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A survey on artificial intelligence in ophthalmology: keratoconus classification

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ABSTRACT

The progressive integration of artificial intelligent tools in ophthalmology can potentially change the fundamental activities and the practices of ophthalmologists. Intelligent systems based on machine learning allow the detection and classification of several diseases such as age-related macular degeneration, glaucoma, diabetic retinopathy and keratoconus with high precision. The dependence between ophthalmology and images processing, given that almost of these diseases are identified by the analysis of the eye topographic maps, represents a point of at-traction for researchers to benefit of capacity and performance of deep learning tools in image processing. These deep learning tools allow a better differentiation between a sick eye and a normal eye and offer several advantages in the detection and classification of different diseases based on the analysis of the eye topographic maps. Among the diseases already mentioned, keratoconus, this non-inflammatory disease characterized by a progressive thinning of the cornea is of-ten accompanied by aspens of vision. This disease has been the subject of several research studies which aim to produce intelligent systems to assist ophthalmologists in the diagnosis and treatment of keratoconus. This paper represents a state of art of the application of artificial intelligence in ophthalmology, particularly in the detection and classification of keratoconus.

Keywords: ***Artificial Intelligence, Machine Learning, Deep Learning, Ophthalmology, Keratoconus.***

I. INTRODUCTION

In recent years, Artificial Intelligence (AI) has made a remarkable change in our society lifestyle by offering intelligent systems for recommendation, automatic car driving and detection of scenes or objects in videos or pictures and many other systems based on AI. In ophthalmology, a discipline which is generally based on the analysis of topographic images of the eye for the detection of certain diseases, Deep Learning (DL) tools can revolutionize this field by the capacity and performance of DL in the image classification [1]. AI, Machine Learning (ML) and DL tools can improve the diagnosis and treatment of many ophthalmic diseases while reducing the time and error rate, unlike classical methods based on the expertise and professional knowledge of ophthalmologists [2]. Several research works have produced intelligent systems able to detect and classify certain ophthalmic diseases such as age-related macular degeneration [3], glaucoma [4], diabetic retinopathy [5] and keratoconus [6]. These systems, taking advantage of the capabilities and performances of ML and DL tools in image processing [7], have demonstrated a good differentiation be-tween the normal eye and the affected eye, particularly the keratoconus one [8]. This paper is organized as follows: Section II represents a background, section III presents a state of the art of AI applications in ophthalmology, section IV illustrates a proposal keratoconus classification system architecture and finally section V represents a conclusion of this work.

II. BACKGROUND

The terms AI, ML and DL are frequently used to qualify certain products. In the same vein, there is a certain confusion between AI, ML and DL. AI is a concept that emerged in the 1950s (Alan Turing), AI was defined as a set of techniques that aim to produce a machine capable to imitate some human behaviors such as task planning and especially independent learning [1]. ML is a branch of AI, which appeared in the 80s and which consists in integrating statistics with algorithms handling a large structured datasets in order to make them more intelligent and capable to provide generalizations (i.e. learning) based on approximations generated by the application of statistics to the algorithms already used [9]. The data structuring must be carried out manually, hence the need for human intervention, while the objective is to produce intelligent systems and this point will make the capital difference compared to DL [10]. Since 2012, DL has seen great interest, the development of a trainable system capable to classify images and winning 1st prize in the imageNet 2012, the competition of image recognition and classification, has made DL more attractive. DL-based systems are made up of a multilevel suite of neural networks that perform all tasks from extraction to classification [1].

Considering the increasing number of patients with ophthalmic diseases worldwide, it’s important to produce intelligent systems to assist ophthalmologists in the diagnosis and treatment of the various ophthalmic diseases, while reducing time and providing a better classification precision, by combining ophthalmologist’s expertise and AI tools classification capacities.

III. Artificial Intelligence In Ophthalmology

A. Ophthalmic diseases classification

The integration of AI in ophthalmology is growing and new technologies are changing the practices of ophthalmologists. Several research projects aim to produce intelligent systems to assist ophthalmologists in different steps of diagnosis and treatment of several ophthalmic diseases. In [11], the authors set up an intelligent system using Convolutional Neural Networks (CNN) for the detection and classification of Diabetic Retinopathy (DR) by the processing of topographic images of the eyes. This system trained on a dataset of 85,650 images provides a classification with an accuracy of 85.7%. The authors of [12] proposed a DL-based system for glaucoma classification with an accuracy of 95.8% on a dataset of 101 images. To classify glaucoma, the authors of [13] have developed systems based respectively on the techniques of Support Vector Machine (SVM), Random Forrest (RF) and KNN. These systems classify glaucoma with an accuracy 97% for all methods. Works [14] and [15] provided classification systems for cataract. These intelligent CNN-based systems allow classification with an accuracy of 94.07% and 96.1% respectively. The authors of [16] developed an Age-Related Macular Degeneration (ARMD) classification system using SVM on data without selecting features then with selecting features, and the classification accuracy of developed systems is about 83.58%. Table 1 below summarizes these different research works.

TABLE I. Summary of previous works on AI in ophthalmology

Authors	Year	Disease	Method	Dataset size	Accuracy
Juneja et all. [12]	2019	Glaucoma	CNN	101	95.8%
Jordi et all. [11]	2019	DR	CNN	85650	85.7%
Qian et all. [15]	2018	Cataract	CNN	420	96.1%
Floriano et all. [16]	2017	ARMD	SVM	397	83.58%
Kim et all. [13]	2017	Glaucoma	SVM, RF, KNN	499	97%
Dong et all. [14]	2017	Cataract	CNN	7851	94.07%

Table 1 shows that AI tools allow developed systems to detect various diseases with good accuracy based on a variety of techniques.

B. Previous works on tools of AI in keratoconus classification

Keratoconus is characterized by a progressive thinning of the cornea; this disease is non-inflammatory but can cause vision problems in patients.

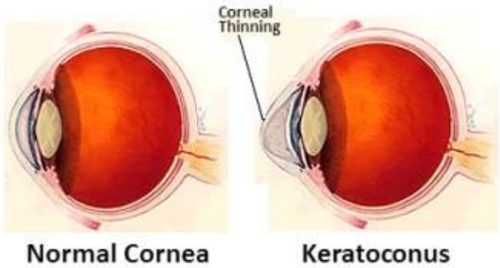

Figure 1. Normal cornea Vs keratoconus cornea [17].

Several research teams have focused on the production of intelligent systems for keratoconus diagnosis and classification. The authors of [18] proposed a CNN-based intelligent system for keratoconus detection trained on a data set of 3000 images. This system provides a classification with an accuracy of 99.33%. In [19], the authors developed a system using Feedforward Neural Network (FNN) to identify keratoconus, of which the accuracy of this system is 96.56% on a dataset of 851 elements. The work [20] represented a system proposal for a keratoconus detection based on the RF, and the system obtained provides a classification accuracy of 76% on a dataset of 500 images. Using a dataset of 124 images, the authors of [21] proposed a keratoconus identification and classification system using Bayesian Neural Networks (BNN), this system allows a classification with an accuracy of 73% and 80% respectively for supervised and unsupervised learning. In [22], the authors proposed a keratoconus classification system based on Unsupervised Machine Learning (UnML). The authors of [23] have developed a classification system for keratoconus based on BNN, of which the classification accuracy of this system on a dataset of 60 elements is 100%. In [24] the authors proposed an intelligent system for detecting keratoconus based on Artificial Neural Networks (ANN); this system uses a dataset of 396 images. Using a dataset of 543 images, the system proposed in [6] allowed the classification of keratoconus using CNN with an accuracy of 99.1%. Based on SVM, the system proposed in [25] allowed keratoconus detection and classification with an accuracy between 92.6% and 98.0% on a dataset of 131 images. The authors of [26] have developed an intelligent classification system based on Decision Trees (DT) on a data set of 372 images. In [27], authors proposed an SVM-based system for keratoconus detection and classification, the accuracy provided is 98.2% on a dataset of 3502 elements. The authors of [28] proposed a classification system for keratoconus with an accuracy of 90% on a dataset of 40 elements. Table 2 below summarizes the works already cited.

TABLE II. ARTIFICIAL INTELLIGENCE IN KERATOCONUS CLASSIFICATION.

Authors	Year	Method	Data set	Inputs	Accuracy
Lavric et al. [18]	2019	CNN	3000	180x240x3 (image)	99.33%
Issarti et al. [19]	2019	FNN	851	141x141 (image)	96.56%
Salem et al. [20]	2019	RF	500	N. A	76%
Hallett et al. [21]	2019	BNN	124	29 parameters	73% (supervised) 80% (unsupervised)
Luna et al. [23]	2019	BNN	60	16 parameters	100%
Kamiya et al. [6]	2019	CNN	543	6x224x224 (image)	99.1%
Yousefi et al. [22]	2018	UnML	3156	420 parameters	N. A
Hidalgo et al. [25]	2017	SVM	131	25 parameters	92.6% to 98.0%
Ali et all. [28]	2017	SVM	40	12 parameters	90%
Smadja et al. [26]	2013	DT	372	55 parameters	N. A
Arbelaez et al. [27]	2012	SVM	3502	7 parameters	98.2%
Accardo et al. [24]	2002	ANN	396	9 parameters	N. A

Developed systems allowed generally keratoconus classification with a good precision, exceeding 90% in general.

IV. CLASSIFICATION METHODOLOGY

A. Classification methodology

To classify keratoconus, the proposed approach consists in 2 steps, the first one allows keratoconus using all the original used dataset and in the second step the classification is performed using just selected features retained by the application of Boruta method of feature selection. Figure 1 bellow illustrates the adopted methodology.

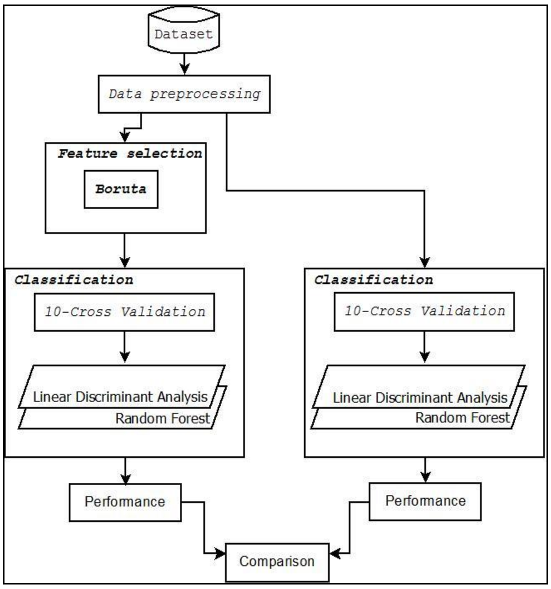

Figure 2. Adopted methodology.

Feature preprocessing. Consists in eliminating outliers, those that are either unreal and out of range. Then, data are normalized to ensure that the learning algorithms manipulate correct data and a specific range to produce a good classification.

Features selection. In this step, redundant and irrelevant features are eliminated to reduce the data size for a simplification of the calculations and a better classification.

Classification. Refers to application of Random Forest (RF) and Linear Discriminant Analysis (LDA) classification methods on the selected features to classify the different eyes.

B. Evaluation metrics

To evaluate performance of proposed systems, the metrics used are the classification precision, the recall and the f1-score as described in the equations 1, 2 and 3 bellow.

$$Accuracy = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1\text{-}score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

Where, True Positive (PT) is the number of images of diseases classified as disease, True negative (TN) is the number of normal images classified as normal , False Positive (FP) is the number of normal images classified as disease and False negative (FN) is the number of diseases of the images classified as normal.

V. SIMULATION RESULTS

A. Data description

The Simulations of the present study are based on the keratoconus database [29]. This dataset is composed of 42 features out of 205 rows describing 5 keratoconus classes of eyes. In our study we considered just 3 keratoconus classes (class 1 representing normal eyes, class 2 for form fruste keratoconus eyes and class 3 for mild and advanced keratoconus eyes) as illustrated in the table III bellow.

TABLE III. ARTIFICIAL INTELLIGENCE IN KERATOCONUS CLASSIFICATION.

Dataset size		**Description of retained classes**		
Features	***Rows***	***Class***	***Number of rows***	***Size in Percentage***
42	205	1	82	40%
		2	40	19.5%
		3	83	40.5%

B. Obtained results using all features of the dataset

The obtained results by the application of RF and LDA models on all the variables of the original dataset, using a 10-cross validation to avoid the overfitting, are illustrated in the figures 2, 3, 4 and 5 bellow.

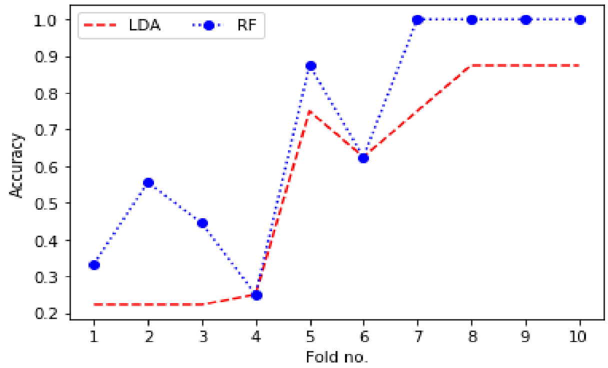

Figure 3. Classification accuracy.

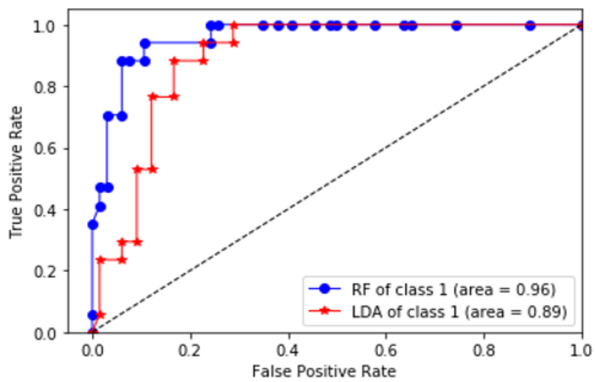

Figure 4. ROC curve of normal eyes (class 1).

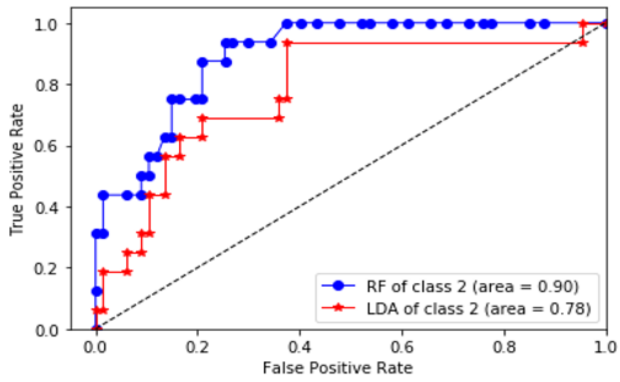

Figure 5. ROC curve of form frust keratoconus eyes (class 2).

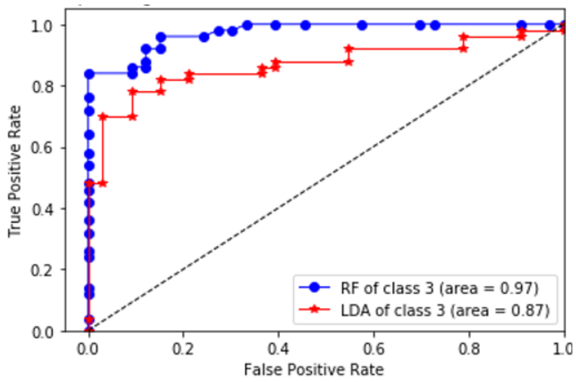

Figure 6. ROC curve of keratoconus eyes (class 3).

C. Classification using Boruta method of feature selection

Obtained results of keratoconus classification by the application of Boruta method of feature selection, using a 10-cross validation to avoid the overfitting, are illustrated in the figures 6, 7, 8 and 9 bellow.

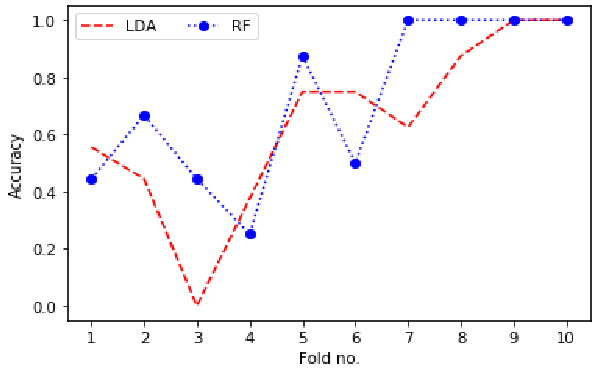

Figure 7. Classification accuracy.

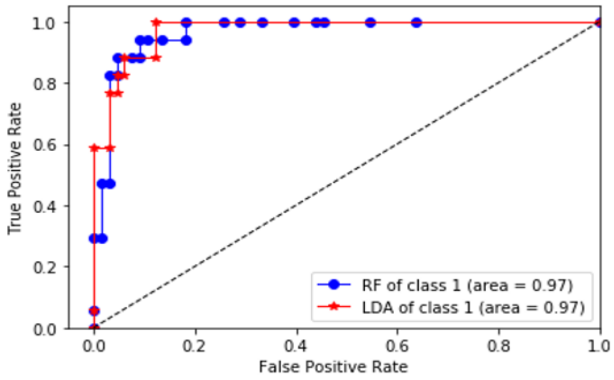

Figure 8. ROC curve of normal eyes (class 1).

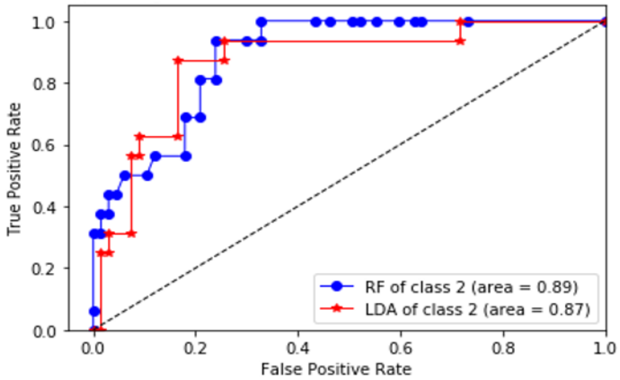

Figure 9. ROC curve of form frust keratoconus eyes (class 2).

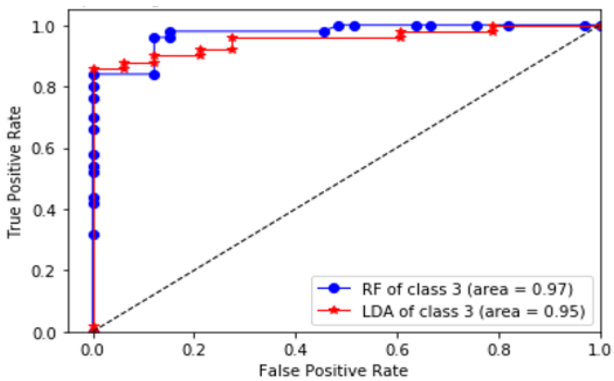

Figure 10. ROC curve of keratoconus eyes (class 3).

In all steps of keratoconus classification, Random Forest classifier represented the best model, considering classification accuracy and ROC curves for different classes of keratoconus.

D. Results Discussion

The obtained results in all cases of keratoconus classification are presented in the table IV bellow.

TABLE IV. CLASSIFICATION PERFORMANCE USING ALL DATASET.

Classification Using All Dataset			
Classifier	***Precision***	***Recall***	***F1-score***
RF	0.70	0.70	0.69
LDA	0.56	0.55	0.55
Classification Using Boruta Method			
Classifier	***Precision***	***Recall***	***F1-score***
RF	0.71	0.71	0.70
LDA	0.63	0.63	0.62

As shown in the table IV above, Random Forest classifier provided the best classification performance in different cases of keratoconus classification. RF generated a classification precision in order of 0.70 and LDA method provided a classification precision of 0.56 while using all the dataset. In the second step, handling just features selected by the application of Boruta method of feature selection, the classification precision was in order of 0.71 and 0.63 by the application of RF and LDA respectively. In the other hand, obtained results demonstrated that the use of the feature selection techniques is useful for different classifier by ensuring the selection of relevant variables and the elimination of harmful data.

VI. CONCLUSION

This paper represents a study of the state of the art of AI applications in ophthalmology, particularly in the keratoconus detection and classification. The studied works, based on machine learning algorithms, allowed a classification with good precisions. ML classification methods are promising, given the order of precision provided. This study was realized as part of a research project that aims to develop an intelligent system for detecting, classifying and predicting the evolution of keratoconus.

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