Review Article

A Review of the Latest Machine Learning Advances in Cataract Diagnosis

Zahra Alaeddini [1,*], MS

1. Department of Computer Science, Alzahra University, Tehran, Iran.

***Corresponding Author:** Zahra Alaeddini
E-mail: alaeddini.zahra@gmail.com

Abstract

Cataract disorder is one of the most common vision disorders in the world. As the average age of the world population increases, many people suffer from it in middle and old age. Timely diagnosis can prevent the reduction of vision and eventually loss of sight. Considering the prevalence of Artificial Intelligence algorithms, especially in the medical industry, they could be used for Cataract diagnosis, IOL determination, and PCO diagnosis. According to the studies, the proposed models for Cataract diagnosis are very accurate. These developed algorithms have been able to make access to ophthalmology services easier and reduce treatment costs significantly.
Keywords: Artificial Intelligence; Cataract; IOL; Machine Learning; PCO.

Article Notes: Received: Mar. 11, 2020; Received in revised form: May. 11, 2020; Accepted: Jun. 10, 2020; Available Online: Sep. 22, 2020.

How to cite this article: Alaeddini Z. A Review of the Latest Machine Learning Advances in Cataract Diagnosis Journal of Ophthalmic and Optometric Sciences. 2020;4(4):46-60.

Introduction

The cornea and lens are two important refractive structures of the eye. Damage to these structures could potentially lead to vision impairment and blindness [1]. According to the report of the World Health Organization (WHO), among the 2.2 billion people with eye disorders, 52.6 million of them are people with cataracts [2–4]. Therefore, cataracts are the leading cause of blindness in the world. Also, as the average age of the world population increases, the demand for cataract surgery is expected to increase [3,5].

To date, ophthalmologists have diagnosed cataracts using a Slit-lamp, so the patient must be in the doctor's office. This has become a significant challenge in, low-income and resource-poor countries and communities due to the lack of skilled ophthalmologists and the high probability of error [6,7]. Early diagnosis of the disease before the appearance of the initial symptoms of the disorder could significantly prevent the progression of the disease and ultimately, vision loss [8,9].

In recent years, Artificial Intelligence (AI) has been widely used in various aspects of medicine, including personalized medicine such as ophthalmology [10]. Machine Learning (ML) is a subset of AI. These days, Many ML algorithms, have been developed to classify cataract stages by using clinical images. These images had been recorded from examinations performed by ophthalmologists. Methods such as Support Vector Machines (SVM) and Neural Networks (NN) like Convolutional Neural Networks (CNN), Multilayer Perceptron Networks (MLP), or attention-based networks have been used more to classify images [10,11]. These algorithms can play an essential role in patient care by improving the doctor's diagnostic performance and predicting possible outcomes.

Due to the increasing use of AI algorithms in diagnosing and identifying the progress of cataracts, in this study, several developed algorithms related to cataract diagnosis, Intra-Ocular Lens (IOL) calculation, and Posterior Capsule Opacity (PCO) have been provided.

In the following, first, a definition of cataract and conventional imaging methods are provided. Then, an introduction to AI and its most widely used techniques, i.e., ML and Deep Learning (DL), which is a subset of ML, have been described. After that, the datasets used in developing AI algorithms in the cataracts field are examined. Finally, a review of the current applications of ML and DL algorithms in the cataract-related disorder have been provided.

Cataracts

The eye lens is one of the body's structures that continues to grow throughout life. The two leading causes of cataracts are associated with genetics and aging. The lens's transparency depends on many factors, including its microscopic structure and chemical components [12]. The new fibers produced in the lens do not replace the existing fibers, and this causes yellow-brown pigments to develop in the lens with increasing age, which is the cause of cataracts. The creation of these pigments reduces the ability of the lens to homogenize light and leads to a disruption in the architecture and regular arrangement of the lens fibers, which reduces the lens's power to transmit light. Cataracts are divided into three groups depending on which part of the lens is affected: Nuclear Cataracts, Cortical Cataracts, and Sub Capsular Cataracts [1].

Ophthalmologists diagnose cataracts when the lens is opaque. But when vision is impaired, surgery is recommended. Of course, external factors are also influential in cataracts, such

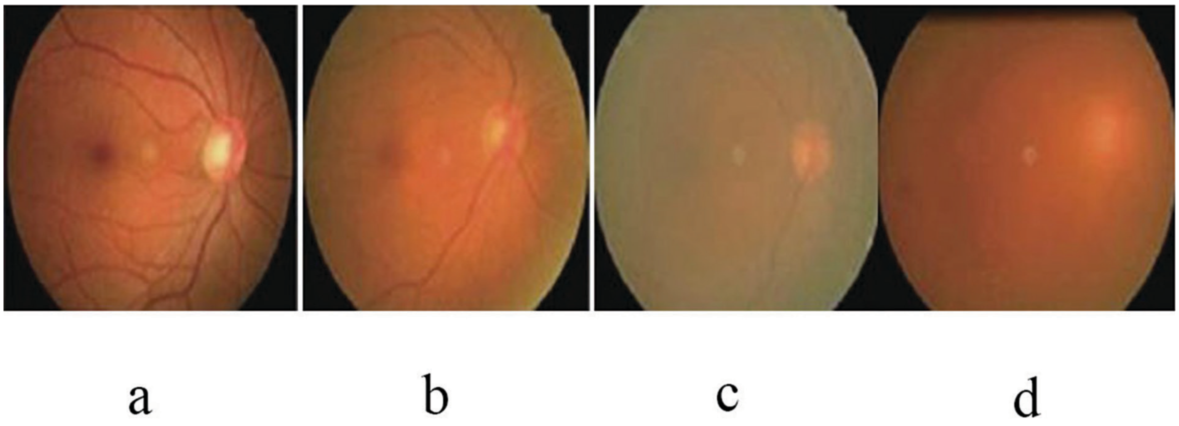

Figure 1: Four levels of cataracts: a- Normal, b- Immature, c- Mature, d-Hyper mature (16)

as socioeconomic differences, especially in developing countries, or excessive exposure to Ultraviolet rays. Therefore, using AI-based technologies in these countries could be helpful in the early diagnosis of cataracts and in reducing the costs for low-income groups [13].

Corneal and lens imaging methods

Fundus and Slit-lamp imaging are used to examine the cornea and lens. In addition, these two methods are important in studying and diagnosing cataracts. Clinical images used in ML algorithms were recorded by ophthalmologists using Fundus and Slit-lamp imaging devices.

Fundus imaging

Fundus [14,15] imaging device consists of a sophisticated microscope with a sensor. This device absorbs light reflected from the inner surface of the eye. Figure 1 shows four severity levels of cataracts. Fundus imaging device examines points within the eye that are biologically important and the complex patterns created by the retina structure.

Slit-lamp

The Slit-lamp [17–19] device consists of a biomicroscope and a high-intensity light source. This device can shine a thin beam of light into the eye. This system is used to examine the anterior and posterior parts of the eye. Ophthalmologists should pay attention to five factors when choosing a Slit-lamp [20]. These five factors are 1- the way of light radiation - 2- magnification power - 3- the width and length of the slit to radiate beam - 4- the filter used and - 5- the type of light source [20]. According to the way of radiating light, Slit-lamp devices could be classified into two types: Haag Streit and Zeiss. In the Haag Streit type, the light radiates from the top of the device. Meanwhile, in the Zeiss type, the light beams from the base of the device. Also, the magnification power should be at least 20 times in Slit-lamp devices. Also, the ophthalmologist uses a secondary hand lens to examine the retina. This lamp magnifies the internal structures of the eye to use the obtained details for the anatomical diagnosis of various cataract diseases. Figure 2 illustrates the four levels of nuclear cataracts.

A glance at Artificial intelligence

Machine learning is one of the broad and vital fields of Artificial Intelligence. ML allows the system to use the available data generated during the clinical encounter between the doctor and the patient to optimize itself [11,21].

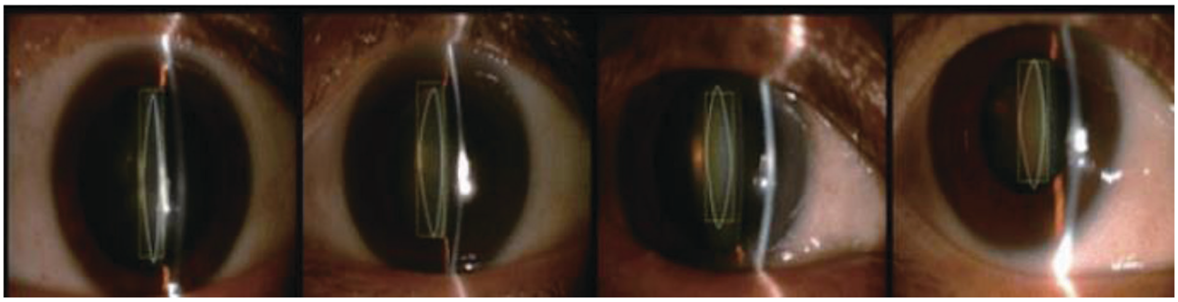

Figure 2: Four levels of nuclear cataracts(4)

Classical ML algorithms such as Random Forest (RF) that need to extract features, can learn high-level features gradually by discovering optimal parameters and weights. Meanwhile, Artificial Neural Networks (ANN), such as CNN, can learn high-level features by extracting features automatically from some layers and finding optimal weights and parameters. Due to this property of ML models, the performance of different ophthalmic image classification models has made significant progress. These models can detect cataracts, calculate the power of the IOL, and also predict the progression of PCO (Figure 3) [8].

ML includes algorithms that, with the availability of more powerful and cheaper hardware, can imitate human thinking using pre-stored data. Deep learning is also a subset of ML [22]. The branch of DL includes more advanced algorithms inspired by neural networks. These algorithms, which are called neural networks, can engineer and automatically extract features from stored data. The decision-making of ML and DL algorithms is based on classification [23]. DL classification algorithms are more widely used. The reason for this is the ability of DL methods to extract features using several hidden layers automatically. This NN particularity makes them perform better in classifiers than ML classical methods, which extract features manually [24] (Figure 4).

The data given to the ML algorithms and their sub-branches for prediction is pre-processed in several stages. After performing the pre-processing steps, features that are distinguishable and non-redundant are extracted. There are several methods to extract features, some of which are: contourlet transform, curvelet transform, principal component analysis, and discrete wavelet transform (Figure 5).

Therefore, feature extraction could reduce model training time. It also avoids overfitting the model. After the feature extraction phase, they feed to classification algorithms to determine the class. There are different classification algorithms, the most widely used of which are: SVM, RF, Logistic Regression (LR), Decision Tree (DT), and K-nearest neighbor (KNN). In addition to the mentioned cases, CNN and Recurrent Neural networks (RNN) are among the most widely used classifiers.

Among the mentioned neural networks, CNN [24,25] is the most widely used in image processing issues such as ophthalmology image processing. In CNN, the architecture of the layers is such that it avoids the problem of image processing in the form of piece processing that was common in NNs such as MLP. CNN can identify patterns in images. In other words, the layers of CNN help this

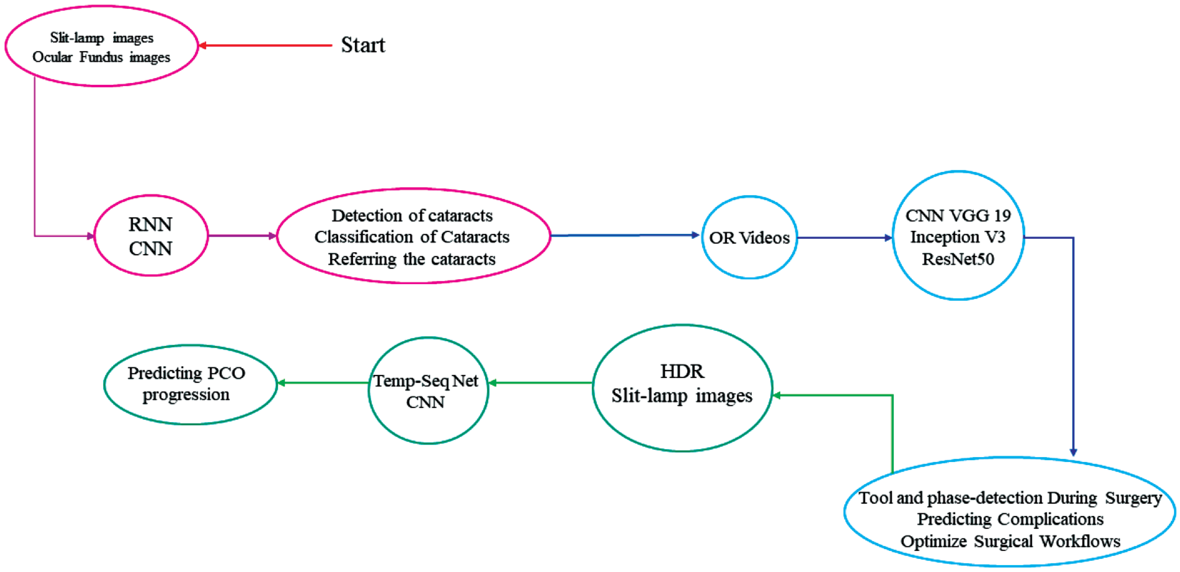

Figure 3: AI workflow for Cataract prediction, IOL calculation, and PCO has been shown by some related studies

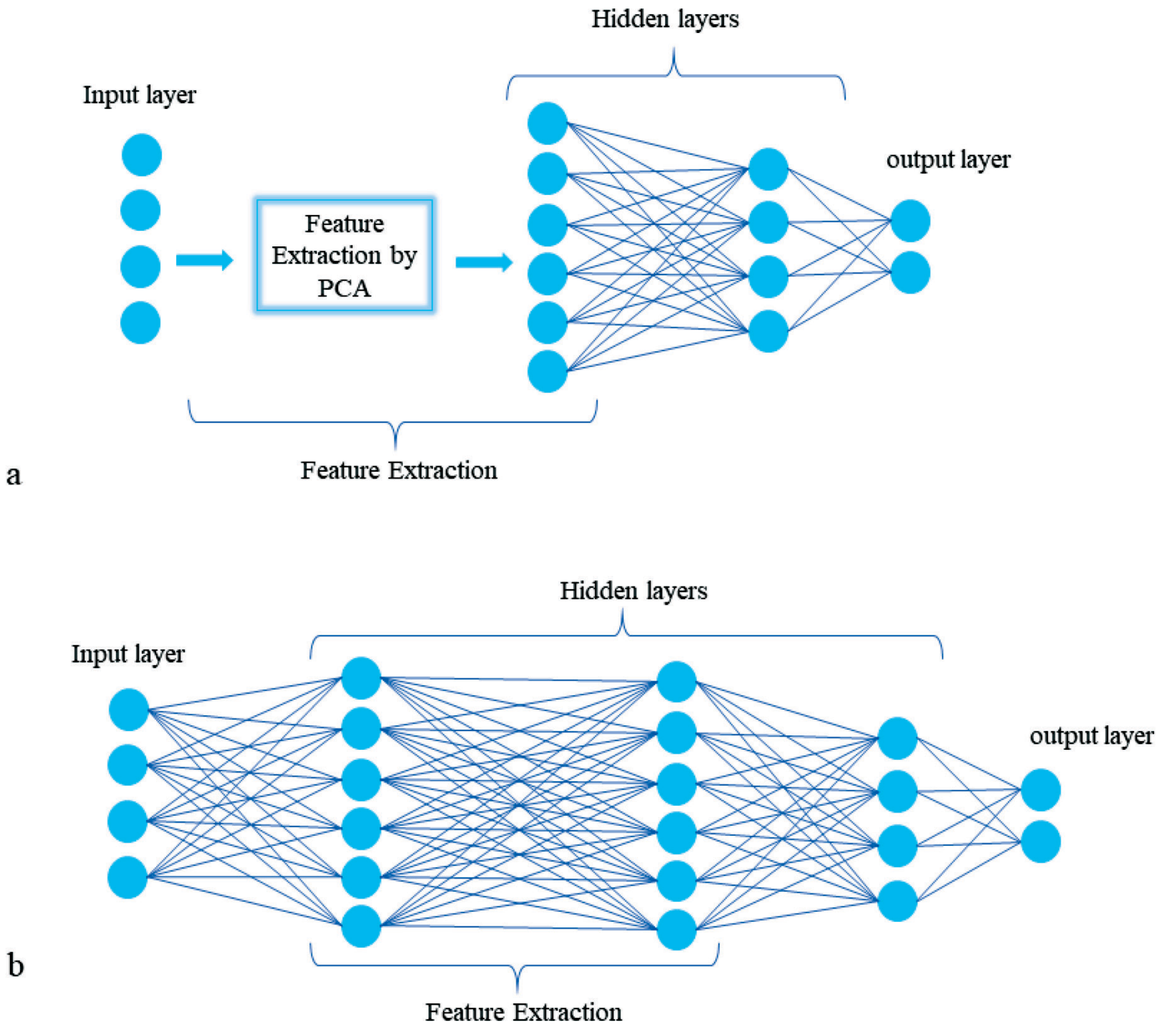

Figure 4: Difference between ML and DL methods: a-Machine Learning workflow, b-Deep Learning workflow

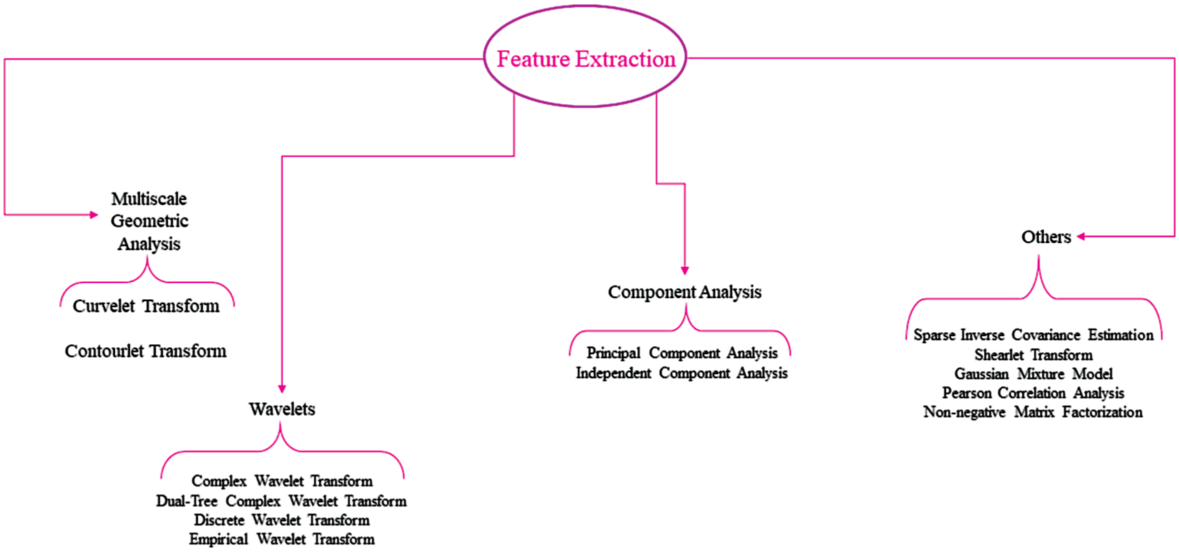

Figure 5: Feature Extraction Categorization

network to learn different features of an image. In general, the architecture of a CNN consists of an input layer, an output layer, and several hidden layers. In each hidden layer, the weight of the neurons and the bias values are the same. But the network constantly updates the weights of the neurons during training. Updating the weights of the neurons in the hidden layers means that the neurons are detecting different features. Three of the most common layers that lie between the input and output layers are pooling, convolution, and ReLU, which transform data to learn specific features. The convolution layer applies a set of filters on the input images that activate certain features of the images. The ReLU activation function allows for faster training. Because by keeping positive values and mapping negative values to zero, it transfers only the activated features to the next layer. By performing sampling, the pooling layer reduces the dimensions of the features, and in this way, the number of parameters that the network must learn and the number of calculations would be reduced.

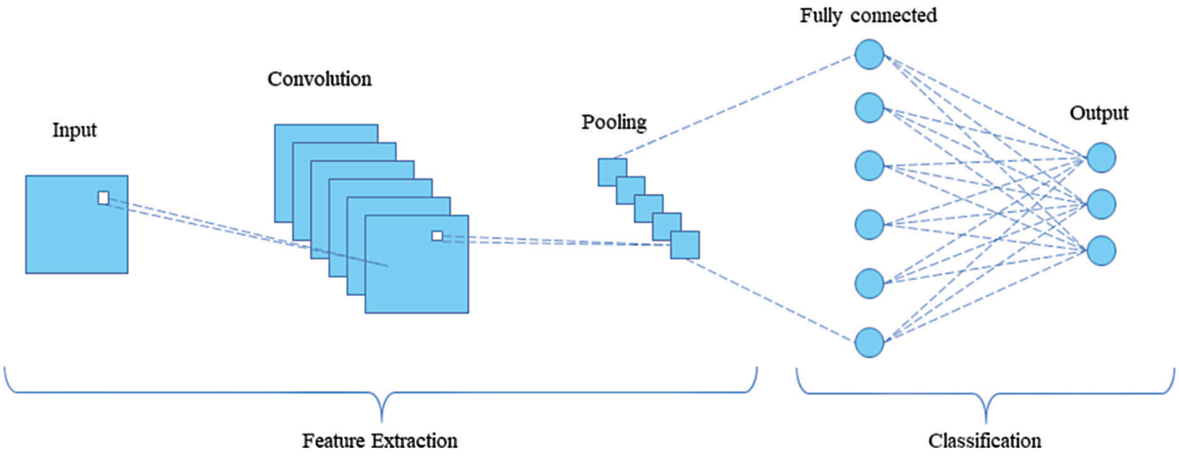

Figure 6: CNN workflow with Convolution, Pooling, and fully connected layer

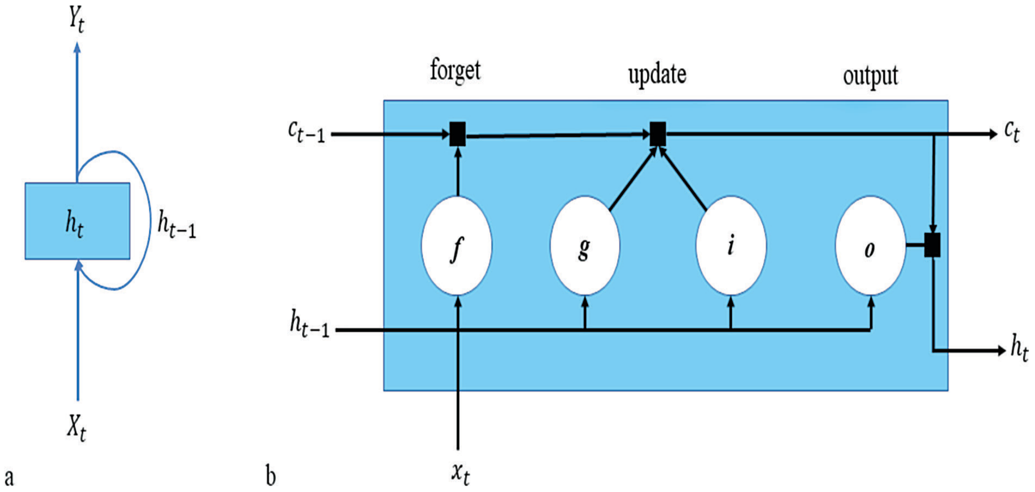

Figure 7: RNN and LSTM comparison. a- RNN ($X_t X_t$: Input, $Y_t Y_t$: Output, $h_t h_t$: Hidden state). b- LSTM ($x_t x_t$: Input, $h_t h_t$: Hidden state, $c_t c_t$: Cell state, f: Forget gate, g: Memory cell, i: Input gate, o: Output gate)

The last layer, which is a fully connected layer, consists of a vector with k length which is the number of classes into which the CNN could classify the data. On this layer, the SoftMax activation function is applied to classify images. Figure 6 illustrates the CNN workflow and association layers.

In addition, RNNs [24] are other types of neural networks that are interesting for researchers in video processing. RNN uses past information on current and future inputs to improve its performance. The structure of the RNN consists of state and hidden loops. Having a loop allows the network to work on sequences such as video processing by storing past information in a hidden state. The RNN has two categories of weights to use the past information. The network learns these weights for both the inputs and the hidden state during the training process. So, the hidden state is based on the previous entries. Finally, the output is based on the current input and the hidden state. To solve the RNN problem by learning long-term dependencies, network training is done through backpropagation. But this causes the RNN to experience gradient disappearance or gradient explosion. As a result, the weight of the network becomes too small or too large and limits the learning of long-term dependencies. A Long-Term Short-Term Memory (LSTM) network is a special type of RNN that can overcome this problem. For the network to learn long-term dependencies better, the LSTM network uses additional gates to control the information in the hidden cell to the output and the next hidden state. Figure 7 demonstrates the RNN and LSTM architecture.

Performance evaluation of ML systems is done using the parameters of accuracy, sensitivity, recall, specificity, Area Under Curve (AUC), and F1 score. Table 1 shows the formulas of the most common evaluation metrics.

In the development of algorithms based on AI for processing ophthalmic images, it is essential to provide statistics on the population on whose eye images the algorithm is based.

Datasets

The set of images used in the training of ML and DL algorithms that are available to the public are Cataract challenge [12], Age-

Table 1: The most common metrics calculate the ML algorithm's performance

Metric	Formula	Methods
Accuracy	$\frac{TN+TP}{TN+TP+FN+FP}$	Binary classification
Recall	$\frac{TP}{TP+FN}$	Binary classification
Specificity	$\frac{TN}{TN+FP}$	Binary classification
Precision	$\frac{TP}{TP+FP}$	Multiple classifications
F1-score	$\frac{2\times precision\times recall}{precision + recall}$	Multiple classifications

Related eye disease study [26], Visual Field [27], CaDIS [28], and EyePACS [29]. Table 2 shows the general information of these datasets. These datasets are used to compare different cataract classification methods. To check the accuracy of the model trained on these datasets, the clinical dataset collected from the participating laboratories is used, and most of them are private.

Developed algorithms for Cataract detection

As has been mentioned before, ophthalmic images such as Fundus and Slit-lamp are used to develop AI algorithms for cataract diagnosis. Until now, many systems using ML algorithms, which are a set of AI algorithms, have been designed for cataract detection. Our review paper investigates cataract classification using DL, and in some studies, has been combined with classical ML techniques for image classification.

XU et al. [30], proposed an architecture that consisted of a ResNet network, along with two SVMs as classifiers and a fully connected neural network. This new architecture has been called Hybrid Global-Local Representation CNN Model (GLCM). This architecture has been trained by using cataract fundus images. To use the potential of fundus images, they used a technique based on multiple stacked features to distinguish the intensity of cataracts. The overall accuracy of this proposed model has been reported over 86 %. This group of researchers used this model to diagnose different stages of cataracts. So, sensitivity and specificity have been reported for four classes Non-cataractous, Mild, Moderate, and Severe. The amount of sensitivity and specificity for images with non-cataractous labels were 95 % and 83.32 %. Also, for the Mild labels, these mentioned metrics have been reported at 79.8 % and 88.38 %. For another two classes, sensitivity and specificity have been reported at 80.05 %, 88.30 % for the Moderate level, 90.10 %, and 84.95 % for the severe level of cataracts.

Gao et al. [31], presented a structure of CNN, RNN, and Support Vector Regression (SVR) algorithms. To teach the proposed method, they used the images obtained from the clinical examinations of ophthalmologists with a slit-lamp device. This model could only reach an accuracy of about 70 % and 0.304 for Mean Absolute Error (MSE). But, Li et al. [32],

Table 2: Some of the well-known Cataract datasets

Dataset Name	images number of samples	Type of dataset	Disease name
Cataract challenge	50 videos	video	cataracts
Age-Related eye disease study	206500	Fundus photograph	AMD, Cataracts, and healthy eyes
Visual Field	4012	Visual Field	Glaucoma, Cataracts, and healthy eyes
EyePACS	1239	Fundus images	Cataracts
CaDIS	4670	50 videos	Cataracts

developed a model called Visionome, which can achieve accuracy between 79 % and 99 % for identifying cataracts or pathology of the anterior part of the eye by using only slit-lamp cataract images.

Xu et al. [30,33], have used a group of CNNs such as (AlexNet) and (VisualDN) to learn features directly from the input data obtained from fundus images. These methods could detect cataracts by their different layers. This proposed method achieved an accuracy of about 86 %, and to some extent, could meet the expectations of telemedicine for eye care. Also, MSE has been reported at 0.336 for this model. In another study, Zhang et al. [34], developed an architecture in which they used eight layers of Deep CNN with a SoftMax activation function to classify cataract images for cataract detection and cataract grading task. The proposed model achieved an accuracy of over 93 % on database_2_G. Also, they have reported sensitivity and specificity for cataract grading tasks on database_4_G. For the suggested method, sensitivity, and specificity have been reported at 95.63 % and 77.99 % on images classified as non-cataractous. Also, sensitivity and specificity for this method were 83.28 % and 90.22 % for the Mild grade, 57.92 % and 91.04 % for Moderate grade, and 81.67 % and 88.60 % for the severe level of cataract. The reported accuracy for grading cataract tasks has been reported at over 86 %. In addition, Dong et al. [35], developed a model using SoftMax activation function and five layers of CNN to classify cataract images in different stages of this ocular ailment. The proposed method achieved accuracy between 81 % and 94 %.

In a newly published paper, Qiang et al. [36], developed a system based on Faster R-CNN and ResNet deep learning framework. The system has been trained on the datasets of EENT Hospital and the Pujiang Eye Study Project. The suggested system had able to achieve an AUC equal to 0.983 for the EENT hospital dataset and 0.977 for the Pujiang dataset in the classification of cataract images.

In a study by Garcia et al [37], a region-based CNN trained on frames of phacoemulsification cataract surgery videos. In addition, this algorithm could recognize the phase of the ongoing surgery. Therefore, machine vision or attention algorithms were applied to the identified phases. Algorithms were able to provide visual feedback to the surgeon. The mentioned algorithm was able to reach AUC equal to 0.972 for phacoemulsification. Finally, this algorithm achieved 90.23 % accuracy in pupil segmentation.

The model implemented by Tauoma et al. [38], was an automated ML model. This model was able to classify ten different stages of cataracts. The team designed the model on Google Cloud AutoML Video Classification. The model was trained on a public dataset including 122 surgical videos. Another data set was used to validate the model. This model achieved an AUC equal to 0.855. In addition, the sensitivity and accuracy criteria have been reported as 81 % and 96 %, respectively. This model could predict the two stages of cataract surgery, Hydrodissection, and phacoemulsification, with 100 % and 92.31 % accuracy, respectively.

In the model developed by Jacob et al. [39], VGG-16 has been used to classify fundus images that were most likely to have a cataract disorder. In evaluating the performance of this model, only accuracy was considered. This model was able to classify fundus images with 98.83 % accuracy.

In another study by Matton et al. [40], a model based on dense CNN and a recursive averaging method has been developed. In this study, cataract surgery videos collected during 2020 and 2021 were used to train the model. Finally, a database containing 190 videos and more than 3.9 million annotated frames, called BigCat, was created from these images. The Area Under the Receiver Operator characteristic Curve (AUROC) value of 0.9985 was reported for the trained model. Also, the F1 score and accuracy of this model were equal to 0.9528 and 0.9935.

CataractNet's deep neural network for cataract detection on Fundus images has been developed by Junayd et al. [41] The computational cost and average execution time of CataractNet are lower than pre-trained CNN models. To train this model, 1130 Fundus images related to cataracts and without cataracts were added to 4746 images and used. The trained algorithm achieved an accuracy higher than 99 % and outperformed many cataract detection methods.

IOL determination using machine learning methods

One of the challenges for ophthalmologists after cataract surgery is the accurate determination of the IOL. Despite significant advances in IOL [42] prescription formulas, refractive errors may occur and require replacement. Therefore, this issue can pose a significant challenge even to patients. In recent years, the use of ML algorithms has led to significant progress in this field.

Wu et al. [43], developed an algorithm that uses different modes to classify the images obtained by taking pictures with a slit-lamp device into two categories mydriatic and non-mydriatic. This proposed architecture is ResNet deep learning network, which can distinguish between a cataract lens and a standard crystalline lens with a 3-step sequence. The AUC value for the proposed architecture has been reported to be greater than 0.99 for postoperative and over 0.95 for cataract mode. Also, the reported accuracy for both of these modes was 98.18 % and 88.79 %. Although the measured sensitivity for postoperative and cataract phases were 96 % and 92 %. Ladas et al. [44,45], have combined SVR, X-Gradient Boosting (XGB), and ANN methods, which are among supervised learning algorithms, with SRK, Holladay II, and Ladas Super formulas. The result of this procedure was an improvement in Mean Absolute Error (MAE) and the number of eyes at 0.5 diopters for each of the mentioned IOL formulations. SVR and XGB had 81 % performance improvement compared to SRK with 61 %.

Kane's [46] formula for predicting IOL is one of the most effective formulas in studies. This formula is a combination of regression and AI has consistently been in the Top 3 new generation formulas in terms of performance. In addition, it has surpassed the Haigis, Olsen, and Barrett Universal II formulas as well as the third-generation formulas. The reported MAE for the Kane formula is 0.377.

In another study, Carmona-Gonzalez et al. [47,48], Used KNN, ANN, SVM, and, RF Machine Learning models, and they developed a method to calculate IOL power called Karmona. This data-driven method uses specific parameters to predict IOL. The results of this method have been exceptionally superior compared to Barrett Universal II and other third-generation formulas. For the Karmona formula, MAE before adjusting has been reported at 0.24±0.18 and after adjusting has been performed, was 0.24±0.18. Another formula has been developed to calculate IOL power called PEARL-DGS [49]. This model predicts the influential position of the lens and biometric values by linearizing the output. In the comparison that was done to evaluate the formula with 13 other formulas, it was ranked after the last generation of formulas, namely Kane, Evo 2.0, VRF-G, and Barrett Universal II [50,51]. But the overall result was evaluated as good. Finally, after the full release of the data, it was found to outperform the Olsen, Evo 2.0, and Barrett Universal II formulas. MAE, Median Absolute Error, and mean Prediction Error have been recorded at ±0.25, ±0.5, and ±0.75.

Ladas et al. [52,53], have developed an incredible formula for the IOL. This formula is the result of the combination of SRK/T, Hoffer Q, and Holladay I formulas with Koch adjustment and also Haigis formulas. Considering that this formula shows an accurate representation of the output sections, compared to Barrett Universal II and Holladay I, couldn't have better performance.

Algorithms for identifying Posterior Capsule Opacity

One of the most common complications after cataract surgery, which has a significant impact on vision, is PCO [54]. To overcome this problem, several algorithms based on AI were developed. Mohammadi et al. [55], presented an algorithm for checking PCO with an accuracy of nearly 87 %, based on ANNs. Also, for this proposed model AUROC reported at 0.71. In addition, Jiang et al. [56], to monitor the progress of PCO over 24 months, presented a hybrid algorithm based on CNN and LSTM. They trained their model using 6090 images from clinical examinations performed by ophthalmologists. This model, called TempSeq-Net, achieved a high accuracy of 92 % and an AUC greater than 0.97.

Algorithms developed in this field of cataract screening can predict the possible risk early. This helps to treat the patient correctly and thus avoid possible complications that affect vision.

Conclusion

In this article, 19 studies were reviewed to evaluate the proposed methods for cataract diagnosis, Posterior Capsule Opacity, and IOL determination. 11 articles related to classification methods of cataract images, six articles for IOL determination formulas, and two articles for suggested methods for posterior capsule opacity detection were reviewed. This article allows researchers to be aware of the advances in Artificial Intelligence algorithms for cataract diagnosis and the necessary care during and after the operation.

Artificial Intelligence and its use in the field of ophthalmology have brought benefits such as cost reduction and accessibility. There are still extensive challenges facing using Artificial Intelligence-based methods in this field, such as data security and patient privacy. But one of the other challenges is that anterior segment diseases such as cataracts are often not imaged. Therefore, the process of model training and validation is complicated due to the lack of data. Of course, the main challenges in undeveloped and developing countries are weak infrastructure, lack of data, and budget. By solving or reducing these challenges, you can benefit from the high potential of Artificial Intelligence in ophthalmology.

Authors ORCIDs

Zahra Alaeddini:
https://orcid.org/0000-0001-6436-9286

References

1. Allen D. Cataract. Clin Evid. 2004;(12):933–8.
2. Blindness and vision impairment. Available from: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment.
3. Flaxman SR, Bourne RRA, Resnikoff S, Ackland P, Braithwaite T, Cicinelli M v., et al. Global causes of blindness and distance vision impairment 1990-2020: a systematic review and meta-analysis. Lancet Glob Health. 2017;5(12):e1221–34.
4. Zhang XQ, Hu Y, Xiao ZJ, Fang JS, Higashita R, Liu J. Machine Learning for Cataract Classification/Grading on Ophthalmic Imaging Modalities: A Survey. Machine Intelligence Research. 2022;19(3):184–208.
5. Wang W, Yan W, Fotis K, Prasad NM, Lansingh VC, Taylor HR, et al. Cataract Surgical Rate and Socioeconomics: A Global Study. Invest Ophthalmol Vis Sci. 2016;57(14):5872–81.
6. Erie JC. Rising cataract surgery rates: demand and supply. Ophthalmology . 2014;121(1):2–4.
7. Ahuja AS, Halperin LS. Understanding the advent of artificial intelligence in ophthalmology. J Curr Ophthalmol. 2019;31(2):115–7.
8. Sudhir RR, Dey A, Bhattacharrya S, Bahulayan A. AcrySof IQ PanOptix Intraocular Lens Versus Extended Depth of Focus Intraocular Lens and Trifocal Intraocular Lens: A Clinical Overview. Asia Pac J Ophthalmol (Phila). 2019;8(4):335.
9. Ting DSJ, Rees J, Ng JY, Allen D, Steel DHW. Effect of high-vacuum setting on phacoemulsification efficiency. J Cataract Refract Surg. 2017;43(9):1135–9.
10. Pettit RW, Fullem R, Cheng C, Amos CI. Artificial intelligence, machine learning, and deep learning for clinical outcome prediction. Emerg Top Life Sci. 2021;5(6):729–45.
11. Pavel AM, Rennie JM, de Vries LS, Blennow M, Foran A, Shah DK, et al. A machine-learning algorithm for neonatal seizure recognition: a multicentre, randomised, controlled trial. Lancet Child Adolesc Health. 2020;4(10):740–9.
12. al Hajj H, Lamard M, Conze PH, Roychowdhury S, Hu X, Maršalkaitė G, et al. CATARACTS: Challenge on automatic tool annotation for cataRACT surgery. Med Image Anal. 2019; 52:24–41.
13. Allen D, Vasavada A. Cataract and surgery for cataract. BMJ : British Medical Journal.

2006; 333(7559):128. Available from: /pmc/articles/PMC1502210/
14. Chen W, Chang J, Zhao X, Liu S. Optical design and fabrication of a smartphone fundus camera. Appl Opt. 2021;60(5):1420.
15. Plesch A, Klingbeil U, Bille J. Digital laser scanning fundus camera. Appl Opt. 1987;26(8):1480.
16. Cao L, Li H, Zhang Y, Zhang L, Xu L. Hierarchical method for cataract grading based on retinal images using improved Haar wavelet. Information Fusion. 2020;53:196-208.
17. Gellrich MM. [The slit lamp as videography console : Video article]. Ophthalmologe. 2018 ;115(10):885–92. Available from: https://pubmed.ncbi.nlm.nih.gov/30006769/
18. MacDonald WW, Swaminathan SS, Heo JY, Castillejos A, Hsueh J, Liu BJ, et al. Effect of SPARC Suppression in Mice, Perfused Human Anterior Segments, and Trabecular Meshwork Cells. Investigative Opthalmology & Visual Science. 2022;63(6):8.
19. Fercher AF, Li HC, Hitzenberger CK. Slit lamp laser doppler interferometer. Lasers Surg Med. 1993;13(4):447–52.
20. 5 Most Important Slit Lamp Features | Coburn Technologies. Available from: https://www.coburntechnologies.com/2017/02/21/5-important-slit-lamp-features/
21. Lee CS, Tyring AJ, Deruyter NP, Wu Y, Rokem A, Lee AY. Deep-learning based, automated segmentation of macular edema in optical coherence tomography. Biomed Opt Express. 2017;8(7):3440. Available from: /pmc/articles/PMC5508840/
22. Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. Electronic Markets. 2021;31(3):685–95.
23. Chauhan NK, Singh K. A review on conventional machine learning vs deep learning. 2018 International Conference on Computing, Power and Communication Technologies, GUCON 2018. 2019;347–52.
24. Lecun Y, Bengio Y, Hinton G. Deep learning. Nature 2015 521:7553. 2015;521(7553):436–44.
25. Mahmud M, Kaiser MS, Hussain A, Vassanelli S. Applications of Deep Learning and Reinforcement Learning to Biological Data. IEEE Trans Neural Netw Learn Syst. 2018;29(6):2063–79.
26. dbGaP Study. Available from: https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study_id=phs000001.v3.p1&phv=53743&phd=1&pha=2856&pht=371&phvf=&phdf=&phaf=&phtf=&dssp=1&consent=&temp=1
27. Li F, Wang Z, Qu G, Song D, Yuan Y, Xu Y, et al. Automatic differentiation of Glaucoma visual field from non-glaucoma visual filed using deep convolutional neural network. BMC Med Imaging. 2018 ;18(1).
28. Grammatikopoulou M, Flouty E, Kadkhodamohammadi A, Quellec G, Chow A, Nehme J, et al. CaDIS: Cataract dataset for surgical RGB-image segmentation. Med Image Anal. 2021;71:102053.
29. Yang JJ, Li J, Shen R, Zeng Y, He J, Bi J, et al. Exploiting ensemble learning for automatic cataract detection and grading. Comput Methods Programs Biomed. 2016;124:45–57.
30. Xu X, Zhang L, Li J, Guan Y, Zhang L. A Hybrid Global-Local Representation CNN Model for Automatic Cataract Grading. IEEE J Biomed Health Inform. 2020;24(2):556–67.
31. Gao X, Lin S, Wong TY. Automatic Feature Learning to Grade Nuclear Cataracts Based on Deep Learning. IEEE Trans Biomed Eng. 2015;62(11):2693–701.
32. Li W, Yang Y, Zhang K, Long E, He L, Zhang L, et al. Dense anatomical annotation of slit-lamp images improves the performance of deep learning for the diagnosis of ophthalmic disorders. Nat Biomed Eng. 2020;4(8):767–77.

33. Xu Y, Gao X, Lin S, Wong DWK, Liu J, Xu D, et al. Automatic grading of nuclear cataracts from slit-lamp lens images using group sparsity regression. Med Image Comput Comput Assist Interv. 2013;16(Pt 2):468–75.
34. Zhang L, Li J, Zhang I, Han H, Liu B, Yang J, et al. Automatic cataract detection and grading using Deep Convolutional Neural Network. Proceedings of the 2017 IEEE 14th International Conference on Networking, Sensing and Control, ICNSC 2017. 2017;60–5.
35. Dong Y, Zhang Q, Qiao Z, Yang JJ. Classification of cataract fundus image based on deep learning. IST 2017 - IEEE International Conference on Imaging Systems and Techniques, Proceedings. 2017:1–5.
36. Lu Q, Wei L, He W, Zhang K, Wang J, Zhang Y, et al. Lens Opacities Classification System III–based artificial intelligence program for automatic cataract grading. Journal of Cataract & Refractive Surgery. 2022;48(5):528-34.
37. Garcia Nespolo R, Yi D, Cole E, Valikodath N, Luciano C, Leiderman YI. Evaluation of Artificial Intelligence–Based Intraoperative Guidance Tools for Phacoemulsification Cataract Surgery. JAMA Ophthalmol. 2022;140(2):170–7.
38. Touma S, Antaki F, Duval R. Development of a code-free machine learning model for the classification of cataract surgery phases. Scientific Reports 2022 12:1. 2022;12(1):1–7.
39. Paul Jacob A, Bansal A, Malhotra R. A Novel Approach for Early Recognition of Cataract using VGG-16 and Custom User-based Region of Interest. ACM International Conference Proceeding Series. 2022;15–8.
40. Matton N, Qalieh A, Zhang Y, Annadanam A, Thibodeau A, Li T, et al. Analysis of Cataract Surgery Instrument Identification Performance of Convolutional and Recurrent Neural Network Ensembles Leveraging BigCat. Transl Vis Sci Technol. 2022;11(4):1–1.
41. Junayed MS, Islam MB, Sadeghzadeh A, Rahman S. CataractNet: An automated cataract detection system using deep learning for fundus images. IEEE Access. 2021;9:128799–808.
42. Hee MR. State-of-the-art of intraocular lens power formulas. Vol. 133, JAMA Ophthalmology. American Medical Association; 2015. p. 1436–7.
43. Wu X, Huang Y, Liu Z, Lai W, Long E, Zhang K, et al. Universal artificial intelligence platform for collaborative management of cataracts. Br J Ophthalmol. 2019;103(11):1553–60.
44. IOLcalc - Ladas Super Formula. [cited 2022 May 6]. Available from: https://www.iolcalc.com/
45. Ladas J, Ladas D, Lin SR, Devgan U, Siddiqui AA, Jun AS. Improvement of Multiple Generations of Intraocular Lens Calculation Formulae with a Novel Approach Using Artificial Intelligence. Transl Vis Sci Technol. 2021;10(3):7–7.
46. Connell BJ, Kane JX. Comparison of the Kane formula with existing formulas for intraocular lens power selection. BMJ Open Ophthalmol. 2019;4(1):e000251.
47. Fernández-Álvarez JC, Hernández-López I, Cruz-Cobas PP, Cárdenas-Díaz T, Batista-Leyva AJ. Using a multilayer perceptron in intraocular lens power calculation. J Cataract Refract Surg. 2019;45(12):1753–61.
48. Carmona González D, Palomino Bautista C. Accuracy of a new intraocular lens power calculation method based on artificial intelligence. Eye (Lond). 2021;35(2):517–22.
49. Savini G, di Maita M, Hoffer KJ, Næser K, Schiano-Lomoriello D, Vagge A, et al. Comparison of 13 formulas for IOL power calculation with measurements from partial coherence interferometry. Br J Ophthalmol.

2021;105(4):484–9.
50. Khatib ZI, Haldipurkar SS, Shetty V, Dahake H, Nagvekar P, Kashelkar P. Comparison of three newer generation freely available intraocular lens power calculation formulae across all axial lengths. Indian J Ophthalmol. 2021;69(3):580.
51. Sramka M, Slovak M, Tuckova J, Stodulka P. Improving clinical refractive results of cataract surgery by machine learning. PeerJ. 2019;2019(7).
52. Kane JX, van Heerden A, Atik A, Petsoglou C. Accuracy of 3 new methods for intraocular lens power selection. J Cataract Refract Surg. 2017;43(3):333–9.
53. Ladas JG, Siddiqui AA, Devgan U, Jun AS. A 3-D super surface combining modern intraocular lens formulas to generate a super formula and maximize accuracy. JAMA Ophthalmol. 2015;133(12):1431–6.
54. Ursell PG, Dhariwal M, Majirska K, Ender F, Kalson-Ray S, Venerus A, et al. Three-year incidence of Nd:YAG capsulotomy and posterior capsule opacification and its relationship to monofocal acrylic IOL biomaterial: a UK Real World Evidence study. Eye (Lond). 2018;32(10):1579–89.
55. Mohammadi SF, Sabbaghi M, Z-Mehrjardi H, Hashemi H, Alizadeh S, Majdi M, et al. Using artificial intelligence to predict the risk for posterior capsule opacification after phacoemulsification. J Cataract Refract Surg. 2012;38(3):403–8.
56. Jiang J, Liu X, Liu L, Wang S, Long E, Yang H, et al. Predicting the progression of ophthalmic disease based on slit-lamp images using a deep temporal sequence network. PLoS One. 2018;13(7):e0201142.

Footnotes and Financial Disclosures

Conflict of interest:

The authors have no conflict of interest with the subject matter of the present manuscript.

Abbreviations

AI: Artificial intelligence
ML: Machine Learning
DL: Deep Learning
IOL: Intraocular Lens
NN: Neural Network
SVM: Support Vector Machine
RF: Random Forest
LR: Logistic Regression
KNN: K-Nearest Neighbor
RNN: Recurrent Neural Network
CNN: Convolutional Neural Network
PCO: Posterior Capsule Opacification
WHO: World Health Organization
MLP: Multilayer Perceptron
LSTM: Long-Term Short-Term Memory
MAE: Mean Absolute Error
AUC: Area Under Curve
AUROC: Area Under the Receiver Operator Characteristic Curve