using images captured with different devices or under varying conditions.

Previous studies have shown that these techniques improve the model's ability to correctly identify malignant lesions [5, 22, 25].

Therefore, these data augmentation techniques have proven to be effective in improving the generalization capacity of the model in image classification tasks. Thanks to these transformations, we were able to increase the dataset to 1000 images per class, reaching a total of 9000 images. This not only improves the distribution of classes, but also provides a greater diversity of images to train the model, making it more robust and reliable in the classification task.

3.3 Training and testing strategy

In this project, the training and testing split was 80 and 20 respectively of the developed classification modules, based on the assumption of "Pareto's Law" referred by Bustamante [34], where the small proportion (20%) are vital while the remaining (80%) are trivial [19].

As mentioned, rotations, cropping and scaling were applied as transformations, resulting in an increase to 1000 images for each class. The result was a total of 9000 images.

Table 2 presents the proposed distribution for the dataset of ISIC and Table 3 shows the segmentation of the images after data augmentation.

Table 2. Images processed per operation (training and testing) in each instance [19]

Process	Number of Images
"Training" (80%)	1886
"Testing" (20%)	471
Total (100%)	2357

Table 3. Quantity of images per operation post data augmentation [19]

Process	Number of Images
"Training" (80%)	7200
"Testing" (20%)	1800
Total (100%)	9000

3.4 Design and development

In designing the convolutional neural network (CNN) model for this study, we followed an architecture inspired by previous work on skin cancer classification using deep learning techniques. Our CNN includes an input layer for image data, followed by multiple normalization and convolutional layers, each accompanied by clustering layers to reduce dimensionality, and concluded with two fully connected layers. The first dense layer uses ReLU activation, and the final layer applies softmax activation for classification. This architecture is similar to those used by some researches [23, 26, 27], who have successfully applied CNN models for medical image classification tasks, demonstrating the effectiveness of deep learning in skin cancer detection using image analysis.

The graph provided by Figure 1 details the development flow of the proposed convolutional neural network (CNN) model. This sequence spans from the initial stages of data collection to the final phase of model analysis.

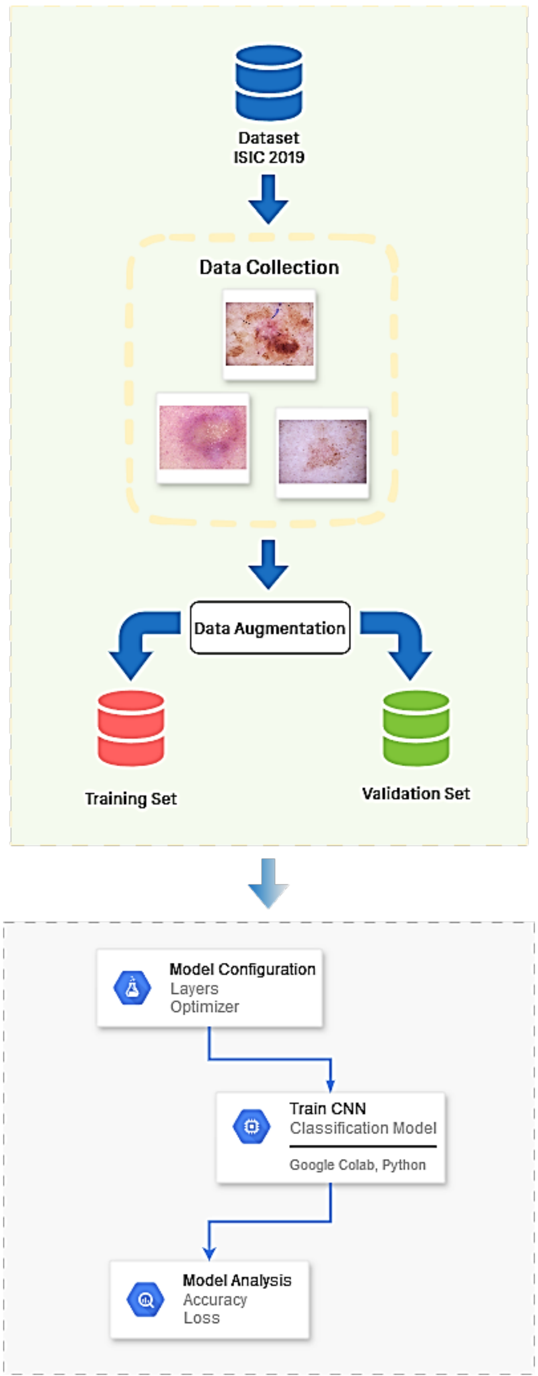

Figure 1. CNN development process

The procedure initiates by identifying data for model training and testing, followed by data augmentation and preparation. Following the steps of another study [7], it is divided into validation and training sets, organized into folders for each class, and efficiently managed in a Google Drive repository.

As we advance in the diagram, we observe the configuration of the layers of the convolutional neural network (Table 4).

Table 4. Layers of the sequential model [19]

Layer	Value
Normalization Layer (Rescaling)	Input: (180,180,3)
Convolutional Layer (Conv2D)	Activation: ReLU
Pooling Layer (MaxPooling2D)	2×2
Dropout Layer	First: 0.15, Second: 0.2, Third: 0.25
Flatten Layer	--
Dense Layer	First: activation ReLU, Second: activation softmax

The structure consists of 19 layers, with the initial Rescaling layer normalizing image pixel values to the [0, 1] range and the images are 180 × 180 pixels and have 3 color channels (RGB) as can be seen in Table 4.

The network consists of convolution layers, each with ReLU activation, and pooling layers utilizing a 2 × 2 pooling window. This pairing (convolution layer – pooling layer) is repeated six times. Filter counts increase progressively from 16 in the first convolution layer to 512 in the sixth. Following the last three convolution layers, dropout layers are applied for regularization. Following is the flattening layer, which transforms the output into a one-dimensional vector for readiness for the dense layers. Next, two consecutive dense layers are employed: the initial layer shows 1024 neurons with ReLU activation, and the subsequent layer shows 9 neurons, representing the number of classes, with a softmax activation function. This function transforms outputs into probabilities, assigning a likelihood to each class, with the highest probability determining the model's prediction [35].

The convolutional neural network will use optimizers that allow improving its prediction level, as shown in Table 5.

Table 5. Optimizer setting

Feature	Value
“Optimizer”	Adam
“Learning Rate”	0.001
“Epsilon”	1e-07

Table 6. Parameters setting for the training

Parameter	Value
“Input Layer”	(180,180,3)
“Epochs”	25
“Optimizer”	Adam
“Loss Function”	Sparse Categorical Cross-Entropy
“Metrics”	Accuracy

The next stage of the figure shows us the training of the model. Table 6 details the parameters for training this model. Where the train and validation data are those found in the validation and training set resulting from the division of the set of images after the data augmentation. Training is performed for 25 epochs, and in each epoch, a number of steps are taken equal to the length of the training and validation data sets, respectively.

Finally, the last stage of the figure refers to the analysis of the model where the training and validation accuracy and loss are analyzed. To improve visualization, line graphs were used.

Just as other study [7], the development of the model was done in Google Colab, using Python 3, keras of Tensorflow, numpy, matplotlib, pandas, seaborn and Data augmentation libraries.

4. RESULTS

In this segment, the developed model's performance is assessed, employing accuracy as the primary metric. This metric is crucial for gauging the reliability of both the tests and the obtained results.

Accuracy is presented as a percentage, indicating the model's overall correctness in its predictions.

Another measure used is Loss, which is a critical measure during training of machine learning models and reflects how well the model is learning the specific task for which it was designed. A low loss value indicates good model performance on the training set.

In Figure 2 we see the performance of the model on accuracy metrics in the training process and validation process. The developed classification model has shown good performance. Regarding training accuracy, the values fluctuate between 82% and 94%, with the final value being 93%. Regarding the validation accuracy, the values fluctuate between 82% and 90%, with a final value of 86%.

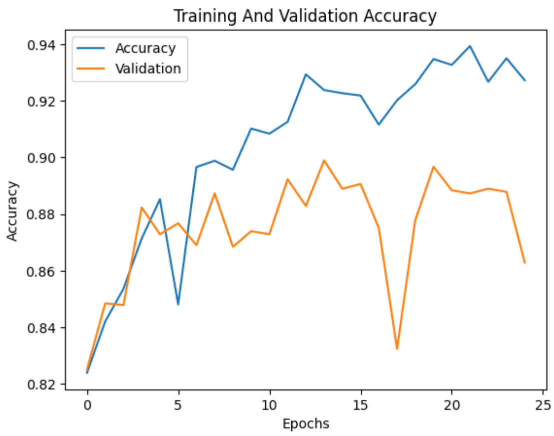

Figure 2. Accuracy of training and validation process

In Figure 3 we see the performance of the model on loss metrics in the training process and validation process. Regarding training loss, the values fluctuate between 15% and 45%, with the final value being 18%. Regarding the validation loss, the values fluctuate between 33% and 50%, with a final value of 47%.

Therefore, when analyzing the results, we have that with an accuracy rate of 94% it indicates that the model has high reliability in the ability to discern between different classes of skin diseases. Whereas, the loss of 0.16 is indicative of effective convergence during the training process, where the model has adjusted its weights optimally to minimize the discrepancy between the predictions and the actual labels.

Figure 3. Loss of training and validation process

Figure 4 shows the confusion matrix, which shows the values of hits and misses that the model predicts in each of the categories to be classified.

The quantities of the main diagonal in the confusion matrix represent the correct predictions in each category, while the values outside it reflect the mistakes made by the model in the evaluation process. So, for the first category “Actinic keratosis”, there are 180 correct predictions and 18 errors, classifying instances as “Nevus” when they were actually “Actinic keratosis”.

Regarding the category that has obtained the highest number of errors, we have the fourth category "Melanoma," with 12 errors in classifying it as "Nevus," 2 error in classifying it as "Pigmented benign keratosis," and 49 errors as "Seborrheic keratosis."

To verify the accuracy percentage, a proportional percentage will be calculated with respect to the total number of images in each category, as shown in Table 7.

Table 7. Percentage of correct and incorrect images per category (testing) [36]

Category	Total Images	Correct Images	%	Incorrect Images	%
Actinic keratosis	198	180	91	18	9
Basal cell carcinoma	219	185	84	34	16
Dermatofibroma	206	205	100	1	0
Melanoma	199	136	68	63	32
Nevus	202	174	86	28	14
Pigmented benign keratosis	190	163	86	27	14
Seborrheic keratosis	190	178	94	12	6
Squamous cell carcinoma	209	203	97	6	3
Vascular lesion	187	187	100	0	0

According to Table 7, it can be observed that the third category "Dermatofibroma" and the ninth category "Vascular lesion" achieved 100% accuracy. Regarding the error percentage, the fourth category "Melanoma" obtained the highest percentage with 32%.

The CNN model developed for skin cancer classification exhibits robust performance, with an accuracy of 94%, highlighting its ability to make accurate predictions in most instances. The precision of 89.88% reflects the ratio of true positives to positive predictions, while the high recall of 89.55% underscores the model's ability to effectively identify real skin cancer cases. The F1 Score, combining accuracy and recall, reaches 89.4%, indicating an effective balance between both metrics, as shown in Table 8. Additionally, the model achieves a specificity score of 98.69%, demonstrating its strong capability in correctly identifying negative cases and minimizing false positives.

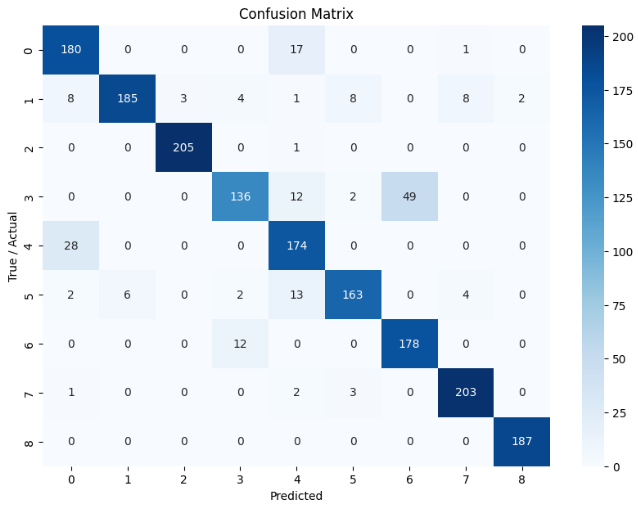

Figure 4. Confusion matrix

Table 8. Model metrics

Metrics	Value
Accuracy	94%
Precision	89.88%
Recall (Sensitivity)	89.55%
Specificity	98.69%
F1 Score	89.4%

These results suggest that the model is promising, although it is crucial to consider the specific context and clinical implications of prediction errors.

We can visualize in Table 9 a classification report for different types of skin lesions. The metrics of precision, recall, F1, and number of samples (support) for each of the categories are detailed.

Table 9. Classification report [36]

Category	Precision	Recall	Specificity	F1	Support
Actinic keratosis	82%	91%	97.56%	86%	198
Basal cell carcinoma	97%	84%	99.62%	90%	219
Dermatofibroma	**99%**	**100%**	99.81%	**99%**	206
Melanoma	88%	68%	98.87%	77%	199
Nevus	79%	86%	97.12%	82%	202
Pigmented benign keratosis	93%	86%	99.19%	89%	190
Seborrheic keratosis	78%	94%	96.95%	85%	190
Squamous cell carcinoma	94%	97%	99.18%	96%	209
Vascular lesion	**99%**	**100%**	**99.87%**	**99%**	187

In general, most categories obtained high precision and F1 values, indicating robust model performance. However, some categories such as "Melanoma" and "Basal cell carcinoma" had lower recall values, suggesting that the model had difficulty correctly identifying some cases in these classes.

On the other hand, "Seborrheic Keratosis" showed an accuracy of 78%, but a recall of 94%, which means that the model correctly identified most of the cases, although it had some difficulties in avoiding false positives.

5. DISCUSSION

When compared with other studies, our results are in agreement with those of previous studies. For example, Benbrahim et al. [26] achieved a similar accuracy of 94.06% using a CNN model trained on the HAM10000 dataset, but their recall was slightly lower, suggesting that our model is more sensitive in identifying positive cases. If we compare with the study [37], which obtained accuracies of 92.30%, 93.95% and 94.31% on ISIC 2019, HAM10000 and a private dataset, respectively, our model performs better on ISIC 2019 and HAM10000 datasets. However, the strength of our model lies in its specificity, which, at 98.69%, exceeds that of many other studies. This indicates that our model is particularly effective in minimizing false positives, which is crucial in clinical settings to avoid unnecessary treatments.

Additionally, when compared to the results of Kassem et al. [38], who achieved a classification accuracy of 94.92% with a sensitivity of 79.8% and specificity of 97% using transfer learning with GoogleNet, our model demonstrates superior recall (89.55%) and specificity (98.69%).

While Kassem's model shows a strong accuracy, the relatively lower recall and precision (80.36%) indicate that our model might offer better performance in detecting true positives and reducing false negatives. This balance between sensitivity and specificity is essential, particularly in medical diagnostics where both false positives and negatives can have significant consequences.

When comparing the results obtained with Cauvery et al. [39], who reported a balanced accuracy of 81.2%, while our model achieved an overall accuracy (Accuracy) of 94%, which represents a remarkable difference in terms of overall accuracy.

Furthermore, our precision of 89.88% exceeds that of the model of Cauvery et al. [39] who reported an average accuracy of 73% in their best ensemble. This suggests that our approach more effectively handles the reduction of false positives. In terms of sensitivity (Recall), our model achieved 89.55%, improving the ability to detect malignant lesions compared to 62% in the model of Cauvery et al. [39], likewise, the F1 score obtained in our work (89.4%) suggests a better balance between accuracy and sensitivity, surpassing the 61% reported by them. These results reflect that our implementation offers superior performance in the detection of skin cancers.

6. CONCLUSION

The performance of the proposed CNN model of skin cancer image classification showed good results, with an accuracy of 94%, precision of 89.88%, recall of 89.55%, specificity of 98.69% and F1 score of 89.4%. of 89.55%, a specificity of 98.69%, and an F1 score of 89.4%. These metrics suggest that the model accurately identifies positive cases, and false positives, as reflected by the high specificity.

The model was built using the ISIC - 2019 dataset, comprising numerous images of skin lesions categorized as benign or malignant oncologic lesions.

Preprocessing consisted of employing "data augmentation" techniques such as rotation, scaling and cropping to improve image variability and ensure a uniform distribution of classes.

The system determines 9 different types of skin lesions. This capability makes it a valuable tool for accurately identifying various dermatological conditions.

The success of the model has tangible benefits by providing users with the ability to know the status of any skin lesion and its corresponding classification. Therefore, this project presents a solution that democratizes and facilitates people to know the state of health of their skin.

To ensure that these technologies are effectively implemented in clinical practice, collaborative research must be conducted between artificial intelligence experts and dermatologists. Clinical experience is critical to validate the findings generated by AI algorithms, and interdisciplinary collaboration will enable the development of more robust and representative databases, which in turn will improve the accuracy and reliability of the models.

AUTHOR CONTRIBUTIONS

Hugo Vega-Huerta carried out the conceptualization, formal analysis, and implementation of the methodology. Manuel Rivera-Obregón wrote the original draft and created CNN models (software) with optimizer setting, Gisella Luisa Elena Maquen-Niño carried out trained model with parameters setting, Percy De-La-Cruz-VdV carried out the evaluation of the model and visualization, Juan Carlos Lázaro-Guillermo carried out the dataset selection and data curation with image's preprocessing, Jorge Pantoja-Collantes conducted the validation of the assessment and drafted the results, Ruben Gil-Calvo supervised the compliance with the methodology and carried out the editing of the final draft. All authors conducted the review of observations and approved the final draft.

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