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Machine Learning and Deep Learning Techniques, Features and Obstacles in the Cataract Diagnosis

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Abstract*: Cataract is a degenerative condition that, according to estimations, will rise globally. Even though there are various proposals about its diagnosis, there are remaining problems to be solved. This paper aims to identify the current situation of the recent investigations on cataract diagnosis using a framework to conduct the literature review with the intention of answering the following research questions: RQ1) Which are the existing methods for cataract diagnosis? RQ2) Which are the features considered for the diagnosis of cataracts? RQ3) Which is the existing classification when diagnosing cataracts? RQ4) And Which obstacles arise when diagnosing cataracts? Additionally, a cross-analysis of the results was made. The results showed that new research is required in: (1) the classification of "congenital cataract" and, (2) portable solutions, which are necessary to make cataract diagnoses easily and at a low cost.

***Keywords:* Cataract Diagnosis, Image Processing, Ophthalmology, Machine Learning Techniques, Deep Learning Techniques.**

I. INTRODUCTION

Cataract is a degenerative condition causing the loss of transparency of the lens which leads to a gradual and painless loss of vision. Early stages of cataract formation include changes in perception of color, greater sensibility to glare, and blurred vision [1]. The speed with which cataracts develop and their extension vary from person to person. [2] Nevertheless, this condition is often detected in aging population. Other factors include medications, cigarettes, alcohol abuse, obesity, malnutrition, hereditary or genetic, trauma, diabetes, vitamin deficiency, long-period aspirin consumption, UV ray exposure, etc. Although in different proportions, these factors contribute to the formation of cataracts, being diabetes the most predominant [3].

According to WHO (World Health Organization), it is estimated that around 1300 million people live with some form of distance or near visual impairment. Cataract is the second main cause of visual disability. WHO's Vision 2020 reported that cataracts cases will increase due to population growth and longevity in underdeveloped countries as well as in industrialized ones. Furthermore, by 2020, an estimated 150 million people will present severe visual impairment caused by this condition. In Perú, a 2018 survey conducted by INEI (National Institute of Statistics and Informatics) reported that 15,7% of people had been diagnosed with cataracts. A literature review was conducted covering various research work related to cataract diagnosis. Nonetheless, to our discretion, they were represented in isolation. In response to this context, the present paper is written and intents to answer the following questions: Which are the existing methods for cataract diagnosis? Which are the features considered for the diagnosis of cataracts? Which is the existing classification when diagnosing cataracts? And Which obstacles arise when diagnosing cataracts? Therefore, a taxonomy for the systematic review of the literature was proposed in order to identify future research. The present paper is divided into different sections. Section II presents the research methodology used to conduct the systematic literature review of research work related to cataract diagnosis. Section III presents the analysis of the systematic literature review results. Section IV presents the systematic literature review results. Finally, section V offers the conclusions and future research work based on the content of this paper.

II. RESEARCH METHODOLOGY

For the purposes of the systematic literature review, [4] proposal was considered as the research methodology following Kitchenham's principles [5] considering 3 phases: (i) Planning the review: research question formulation and definition of review procedures. (ii) Conducting the review: the selection of the primary studies based on the inclusion and exclusion criteria (iii) Reporting the review: statistics and analysis of the previous selected studies.

A. Planning

In this phase, the following research questions were considered **RQ1**: Which are the existing methods for cataract diagnosis? **RQ2**: Which are the features considered for the diagnosis of cataracts? **RQ3**: Which is the existing classification when diagnosing cataracts? **RQ4**: Which obstacles arise when diagnosing cataracts?

Searches were undertaken using the following databases: SCIENCE DIRECT, IEEEE Xplore Digital Library and ACM Digital Library. They comprise the period from January 2014 to December 2019.

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The query sequence was TITLE-ABS-KEY ("Cataract diagnosis") applied to the title, abstract and keywords. Then, the inclusion and exclusion criteria were applied as shown in Table I.

Table - I. Inclusion and exclusion Criteria

Inclusion criteria	Exclusion Criteria
Studies using Learning Machines in cataract diagnosis.	Studies found in other documents but in Journals or Proceedings.
Factors considered in the diagnosis of cataracts.	Studies written in other languages but Spanish and English.
Cataract diagnosis methods	Studies on cataracts in humans
Obstacle when diagnosis cataracts	

B. Conduction of the review

This phase explains the form in which the review process was conducted contemplating the databases, sentence and inclusion and exclusion criteria explained in Table I. Fig. 1 shows the search process flow chart.

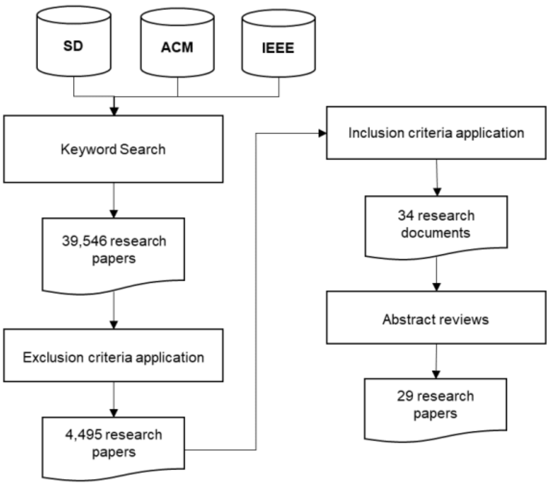

Figure 1. Literature systematic review process

C. Results

This phase shows the search results in which 39 546 sources were obtained. Out of this number, 34 sources were selected following the inclusion and exclusion criteria. During this process, each source was analyzed using the set of research questions stated above. Table II shows the number of studies per source.

Table - II: Selected studies

Repository	Potentially eligible studies	Selected studies
Science Direct	39240	6
IEEE	55	21
ACM	251	2
TOTAL	39546	29

Fig. 2 shows the number of studies related to the diagnosis of cataracts during the year 2014 to 2019. These 29 studies correspond to different aspects of cataract diagnosis: methods, features, classification, and obstacles.

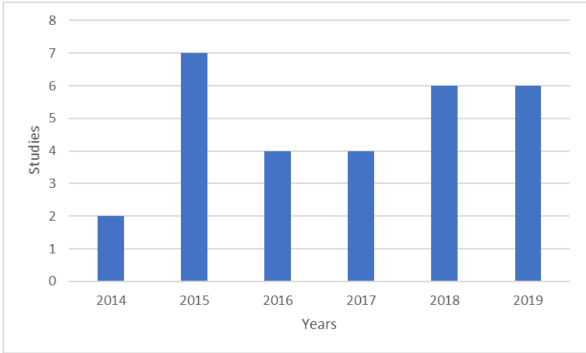

Figure 2. Cataract diagnosis studies during the period of 2014 to 2019.

III. PROPOSE FRAMEWORK

To carry out the analysis of the studies obtained from the literature review about cataract diagnoses, a taxonomy was developed (Fig. 3) in alignment with the research questions formulated above: "Methods" (RQ1), "Features" (RQ2), "Classification" (RQ3) and "Obstacles" (RQ4).

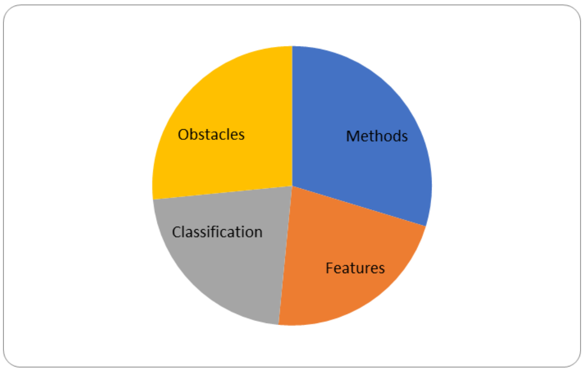

Figure 3. Proposed taxonomy

The classification "Methods" is related to studies on the application of different methods in the cataract diagnosis. "Features" is related to studies on the features considered in the cataract diagnosis. "Classification" is related to studies on the classification of the results obtained. Finally, "Obstacles" is related to studies on the existing obstacles in the cataract diagnosis. Table III shows a summary of the literature classification.

Table - III: Literature classification Summary.

Taxonomy	Sources	Total
Methods	[6], [7],[8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]	19
Features	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10]	14
Classification	[6], [7], [8], [9], [11], [32], [12], [28], [30], [21], [18], [27], [29], [31]	14

Obstacles	[5], [6], [7], [8], [9], [10], [11], [12], [14], [18], [21], [22], [23], [24], [25], [27], [28]	17

A. Methods

Table IV shows research works related to the method applied in cataract diagnosis with their respective sources. The methods identified were of automatic and manual type.

Table - IV: Types of methods applied in cataract diagnosis

Identifier	Methods	Source
M01	Automatic	[6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23]
M02	Manual	[8], [9], [17], [24]

Regarding the automatic methods, [6] proposed a method to find the macular area and identify the druses in a way to ease the diagnosis task by using thresholding and Canny Edge Detection. [7] proposed the use of the Machine Learning algorithm AdaBoost for cataracts classification utilizing fundus images which were preprocessed through the extraction of the green channel. The authors achieved 95.22% and 81.52 % in two-class and four-class classification, respectively. [8] utilized Deep Learning along with a convolutional recurrent neural network (CRNN) able to learn image features and, later, the application of a support vector regression (SVR) classifier to determine 5 different grades of cataracts. [9] proposed the use of a grid for cataract detection which analyzes front images of the lens and based on the pupil's opacity, determines the cataract grade. [10] presented a smartphone application implementing an artificial neural network (ANN) that classifies retinal images taken with the smartphone's camera and an attached microscopic lens. [11] also present a smartphone application called MCataract". They captured the images, turned them into grayscale, extracted the statistical texture features (contrast, dissimilarity, and uniformity) and applied the K-NN classifier achieving a 97.5% accuracy. [12] developed a framework for a computer-aided healthcare system for fundus image analysis. Such framework allows patients from remote regions to receive medical care with a double validation of artificial intelligence and a doctor. [13] proposed an automatic classification and grading system based on blood vessel visibility. The researchers applied the SVM classifier algorithm getting as a result of a 9% sensitivity and 93.33% specificity. [14] conducted a literature survey on cataract classifiers that implement three basic steps: Pre-processing, Feature extraction and Classifier construction, and concluded that there is a need for a portable solution. [15] put forward software for automatic detection and classification with multiple classification protocols accepted world-wide. [16] implemented a genetic algorithm-based SVM classifier utilizing non-prep processed images with a 95.33% accuracy in two-class classification and 87.52% in four-class classification. [17] suggested a real-time cataract detecting mobile application to enable the general public to carry out self-screenings. [18] proposed a fundus retinal image segmentation algorithm based on a fully convolutional network (CNN). [19] proposed a sparse range-constrained learning algorithm for image grading. Nonetheless, they acknowledge its high computational cost and image noise limitation. [20] proposed an iris localization algorithm through the use of edge estimation based on fuzzy logic as a Hough Transform algorithm entry. [21] combine the pre-trained Res-Net18 model with the SVM classifier resulting in 91.5% accuracy in six-class classification and 93.5% in four-class classification. [22] combined the pre-trained Alex-Net model and the SVM adding a quality image evaluation. The authors achieved a 100% accuracy in two-class and 92.91% in four-class classifiers. [23] proposed the use of Semi-Supervised Learning (SSL) for cataract classification. Regarding manual methods, [8] describe 3 manual methods for cataract diagnosis: image comparison with the Lens Opacities Classification System III (LOCS III), Density measurement in nuclear regions from an Optical Coherence Tomography and determination of the optical density of the lens based on 3D images through Scheimpflug imaging devices. [9] explain cataract diagnosis by analyzing the eye employing a slit lamp. [17] mention a manual approach consisting of opening eye examination, red reflex, and light scrambling techniques where the seriousness of the cataract is defined by the red reflex. [24] conducted a literature review in which they mention ultrasound, fluorescent imageology, and biomicroscopy based on retroillumination.

B. Features

Table V shows research works related to the features considered in cataract diagnosis with their respective sources. The identified features are optic disc and macula, image properties, lens (nucleus and cortex, pupil, and blood vessels).

Table- V: Features considered for cataract diagnosis

Identifier	Features	Source
F01	Optic disc and macula	[6], [30]
F02	Image properties	[7], [11], [27], [29], [32], [33]
F03	Lens: nucleus and cortex	[8], [28]
F04	Pupil	[9]
F05	Blood vessels	[18], [21], [31]

Regarding the optic disc and macula, [6] proposed a method for automatically detecting the macula area and finding the macular druses. The authors used the geographical features to localize the macula having the optic disc as a reference. Once localized, druses are detected, and Edge Detection was used to identify the exact edges of the abnormalities. The seriousness of the abnormality is determined according to the number of pixels within the edges.

In their method, [30] proposed a deeper analysis of the optic disc features, retinal injuries and aneurisms, and vessels.

Regarding image property features, [7] state that identifying evident cataract features alone is necessary for cataract diagnosis in a way to reduce the computational cost.

Their proposal utilizes the spectrum obtained from the application of the discrete Fourier transform. Therefore, the more regular the spectrum form is, the higher the cataract grading raises. [32] used discriminating mathematics to evaluate the disk halo to quantify the quality of vision. For their proposal, [11] considered the following image properties: contras, dissimilarity, uniformity, correlation, and homogeneity. Among the different combinations the authors made, they found that the performance of their proposal remains the same when using 5 or 3 of the properties (dissimilarity, contrast uniformity). [33] focus on the image texture features such as luminescence, gray co-occurrence matrix and gray-level co-occurrence matrix, the outline of the affected area, and frequencies obtained from Haar transform. [27] base their results on intensity, the average of gray values presents in the pupil, and uniformity, the value of pixels similarly presents in the pupil. [29] use two types of features: traditional and visual structure based. In terms of traditional types, an improved Haar transform is used which decomposes the image into layers. In visual structure based, they found 9. The types of visual structures include the percentage of visible structures, the medium value of the visual segmented retinal structure and the average value of the local standard deviation.

Regarding lens features: nucleus and cortex, [8] in their proposed method for nuclear cataract grading, they utilized intensity profile all along the visual axis to localize the reference point in the ocular lens. Ten features are extracted from these points including intensity and standard deviation. The number can be reduced through a model of linear regression which results in two important features: curve intensity and relationship between the posterior and anterior part of the ocular lens. [28] analyzed the features found in the nucleus and cortical region where an amino acid named called tryptophan is located. When exposed to UV rays, this amino acid has a fluorescent effect. Thus, the higher measurement of this effect is the higher grade of cataract it indicates.

Regarding features found in the pupil, in their proposal, [9], extract rays, shades, texture, size, intensity and special localization and pupil shape to identify the type of cataract.

Regarding blood vessels, [18] state that abnormalities can be observed in the retinal vessels which are essential indicators for the risk evaluation of both cataract and other types of cardiovascular and brain vascular diseases. [21] lie cataract grading in the visibility of blood vessels and for greater contrast of the retinal fundus, they employ a green filter in the image to identify vessel segmentations. Nevertheless, this is affected when image quality is low. [31] take tissue visibility as blood vessels and optic discs this is because, according to the authors, different grades of cataracts can be distinguished effectively.

C. Classification

Table VI shows research works related to the existing classifications when diagnosing cataracts with their respective sources. The identified classifications are cataract grades and cataract location.

Table- VI: Types of classification in cataract diagnosis

Identifier	Classifications	Source
CL01	Cataract grades: Normal, Mild, Moderate and Severe	[7], [16], [25], [26], [27], [29] [31], [33]
CL02	Cataract location: Cortical, Nuclear and Subcapsular	[9], [14], [15], [24], [28]
CL03	Congenital cataract	[34]

Regarding cataract classification, [7], [33], [29] use a normal grading: it is clearly observed that the arterioles and retinal venules in the of the retina in the nervous fiber layer of the retina; mild: it is observed that there is an apparent vail before the retina that prevents the visualization of most micro vessels and other details; moderate: the thickest stem vessels can be distinguished; severe: almost nothing can be observed. [16] classify cataracts in eye without cataract, where the optic disc and large and small blood vessels are clearly visible; mild: fewer blood vessels can be seen; moderate: only large blood vessels and the optic disc can be observed; severe: blood vessels and optic disc can barely be seen. [27] utilize a classification including normal, mild, severe, and unidentified. Such classifications were given based on the intensity which in the normal eye will tend to be small and uniformity value of pixels will tend to be closer to 1 while in mild and severe cataract the intensity will tend to be larger and uniformity value of pixels will tend to be smaller. [25] have a classification consisting of normal eyes, mono ocular cataracts, and bilateral cataracts. In their proposal, [26] achieve to classify cataracts in the normal eye and eye with cataracts. [31] use a six-class classification: eyes without cataracts, slightly small cataracts, mild, moderate, slightly severe, and severe.

Regarding cataract classification based on the localization to the cataract, [9], [14] and [28] mention the following types: cortical cataract, present in the lens cortex with a radial structure, nuclear cataract, present in the lens nucleus and subcapsular cataract, present in the posterior part of the lens. [15] add that these types of classifications are compared with standard photographs in accordance with the protocols given by classification systems as LOCS III or the Wisconsin Grading System (WGS). [24] agree with such classification adding that they are known as senile or age-related cataracts, and depending on their shape, they receive different image treatments due to their morphology.

Regarding congenital cataract classification, [34] make their proposal for cataract detection in babies, due to the fact that these are caused by congenital diseases as maternal diabetes, intrauterine infections and due to chromosomal defects, such as trisomy 21, 13 and 18.

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D. Obstacles

Table VII shows research works related to the existing obstacles when diagnosing cataracts with their respective sources. The identified obstacles: lack of resources, lack of expertise and diagnosis delay.

Table- VII: Obstacles in cataract diagnosis

Identifier	Obstacles	Source
OB01	Lack of resources	[6], [7], [10], [11], [12], [14], [21], [22], [24], [25], [28]
OB02	Lack of expertise	[8], [24], [21], [26], [28], [29]
OB03	Diagnosis delay	[7], [9], [12], [18], [21], [23]

Regarding the lack of resources, [6], [7], [10]-[12], [14], [21], [22] [24], [25] were motivated to formulate their proposals by the fact that in rural areas, the number of ophthalmologists and medical equipment is scarce as well as the possibility of affording the high cost of a diagnostic test; therefore, they don't receive timely treatment which is why cataracts are developed causing vision impairment leading to blindness. Some of these proposals offer the possibility of distance medical assistance which would reduce the cost of diagnostic tests. Through these proposals, a reduction of workload can be achieved for the reduced number of personnel. [28] put to evidence that due to the increasing number of elderly citizens, focusing more resources on the attention of cataract will become more demanding.

Regarding obstacles caused by lack of expertise, [8] mention that manual methods can be subjective, slow, and unaffordable. The lack of expertise would lead to an inadequate diagnosis or a slow and unaffordable one. [24] and [28] agree with this idea. [21] add that medical judgment could be affected by surrounding noise such as illumination and shooting angles. [26] express that due to this the developed systems could be affected in their diagnosis precision. Hence, Machine Learning and Neural Networks algorithms are key since they learn image features. [29] in agreement with the lack of expertise of doctors in rural areas, opts for the use of eye fundus images given that they can be easily taken with the help of technicians. These images have been recently used for the proposal of various solutions that allow the completion of cataract diagnosis.

Regarding the obstacles caused by diagnosis delays, [7], [18] and [21] try, with their proposals, to deal with the delay of given diagnosis since manual methods are complex and expensive ophthalmologist. [9] add that a precise diagnosis and a timely surgical treatment could prevent vision loss. [12], [23] mention that finding the right ophthalmologist is a real struggle since is considered a scarce resource causing a great workload requiring the doctor to be with the patient.

IV. RESULTS ANALYSIS

A. Methods (RQ1)

According to the obtained results from the systematic analysis of literature, 19 works correspond to different *"Methods"* for cataract diagnosis representing 65.52% of the total reviewed works from which it can be observed that the majority of works [6]-[23] are focused on the *"Automatic"* method, representing 94.74% (see Table IV). For example, [8] used Deep Learning with Convolutional Recursive Neural Networks (CRNN) that learn image features and, later, a Support Vector Regression classifier (SVR) to determine 5 nuclear cataract grades. Moreover, out of the 19 reviewed works, just there proposed a portable solution in smartphones.

B. Features (RQ2)

The results on literature corresponding to *"Features"* considered in cataract diagnosis represent 42.28% where most of the works [7], [11], [27], [29], [32], [33] are focused on *"Image properties"* representing 42.86% (See Table V). For example, [7] employed image spectrum to determine the cataract grade. In addition, there was just one work found related to the pupil's features.

C. Classification (RQ3)

The total number of works found in the literature regarding *"Classification"* results in cataract diagnosis corresponds to 48.28% where the majority of works employ the classification "cataract grading" [7], [16], [25]-[27], [29] [31], [33]. [16], for example, classify the cataract grades in eyes without cataract, eyes with mild cataract, eyes with moderate cataract and eyes with severe cataract. Furthermore, it is noted that the less used classification is *"Congenital Cataract"*, mentioned in only one reviewed work: [34] classify their results in congenital cataracts caused by specific infections or diseases (see Table VI).

D. Obstacles (RQ4)

Regarding the works about *"Obstacles*" found in the literature, they represent 54.84% of the total reviewed works where it can be observed that the majority of works [6], [7], [10], [11], [12], [14], [21], [22], [24], [25], [28] is focused on the obstacle *"Lack of resources"* representing 64.7% (see Table VII). For instance, [10] grouped all the obstacles under lack of resources in rural regions which is why their solutions emphasize a low-cost accessible diagnosis.

E. Cross analysis: Methods vs Classification

In order to have a more in-depth analysis of the different contributions that have been previously analyze, a cross-analysis was carried out between the *"Methods"* found and the *"Classification"* applied for the cataract diagnosis. Table VIII shows the relationship between the different *"Methods"* used by researchers versus the *"Classification"* of their results. It is observed that the *CL01* classification (Cataract grades) is used by most methods, which represents 66.67%. For example, to classify the cataract grade, AdaBoost [7], CRNN + SVR [8], ANN [10], FCN [18], SVM [13], [16], ResNet-18 + SVM [21], AlexNet + SVM [22] and SSL [16] was used. Furthermore, it is observed that in the *CL03* classification (congenital cataract) they have not applied any of the revised *"Methods"*.

Table- VIII: Methods vs Classification

Methods \ Classification		CL01	CL02	CL03
M01	AdaBoost	[7]	[14]	
	CRNN + SVR	[8]		
	ANN	[10]		
	KNN		[11]	
	FCN	[18]		
	SRCL		[19]	
	SVM	[13], [16]		
	RestNet-18 + SVM	[21]		
	AlexNet + SVM	[22]		
	SSL	[23]		
M02	SLIT-LAMP		[9]	
	Ultrasound, Imageology of Fluorescence and Bio microscopy		[24]	

V. CONCLUSIONS

In this article, a systematic literature review of 39 546 articles on cataract diagnosis was presented. Within this amount, the abstracts of 34 studies were reviewed which helped to obtain 29 relevant articles for this study. The articles were analyzed based on the proposed taxonomy in Fig. 3 and the conclusions were drawn in line with the four research questions formulated in the planning phase. The majority of reviewed works focus on automatic methods. The most considered feature, based on the works reviewed, is *"image properties"*. *"Cataract grading"* is the most frequent among the majority of works. Concerning obstacles, the *"lack of resources"* is mentioned in most of the works. In addition to this, a cross-analysis was made between two of the proposed taxonomy components: "Methods" and the "Classification" applied to cataract diagnosis. In this cross-analysis, it was found that the *"cataract grading"* classification is mostly used in the reviewed methods. On the other hand, the *"congenital cataract"* classification is not present in any of the reviewed work, therefore new research on this topic is suggested. Finally, it can be noted that there are a few proposals for portable solutions, essential due to its easy-to-carry feature, and an option for low-cost cataract diagnosis for rural areas.

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