Web System Based on Convolutional Neural Networks to Support Early Identification of Ocular Pterygium

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Abstract—**This research aligned with SDG No. 9, "Industry, Innovation, and Infrastructure," as it promotes health and well-being using innovative technologies. The objective was to determine whether the development of a web-based system based on convolutional neural networks improves the early identification of pterygium. Sensitivity, specificity, and accuracy metrics were used to measure the results, yielding excellent incremental values of 96%, 98%, and 97%, respectively. The study was applied research with a quantitative approach and an experimental design, specifically pre-experimental. The study variable was the early identification of ocular pterygium, consisting of a sample of 100 images, which were divided into 50 images corresponding to individuals with ocular pterygium and 50 from healthy individuals. The type of sampling used was non-probabilistic convenience sampling. The results obtained showed an increase in sensitivity of 4.35%, specificity of 2.80%, and accuracy of 3.56%. It is concluded that the proposal positively improves support for the early identification of pterygium, thanks to the high results obtained with the indicators evaluated, which makes it executable and scalable for future research.**

Keywords—Ocular pterygium; web system; convolutional neural networks; early identification; technology

I. INTRODUCTION

In the field of visual health, eye diseases such as pterygium pose a constant risk to people's quality of life, especially when they are not detected and treated in time. This is because the condition can develop silently, affecting vision if not treated early. Considering this reality, a proposal has been put forward to develop a web-based system using convolutional neural networks to aid in the early identification of pterygium based on images previously captured with a cell phone and subsequently uploaded to the web-based system for automatic analysis.

Pterygium, commonly known as "surfer's eye," is a lesion characterized by the growth of triangular-shaped fibrovascular tissue that advances from the conjunctiva toward the corneal surface [1]. It is classified into the following grades: Grade 1, mild appearance between the limbus and the edge of the pupil. Grade 2 begins to invade the edge of the pupil. Grade 3 completely affects the pupil, causing blurred vision and more intense discomfort. Finally, in grade 4, the pterygium invades beyond the pupil [2].

Pterygium is considered one of the most common ophthalmic conditions worldwide [3], whose origin and hereditary factors still raise questions, despite years of study on its symptoms and treatments [4]. Although initially asymptomatic, pterygium can cause discomfort such as irritation, redness, and foreign body sensation, and can lead to vision loss when its growth compromises the optical axis [5].

Various studies have estimated that the frequency of this condition varies widely worldwide, ranging from 1.2% to approximately 40%, depending on environmental and demographic conditions [6], most commonly affecting middle-aged men, who tend to spend more time outdoors without adequate eye protection. In addition, those who suffer from allergic or inflammatory diseases in the eye area are at greater risk, as constant inflammation leads to changes in the surface of the eye that can facilitate the development of pterygium [7].

It is more common in tropical and subtropical regions, where conditions such as exposure to ultraviolet (UV) light, dust, wind, and dry climates predominate [8]. In addition, the progression of pterygium can vary significantly in symptoms between patients, making timely detection even more difficult [9]. Despite advances in ocular imaging techniques, challenges remain associated with the subjectivity of clinical evaluation and the lack of standardized diagnostic criteria for ocular conditions [10].

For this reason, we propose designing a web-based system based on convolutional neural networks, which processes images previously taken with a cell phone, uploads the images to the system, and finally performs a diagnosis based on the percentage of ocular pterygium presence. The model extracts the specific features of the lesion, prioritizing the following dimensions: sensitivity, which reliably examines true positives; specificity, reinforced to reduce the number of false positives as much as possible; and finally, optimizing diagnoses with absolute accuracy. In this way, it provides an accessible resource for both ophthalmology professionals and patients with this type of condition, intending to facilitate diagnoses through technology, combined with the accessibility and clinical rigor required for the effective detection of ocular pterygium.

In this regard, this valuable alternative has emerged thanks to the system's use of Artificial Intelligence (AI), mainly convolutional neural networks, to optimize the speed and accuracy of ocular pterygium diagnosis, enabling medical professionals to perform interventions more effectively and in a timelier manner [11].

Therefore, this initiative contributes to the improvement of preventive diagnosis, aligning with Sustainable Development Goal (SDG) No. 9, which promotes health and well-being through the use of innovative technologies.

For this reason, the objective is to develop a web-based system based on convolutional neural networks to support the early identification of ocular pterygium.

II. RELATED WORKS

According to [12], a mobile application based on convolutional neural networks was developed with the aim of improving the early diagnosis of rosacea. This research used a pre-experimental design with a quantitative approach. The sample consisted of 100 images, divided between 50 patients with rosacea and 50 healthy individuals. Observation was used as the data collection technique, and the metrics of sensitivity, specificity, and accuracy were evaluated, resulting in positive values of 2.7%, 1.97%, and 0.10%, respectively. It was concluded that the mobile application based on convolutional neural networks efficiently improves the early diagnosis of rosacea, optimizing the evaluated indicators.

Regarding [13], they investigated the use of convolutional neural networks with the aim of detecting pterygium from eye images. In this research, an in-depth analysis of previously existing systems was carried out, highlighting the transition from classical algorithms to more accurate models. They demonstrated high effectiveness in the segmentation, classification, and localization of the condition thanks to the use of computer vision techniques. They demonstrated that the implementation of these models can positively contribute to the early diagnosis of eye diseases, even using cell phone cameras in areas with limited resources.

Regarding [14], they developed a system based on convolutional neural networks to detect ocular pterygium based on cell phone images. Six pre-trained networks were evaluated using 10-fold cross-validation and a Softmax classifier. The data showed that the VggNet16-wbn model had the best results in the calculated metrics, achieving an accuracy of 99.22%, a sensitivity of 98.45%, and a specificity of 100%. They concluded that the proposed system has high performance in terms of pterygium detection, making it scalable for future work and useful in areas and centers where medical resources are limited.

As mentioned in [15], they implemented the use of smartphones through an integration approach to improve pterygium detection with images. They achieved an accuracy of 95.24%, showing a result similar to that of experts in the field, due to the combination of more than 20,000 clinical images with 1,094 mobile images, using learning prototypes such as Faster R-Convolutional Neural Network (CNN) and SRU-Net. This validated the effectiveness of the model, highlighting its ability to provide early diagnosis of pterygium.

On the other hand [16], two systems were developed using AI, one to detect whether an image of the eye shows pterygium, using a binary classification model, and another to determine the affected area in these images, which would correspond to segmentation. To do this, neural network architectures such as VGG16 and PSPNet were used, training them with 734 photographs to determine their functionality, measuring their performance using indicators such as accuracy, detection capability, and mean intersection over union (MIOU). The VGG16 system was able to correctly diagnose 99.0% of the images, while PSPNet managed to segment the affected areas with an accuracy of 86.57%. Therefore, these systems are considered to have great potential for practical use in the medical field, as they facilitate evaluation and support for specialists in diagnosis in order to plan early interventions.

As for [17], they analyzed how to improve the diagnosis of ocular pterygium using AI, beginning with an exploration of different techniques, including computer vision, deep learning, and machine learning. The final result highlighted the efficiency and accuracy of these tools in achieving a good diagnosis. Finally, they concluded that the use of AI allows for the optimization of advanced medical systems for the early detection of pterygium.

According to [18], they evaluated the use of tools for imaging studies in the field of telemedicine with the aim of establishing a diagnosis for corneal diseases, including pterygium. A review of 51 technological tools was conducted, including smartphones and slit lamps, highlighting their ability to identify eye conditions remotely. They concluded that only some of the devices have been clinically validated despite showing great potential, which emphasizes the need for much more meticulous studies to support their use for actual diagnoses.

On the other hand [19], they emphasized the crucial role that AI plays in the field of ophthalmology, as it is capable of analyzing medical images, even using a smartphone, thus providing accurate diagnoses. This allows specialists to make determinations and facilitates long-distance evaluations. Although it is often presented as a challenge, the evolution of technology in terms of applications is increasingly predictive.

According to [20], they explored the existence of diseases present on the ocular surface using AI. Although they were initially focused on studying the posterior segment of the eye, they were able to demonstrate the usefulness of AI in conditions such as dry eye and ocular pterygium. Using models such as deep neural networks, which increase the accuracy of diagnoses, especially in environments where ophthalmic professionals are scarce. They concluded that despite all of the above, AI currently appears to be a viable tool for enhancing eye treatments and diagnoses.

Regarding [21], they studied the progress of AI in identifying conditions affecting the surface of the eye, such as keratitis, keratoconus, dry eye, and pterygium. Although AI has been used largely for diseases of the fundus, its application to the surface reflects an increase due to its ability to identify, classify, and segment various lesions. Therefore, it is concluded that, despite current challenges, such as the demand for reliable databases and validation in clinical settings, its great capacity to improve access to diagnosis is recognized, especially in regions or localities with limited resources and a shortage of healthcare professionals.

III. METHODOLOGY

The methodology chosen for the development of the web system is the Waterfall methodology.

The Waterfall methodology is a model that allows for the sequential simulation of software development, enabling the identification of bottlenecks in each phase, starting from the requirements phase through to product maintenance [22].

1) Phase 1: Analysis

Phase in which the functional requirements as well as the non-functional requirements of the system are collected and documented, with the participation of customers and users [23].

This first phase comprises the requirements that define the essential functionalities that the system will have for the identification of ocular pterygium.

a) Scope definition: Develop a web-based system using convolutional neural networks for the early identification of ocular pterygium.

Table I shows the functional requirements that the system must fulfill.

TABLE. I.   TABLE OF FUNCTIONAL REQUIREMENTS

Code	Requirement	Description
RF001	User Registration	The system must allow new users to register by providing personal data and access credentials.
RF002	User Authentication	The system must allow users to authenticate themselves using their email address and the password they initially created.
RF003	Reliable information	The application should provide reliable information about ocular pterygium and offer links to additional resources.
RF004	Perform evaluations	The system must allow the user to upload images of the eye in compatible formats (.jpg, .png, .tiff).
RF005	Process images	The system must process the images using a convolutional neural network to detect signs of pterygium.
RF006	Display evaluation results	The system must display the result of the diagnosis to the user with a visualization of the affected areas.
RF007	Data recording	The system will automatically save the diagnostic results, the analyzed image, the date, and the patient's user in the database.
RF008	Clinical History	The system will allow users to access a history of previous analyses, viewing uploaded images, results, and dates.
RF009	User Update	The system will allow users to modify personal information such as names, email addresses, and passwords.
RF010	Logout	The system will allow users to log out securely.
RF011	Error Handling	The system must notify the user with a message when the model cannot process the uploaded image, either due to an error or incorrect formats.

2) Phase 2: System design

The second phase involves transforming the requirements obtained in the analysis phase into a technical architecture that defines how the system works internally. The aim is to have a basic functional initial version of the system and adjust it to the end user's expectations [23].

a) CNN-based web system workflow diagram: Fig. 1 illustrates the workflow of the proposed web system based on a convolutional neural network (CNN). The process begins when the user accesses the interface using their credentials. If the user is successfully authenticated, they can upload the eye image. The image will be sent to the server, where it will be processed with the previously trained CNN model for analysis. Finally, the result will be received by the system, stored in the database, and displayed to the end user.
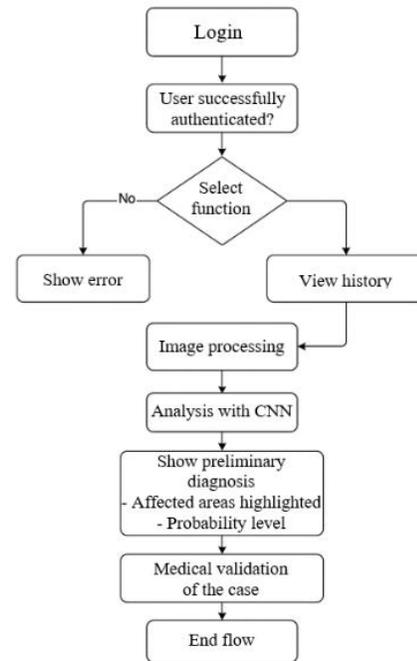

Fig. 1.   CNN-based web system workflow diagram.

b) Web system architecture: Fig. 2 shows the diagram of the web system's technological architecture. The system is built with technologies such as HTML, CSS, PHP, and JavaScript for the user interface. The data is sent to the MySQL database, which is part of the back end, to later use web services and a model developed in Python to process information and generate a response.
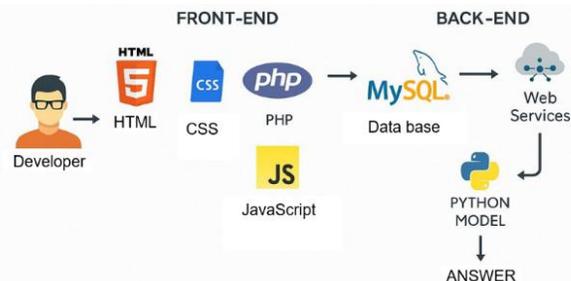

Fig. 2.   Architecture of the proposed system.

c) Final system design: The final design is based on the initial prototype, with each of the modules initially proposed.

Fig. 3 shows the final design of the system login interface with the option to log in using a registered username and password.
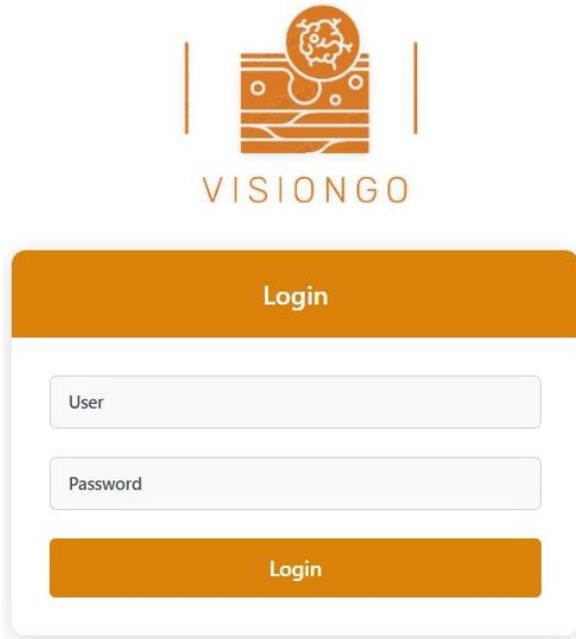

Fig. 3.   Final design of the login interface.

Fig. 4 shows the final design of the system's main interface, which displays the total number of cases analyzed, along with the severity level of each case analyzed.

Fig. 4.   Final design of main interface.

d) Environment configuration: The following are the components that were necessary for configuring the web system development environment:

Hardware:

PC used for development with the following characteristics:

- Processing: Intel Core i7 4790k.

- RAM: 32GB DDR3 1866mhz RAM.

- Graphics Card: NVBIDEA GeForce RTX 4060TI 8GB DDR6.

- Storage: 1TB NVMe SSD by MSI. Ensures fast access speeds for managing data sets, models, and files required by the system.

- Camera: Teros FHD camera.

Software:

- Operating System: Windows 10 Pro 64-bit.

Integrated Development Environment (IDE):

- Front-End: HTML, CSS, JavaScript, PHP. These enable the development of the system interface, facilitating user interaction with web functionalities in a dynamic and accessible way.

- Back-End: MySQL, REST API. These manage structured data storage and enable secure and efficient communication between the server, the database, and the client application.

- AI: Python, Google Colab. These are used for the implementation, training, and validation of the computer vision model, leveraging libraries and computing resources in the cloud.

- Complementary Tools: Visual Studio Code, Web Browser. These facilitate code editing, functional testing, and application deployment during development.

3) Phase 3: Implementation

a) Graphical interface development: The start window was implemented, providing access to view the number of pterygium cases analyzed within the system.

b) MobileNetV2 neural network integration: The MobileNetV2 neural network model, which is already pre-trained for object detection, was integrated and adapted for the identification of the medical problem.

History log:

The validation window was developed, which provides access to the history of all pterygium cases analyzed by severity, allowing the information to be downloaded in a PDF or Excel file.

4) Phase 4: Testing

In this phase, we thoroughly validate that the system complies with each of the requirements initially set out. Basically, we validated that each of these points is being met as planned. See Table II.

5) Phase 5: Maintenance

During this phase, errors identified during the testing phase were corrected, and adjustments were made to improve the accuracy and performance of the web system. Likewise, improvements were analyzed to refine the design of a more intuitive graphical interface to offer a better user experience. The most important information was duly recorded in the system and user manual to ensure an accessible and clear guide for use.

TABLE. II.   STATUS OF TESTING BASED ON REQUIREMENT

Code	Functional Requirement	Description
RF001	The system must allow new users to register by providing personal data and login credentials.	Meets the requirement
RF002	The system must allow users to authenticate using their email address and the initially created password.	Meets the requirement
RF003	The application must provide reliable information about ocular pterygium and offer links to additional resources.	Meets the requirement
RF004	The system must allow users to upload images of the eye in compatible formats (.jpg, .png, .tiff).	Meets the requirement
RF005	The system must process the images using a convolutional neural network to detect signs of pterygium.	Meets the requirement
RF006	The system must show the user the diagnosis result with a visualization of the affected areas.	Meets the requirement
RF007	The system will automatically save the diagnostic results, the analyzed image, the date, and the patient's user information in the database.	Meets the requirement
RF008	The system will allow the user to access a history of previous analyses, viewing uploaded images, results, and dates.	Meets the requirement
RF009	The system will allow the user to modify personal information such as names, email, and password.	Meets the requirement
RF010	The system will allow users to log out securely.	Meets the requirement
RF011	The system must notify the user with a message when the model cannot process the uploaded image due to an error or incorrect formats.	Meets the requirement

IV.   RESULTS

The objective of this research is to determine whether a web-based system based on convolutional neural networks supports the early identification of ocular pterygium.

A. Calculation of Indicators

Table III shows the confusion matrix corresponding to the system's performance in supporting the identification of ocular pterygium with a set of 100 images. It shows that of 50 images of people with pterygium, 48 were correctly classified as positive, while 2 of the results were incorrectly classified as negative. As for the 50 images of people without pterygium, 49 were correctly classified, and only 1 had an erroneous result, classifying it as positive. This resulted in a sensitivity of 96%, a specificity of 98%, and demonstrated that the model has an accuracy of 97%.

TABLE. III.   CONFUSION MATRIX

		Prediction				
		Sensitivity	Specificity	Total	Function test	
		Person with pterygium	A person without pterygium			
Current	**Positive**	48	1	49	0.96	Pterygium
	Negative	2	49	51	0.98	Without pterygium
	Total	50	50	100		
	Laboratory test	0.96	0.98		0.97	

From the confusion matrix analyzed, the following results are obtained for the metrics proposed:

% Sensitivity = 96%

% Specificity = 98%

% Accuracy = 97%

1) Analysis of the ROC curve and the area under the curve (AUC): Fig. 5 corresponds to the ROC curve, showing the blue line approaching the upper left axis, which indicates that the model's performance has high capacity, with high specificity and sensitivity values. In contrast, the red line represents the behavior of a test to make predictions without discrimination, i.e., an AUC of 0.5.

The notable distance between the two curves demonstrates that the model performs excellently (AUC = 0.985; $p < 0.001$), indicating that it is capable of efficiently differentiating between people with and without pterygium, as shown in Table IV.
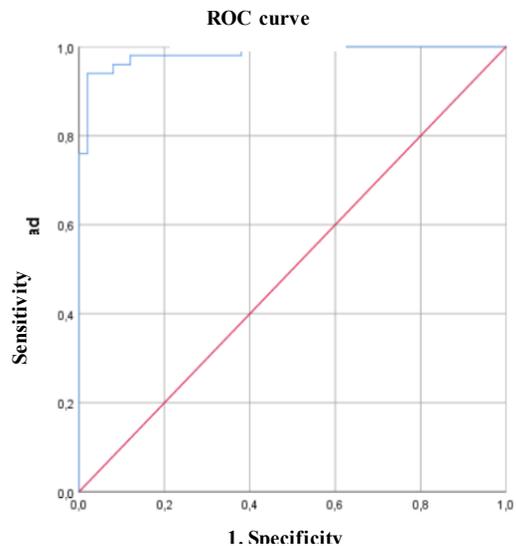

Fig. 5.   ROV curve.

TABLE. IV. AREA UNDER THE CURVE

Area	Std. Error	Asymptotic significance	95% asymptotic confidence interval	
			Lower limit	Upper limit
,985	,010	,000	,966	1,000

B. Analysis of the Pre-Experimental Design

a) Pre-test: Table V presents a comparison of the different CNN architectures studied for the binary classification of pterygium and non-pterygium cases, considering the sensitivity, specificity, and accuracy metrics of Zhu's ResNet18 model [16] selected as a reference, comparing them with the ocular pterygium values of the proposed web system model.

b) Post-test: For the post-test, 100 images obtained from datasets were used, with the results obtained through the web system report. Table VI shows the metrics and percentages for each indicator, with a sensitivity of 97%, a specificity of 98%, and an accuracy of 97%.

TABLE. V. PRE-TEST VALUES RESULT

Model	AlexNet		VGG16		ResNet18		ResNet50	
Evaluation indicators	Normal	Pterygium	Normal	Pterygium	Normal	Pterygium	Normal	Pterygium
Sensitivity	98.00%	96.00%	99.33%	98.67%	95.33%	92.00%	93.33%	92.67%
Specificity	96.00%	98.00%	98.67%	99.33%	92.00%	95.33%	92.67%	93.33%
F1-score	97.03%	96.97%	99.00%	99.00%	93.77%	93.56%	93.02%	92.98%
AUC	0.97		0.99		0.94		0.93	
95%CI	0.95-0.99		0.98-1		0.91-0.97		0.90-0.96	
Kappa	94.00%		98.00%		87.33%		86.00%	
Accuracy	97.00%		99.00%		93.67%		93.00%	

TABLE. VI. RESULTS OF THE INDICATORS FOR THE POST-TEST

Quantity	VP	VN	FN	FP	Sensitivity	Specificity	Accuracy
100	48	49	2	1	96%	98%	97%

Table VII shows a comparison of the results between the percentages of the specificity, sensitivity, and accuracy indicators between the ResNet18 model and the web system.

TABLE. VII. COMPARISON OF RESULTS

Indicator	ResNet18	Web System
Sensitivity	92%	96%
Specificity	95.33%	98%
Accuracy	96.67%	97%

C. Hypothesis Testing

a) Specific scenario HE1: $HE1_0$: A web-based system based on convolutional neural networks does not increase sensitivity in supporting the early identification of ocular pterygium.

$HE1_1$: A web-based system based on convolutional neural networks does not increase sensitivity in supporting the early identification of ocular pterygium.

% Sensitivity variation = (96-92) / 92 X 100 = 4.35%

There is a 4.35% increase in sensitivity, indicating that the system has a greater capacity to correctly identify cases. Therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

b) Specific scenario HE2: $HE2_0$: A web-based system based on convolutional neural networks does not increase specificity in improving early identification of ocular pterygium.

$HE2_1$: A web-based system using convolutional neural networks increases specificity in improving early identification of ocular pterygium.

% Change in specificity = (98-95.33) / 95.33 X 100 = 2.80%

There is a 2.80% increase in specificity, indicating that the system has a greater capacity to correctly identify cases. Therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

c) Specific scenario HE3: $HE3_0$: A web-based system based on convolutional neural networks does not increase accuracy in improving early identification of ocular pterygium.

$HE3_1$: A web-based system using convolutional neural networks increases accuracy in improving early identification of ocular pterygium.

% Variation in accuracy = (97-93.67) / 93.67 X 100 = 3.56%

There is a 3.56% increase in accuracy, indicating that the system has a greater capacity to correctly identify cases. Therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected.

D. Results of Indicator Increments

Table VIII shows the results of the variation for each indicator, whose results show that a positive number is grounds

for accepting the hypotheses, whereas a negative result would automatically reject the hypotheses.

TABLE. VIII. RESULTS OF THE INCREMENTS FOR EACH INDICATOR

SENSITIVITY VARIATION (%)	SPECIFICITY VARIATION (%)	ACCURACY VARIATION (%)
+4.35%	+2.80%	+3.56%

E. General Hypothesis

HG0: A web-based system based on convolutional neural networks does not improve early identification of ocular pterygium.

HG1: A web-based system based on convolutional neural networks improves early identification of ocular pterygium.

Evidencing the results of HE1, HE2, and HE3, the general hypothesis is accepted.

V. DISCUSSION

The results showed a sensitivity of 96%, resulting in a variation of 4.35% compared to the ResNet18 model, which achieves a sensitivity of 92%. This was mainly due to improvements in the training of the MobileNetV2 architecture, which contributed to more accurate feature extraction in images of eyes with and without the condition. This result is slightly higher than that obtained by Y. Liu et al. [15], who presented a sensitivity of 93.60% in their fusion segmentation model trained with smartphone and slit lamp images for the accurate detection and classification of pterygium. This difference could be due to the incorporation of better performance techniques in the training of the MobileNetV2 network, minimizing generalization loss and optimizing accuracy in the correct analysis of the characteristics of the condition. Similarly, the results obtained by S. Zhu et al. [16] are compared, who report a sensitivity of 98.67% using the VGG16 neural network model. This difference in values may be due to the high complexity of the model, as it requires greater computational capacity than that used in the research. However, the result obtained achieved a significant increase in sensitivity for the preliminary diagnosis of ocular pterygium, demonstrating that it is feasible to achieve competitive levels of sensitivity using a more competent and less resource-intensive neural network, making it more feasible for future developments.

In addition, a specificity of 98% and a variation of 2.80% demonstrate the model's high performance in accurately detecting negative cases of pterygium and minimizing false positives. Compared to the specificity report of 96.13% presented in the work of Y. Liu et al. [15], this difference could be due to the variability in the resolution of images taken by different smartphones and the variability of the datasets used, which affected the robustness of the training. Similarly, the study by Zhu et al. [16] obtained a specificity of 99.33%, surpassing the results of this research. This may be due to the large dataset with which the model was trained, which favored the diagnosis of pterygium.

On the other hand, the results revealed an accuracy of 97%, resulting in a variation of 3.56%, showing a high level of performance in the computer-assisted classification of

pterygium and eyes without the condition. Compared to Zamani et al. [14], who obtained an accuracy of 99.22% using their pre-trained VGGNet16-wbn model, it is analyzed that the magnitude of the differences between results may be because the system was developed under a much deeper and improved architecture with layers (batch normalization), obtaining a highly effective training result. It is also attributed to the use of better datasets, which were carefully labeled, thus optimizing the generalization process. On the other hand, this result is slightly higher than the 99% accuracy reported by Zhu et al [16], using the VGG16 architecture. This may be due to the precise control of the image collection parameters and the uniformity of the dataset, which contributed to the accuracy of the model chosen for the development of their research work. Taken together, these results confirm that accuracy is competitive based on the complexity of the architecture and the quality of the images used for training.

The values obtained reinforce the effectiveness of the web-based system for diagnosing ocular pterygium, reflecting high values for sensitivity, specificity, and accuracy metrics in the post-test. Overall, it is evident that the model used to develop the system based on MobileNetV2 demonstrates its high-performance capacity when adjusted to the ophthalmological context specifically for the diagnosis of ocular pterygium. Many of the previous studies compared with the development of the system have competitive values. For example, Zamani et al. [14] present a sensitivity of 98.45% and an accuracy of 99.22%, focusing on the use of the VGGNet16-wbn architecture, while Zhu et al. [16] achieved a competitive range with a sensitivity of 98.67% and an accuracy of 99% based on the use of the VGG16 neural network. Although the differences are slight, they may be due to many of the factors presented in the research, mainly the size of the images used for training and the heterogeneous images with excellent variable lighting conditions.

Similarly, Liu et al. [15] implemented a fusion training model integrating 20,987 slit lamp images and 1,094 smartphone images, obtaining a sensitivity of 93.6%, specificity of 96.1%, and accuracy of 92.38%. Likewise, Fang et al. [24] trained deep learning models for the detection of ocular pterygium by integrating images taken with both slit lamp cameras and portable cameras, achieving a sensitivity of up to 98.6% and specificity of 99.0%. The differences compared to the model used in the present study may be due to the use of higher-quality clinics and a larger volume of data.

Overall, the findings show that the adapted MobileNetV2 neural network model achieves an outstanding balance between accuracy, computational efficiency, and applied impact, positioning itself as a viable option for the early identification of ocular pterygium in social and medical contexts. Its performance with ResNet10, VGG16, or AlexNet, even using a reduced number of datasets, demonstrates the network's efficiency in terms of transfer learning and adequate preprocessing in the development of intelligent clinical diagnostic systems.

VI. CONCLUSION

Regarding the main objective, it was concluded that the implementation of the CNN-based web system based on the

use and improvement of the MobileNetV2 architecture contributed to the improvement in the identification of ocular pterygium. This was verified by the high metric values of 96% sensitivity, 98% specificity, and 97% accuracy obtained in the research project. Therefore, it has been demonstrated that the initial objectives were achieved, reflecting the positive contribution of trained deep learning models and learning method strategies to the early detection of ocular pterygium from ocular images taken with smartphones.

About the first specific objective set, the web system achieved a sensitivity of 96% and a variation of 4.35%, demonstrating that the model is capable of significantly minimizing false positives. The results are undoubtedly attributable to the use of the MobileNetV2 network as a basis, as its lightweight and optimized structure facilitates better and more detailed extraction of the most relevant features for eye images. Likewise, the use of data augmentation techniques and the wide variety of datasets provided for training contributed to the improvement of the model, resulting in correct identification in a large number of positive cases of ocular pterygium, even in images that were uploaded under different lighting conditions.

In relation to the second specific objective, the web system achieved 98% specificity and a variation of 2.80%, demonstrating that the model is highly accurate in correctly identifying photographs without pterygium, thereby reducing false positives. These results are attributed to the application of correct image preprocessing, as the images were resized to 224×224 pixels, in addition to the customization of the model with the modification of the dense layers, which enhanced the system's ability to differentiate between images with pathological alterations and images of eyes without the condition.

Regarding the third specific objective, the web system achieved an accuracy of 97% and a variation of 3.56%, indicating the model's high predictive capacity overall. This performance was achieved through rigorous training, using 80% of the images for training and 20% for validation, as well as the application of the categorical cross-entropy loss function and the ADA optimizer, which benefited the stable and effective learning of the model. All of this made it possible to create a system with an optimal balance between sensitivity, specificity, and accuracy, supporting the system's effectiveness for the classification and detection of pterygium.

Among the limitations of this study is the sample size, which was limited as only 100 images were considered, which may affect the generalization of the findings. In addition, only static images were considered for the development, and other factors that could influence the diagnosis of ocular pterygium were not considered. Another limitation is the insufficient time available for long-term follow-up and validation, which limits the evaluation of the system's effectiveness in real-world conditions.

Finally, for future research, it is suggested that, in order to strengthen and expand the results obtained, a much larger sample be considered, including grades and other conditions similar to ocular pterygium. In addition, it would be significant to implement additional clinical data and explore the incorporation of other artificial intelligence techniques to improve diagnostic accuracy. It is also recommended that longitudinal studies be conducted to evaluate the performance of the system over time in real clinical settings.

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