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ORIGINAL RESEARCH

A literature review: various learning techniques and its applications for eye disease identification using retinal images

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Abstract In the recent world, artificial intelligence (AI) based learning models are widely used in various applications for medical image analysis. These models based on machine learning. The deep study is implemented for the solution of problems like disease identification and classifying various types of medical images. The detection of glaucoma-related eye disease is a major concern for avoiding early blindness and diagnosis of diabetic effect on the eye. There were many models implemented for the detection of glaucoma-related eye disease. In this paper, various existing models along with its performance are discussed to detect eye disease. This paper discusses the detection of glaucoma using various learning models based on retinal images. Further, future research in this research domain is also discussed based on learning models.

Keywords Artificial intelligence · Classification · Deep learning · Image · Machine learning · Object detection

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1 Introduction

Machine learning (ML) is one of the applications of artificial intelligence (AI) [1]. The machine learning algorithms provide automatic learning ability of systems. The performance of this system can improve the learning experience without any complicated programming. The machine learning mainly focuses on the implementation and developing of a new model based on the computer system and program that can access the information and use this information to learn for them [1]. These algorithms determine a unique feature or pattern in the given input data that helps in making a better decision-making process. These algorithms are mainly used in applications related to the medical image, computer vision, biometric recognition, object detection, and automation, etc. [1, 2]. There are three types of machine learning [1, 2] such as supervised learning, unsupervised learning and reinforcement learning.

1.1 Supervised learning

This type of learning is mainly used in real time applications and practical approach. In this learning, the model tries to learn information from the previous experience of information that is given to it. This learning is where the input (x) and output (y) and determine an algorithm that gives mapping function (f) from the input to the output like this:

$$y = f(x). \tag{1}$$

The problem related supervised learning is divided into two types such as classification and regression. The classification problem is where the output is a specific value, group or category. For example, 'cat' or 'dog'. The regression problem is where the output is a continuous value or real value, for example; temperature or currency. There are dozens of algorithms developed for supervised learning and each of them uses various methodologies to predict the value of output [4].

1.2 Unsupervised learning

In unsupervised learning, the algorithms try to discover a unique pattern or feature themselves without knowledge of previous experience. Mathematically, this type of learning is where the model has input (x) but not have a corresponding output. This type of learning is called unsupervised because the machine or system itself to finds the answer of input and not given the correct output. The algorithms based on unsupervised learning are mainly used in problems related to association and clustering.

1.3 Reinforcement learning

In this type of learning, a machine or system takes a particular action to maximize output for a given input. It uses various software and algorithms to find the best possible output or behavior of the machine for a given input task.

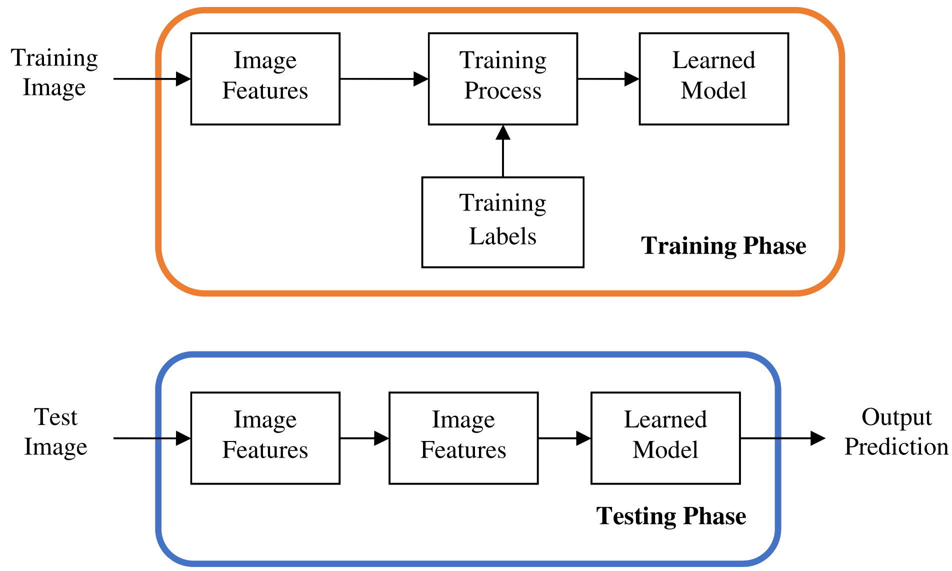
No machine learning algorithm fits all requirements of real time applications. Therefore, finding the right algorithms is a challenging task and it is a trial and error method. To solve this, researchers [1–5] suggest that the selection of algorithms depending on the size of input data, nature of input data and what type of output required from the given input data. Thus, in practice, machines are used as reinforcement learning. It exposes to the platform where it continuously trains itself to achieve better predict the output. The common supervised ML algorithms are available in the literature [1–6] support vector machine (SVM), decision tree and random forest, nearest neighbor, naïve Bayes, linear regression, k-means clustering, etc. In real time applications related to machine learning, multimedia information such as images, videos, speech signals, etc. are used as input data. The image related to machine learning applications is very famous in the research community due to its simple visualization and easy to understanding [6]. The basic steps of the machine learning algorithm for image processing are given in Fig. 1. This algorithm is working into two phases such as the training phase and testing phase. In the training phase, the model learns unique features or patterns from the input image. While in the testing phase the model gives the specific output based on learner features or patterns. The features or patterns of the image may be edges, a region of interests, etc. which extracts using various feature extraction methods. The selection of extraction methods depends on the type of input image, the specific output of the model.

For main applications such as disease identification and diagnosis, the analysis was higher resolution medical images are required. For these types of applications, traditional machine learning algorithms are required. The higher number of features and experts analyzed to predict the output. Also, due to the random nature of the medical image, the traditional machine learning algorithms are not given reliable output [7]. Thus, researchers have introduced a new supervised learning approach which is effective for random types of medical images. This approach was designed using a neural network which has similarities to the neural system of the human brain. The term of deep learning comes due to its used deep neural network model [7]. The deep learning is a subtype of machine learning which is inspired by the function of artificial neural networks (ANN).

Recently, many applications related to medical images are used for deep neural network-based models and better detection and diagnosis of eye disease [8, 9]. Thus, in this paper, different learning-based models for detection of eye disease particularly glaucoma are discussed along with its performance. The reason behind doing this survey is; According to the WHO report [8], various eye-related diseases are coming in many poor income countries and more industrialized areas of many countries. The types of eye diseases such as cataract, onchocerciasis, childhood blindness, macular degeneration, corneal opacities, diabetic retinopathy, and glaucoma are solved using retinal images. These diseases mainly cause blindness in human life. As per literature [9], glaucoma is the third disease causes blindness in India. It is a very serious illness and as per survey of glaucoma society of India [9], around 12 million people in India are suffered from this disease. In India, many people are suffered from this disease but there are not identified and diagnosis. In this disease, damage in the retina is a processive manner and less detected by the person. Therefore, early detection of this disease and diagnosis is necessary to prevent blindness. The various types of image processing algorithms along with various machine learning algorithms are used for classification and detection of the glaucomatous retinal image in modern glaucoma detection schemes. Two types of machine learning algorithms such as supervised and unsupervised are used in glaucoma detection schemes. The unsupervised machine learning algorithms are used mainly for the segmentation of disk and cup in the enhanced retinal image. While supervised machine learning algorithms are used for classification of the normal image and glaucomatous image for a given database of the retinal image.

The main motivation of this paper is to provide a comprehensive review of various techniques regarding the detection of glaucoma eye disease using retinal images. The main points covered in this paper are as below:

Fig. 1 Steps of machine algorithm for image related applications



1. This study provides a comprehensive review of various learning methods.
2. A comprehensive review of various deep learning algorithms with advantages and disadvantages.
3. The details of various machine learning based models for the detection of glaucoma eye disease using retinal images with its performance parameters are covered.
4. Finally, limitations of existing models and possible future direction for glaucoma detection using retinal images are discussed.

2 Neural network and deep learning

The first neural network (NN) was introduced by Dr. Robert Hecht-Nielsen who was the inventor of first neurocomputers [10]. This network basically is known as an artificial neural network (ANN). He defines a neural network as "a computing system made up of a number of simple, highly interconnected processing elements which process information by their dynamic state response to external inputs" [10, 11]. This network mainly used in applications such as big data analysis, person recognition, and data prediction, etc. This network is also referred as forwarding neural network (FNN). This network is used numbers of neurons which are based on the parallel operation and put in tiers. A simple model for the neural network is shown in Fig. 2. The network has mainly three layers such as the input layer, hidden layers, and the output layer. The number of neurons or nodes is depended on the size of inputs and outputs. Each node is fully connected to its adjacent layers. Two nodes of each adjacent layer are connected by a link with a specific weighting value.

The output of this model (seen in Figs. 2, 3) can be given by the below equation:

$$\hat{y} = P + b, \tag{2}$$

$$P = W_1 \cdot x_1 + W_2 \cdot x_2 + W_3 \cdot x_3 + b, \tag{3}$$

where x is the input value, W is the weights that to be learned, b is the bias and $\hat{y}$ is the predict output value given by the model. The detail working of this model is given in Fig. 3. The neural network is unable to learn weights for unstructured data such as images and videos. Therefore, activation functions such as sigmoid and ReLU (rectified linear unit) are with the neural network when it is used in machine learning applications. Here, the bias is used for the shifting of activation function for better prediction of data.

A deep learning algorithm is an extension of the artificial neural network. The deep learning algorithm consists of an input layer, several hidden layers, and an output layer. Here, each layer is connected via nodes where each hidden layer gives predicted results based on a prediction of the previous layer. The main difference between ANN and deep learning algorithms is that ANN has one hidden layer while deep learning algorithms have two or more than two hidden layers. The basic architecture of a deep learning algorithm is given in Fig. 4.

A convolutional neural network (CNN) is the most popular deep learning neural network used for image-related applications [12–15]. CNN has three layers such as an input layer, the output layer and many hidden layers in between them. The basic architecture of CNN is given in Fig. 5. In the hidden layer of CNN, different operations such as feature extraction, flattening of features and classification of features are performed.

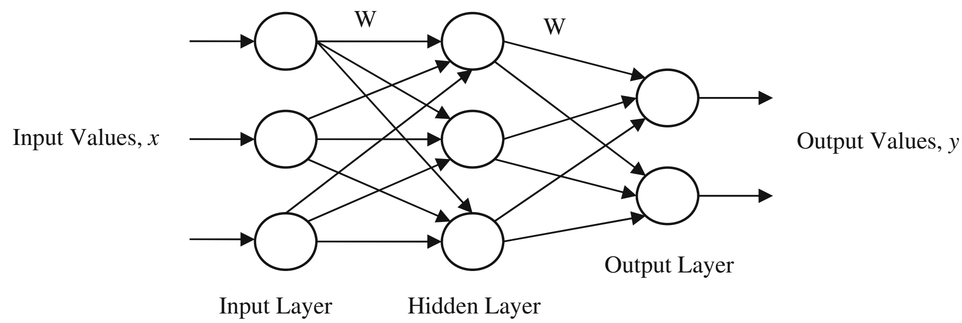


Fig. 2 Basic model of artificial neural network (ANN)

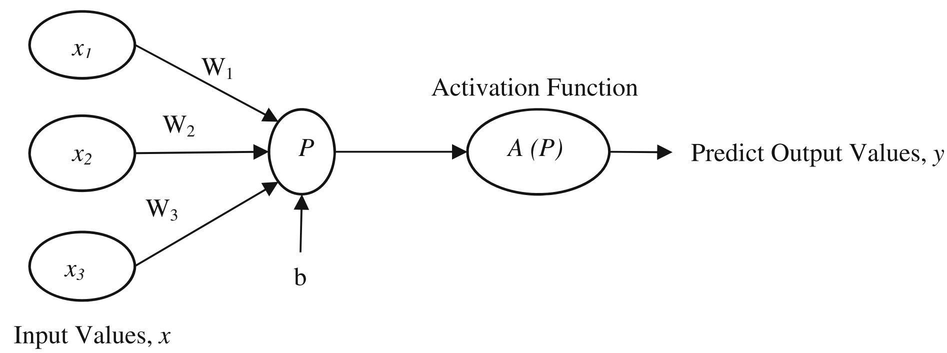


Fig. 3 Working of artificial neural network (ANN)

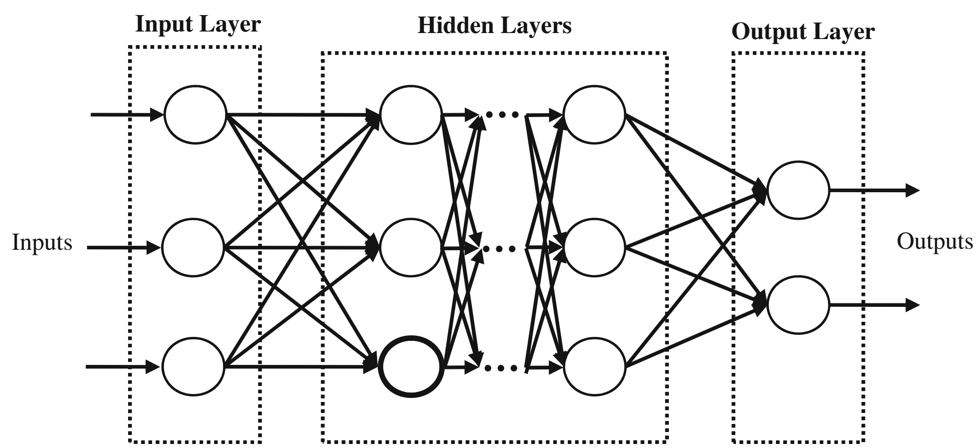


Fig. 4 Basic model of deep learning neural network (DLNN)

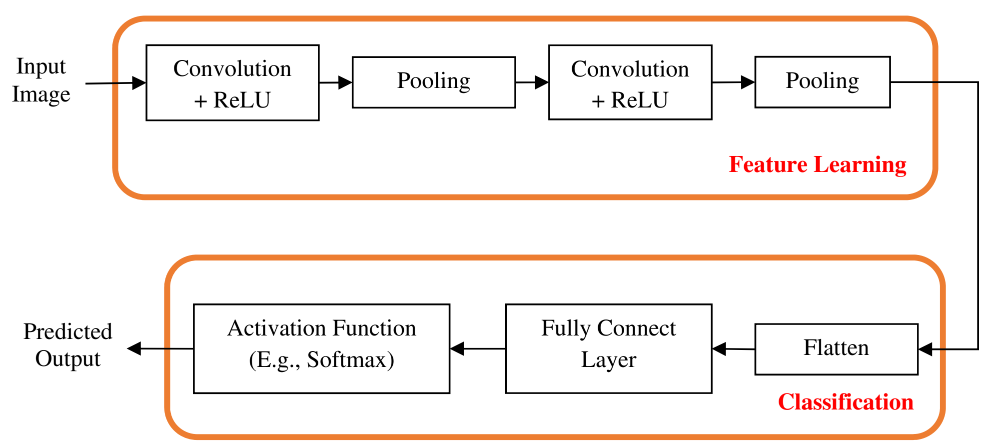


Fig. 5 Working of convolutional neural network (CNN)

2.1 Feature extraction

The feature extraction operation performed different tasks such as convolution, non-linearity rectified linear unit (ReLU) and pooling. The operation of each task is given below.

2.1.1 Convolution operation

This is the first step of feature extraction of the input image on CNN. It is a similar process of spatial filtering of the image and gives the relationship between image pixel by obtaining image features using small information of input image. Mathematically, it is output that uses two input values such as the value of image pixel and value of filter mask. The dimension of output can be obtained using the below relationship:

$$O = (M - f_M + 1) \times (N - f_N + 1), \tag{4}$$

where O is output, the dimension of an image pixel is $f_M \times f_N$ and dimension of a filter mask is $M \times N$.

Consider an image matrix with a size of 5×5 with values of 0, 1 and size of a filter mask is 3×3 as shown in Fig. 6. The convolved values of these two are also shown in Fig. 6. The convolution of the image with different filter masks is given different features such as edges, sharping information, etc.

The operations like strides and padding are also used after the convolution process for better extraction of the feature. Strides operation is used for shifting value in the image matrix to obtain better features from the input image. Sometimes, the application of a filter to the input image is not fit perfectly then padding operation is performed. In this operation some images with zero values, so that filter works effectively on it.

2.1.2 Non-linearity ReLU

The meaning of non-linearity ReLU is nothing but a rectified linear unit that performed a non-linear operation on convolved features. It is basically removing negative values in the convolved features (an example is seen in Fig. 7). This unit various operations such as max, min, mean, etc.

$$\underset{\textbf{Image Matrix}}{\begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}} \times \underset{\textbf{Filter Mask}}{\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}} = \underset{\textbf{Convolved Features}}{\begin{bmatrix} 2 & 4 & 4 \\ 2 & 3 & 3 \\ 1 & 3 & 3 \end{bmatrix}}$$

Fig. 6 Convolution operation

$$\begin{bmatrix} 1 & 26 & -7 & 35 \\ 16 & -116 & 24 & -9 \\ 26 & -18 & 19 & -50 \\ 101 & 75 & 14 & 45 \end{bmatrix} \xrightarrow{\textbf{Transfer Function}} \begin{bmatrix} 1 & 26 & 0 & 35 \\ 16 & 0 & 24 & 0 \\ 26 & 0 & 19 & 0 \\ 101 & 75 & 14 & 45 \end{bmatrix}$$

Fig. 7 ReLU operation

2.1.3 Pooling

The process is also known as upsampling or downsampling which reduces the dimension size of each feature. The different types of pooling operations such as max, sum, and average are used in CNN for dimension reduction of extracted features. The example of average pooling is shown in Fig. 8.

2.2 Classification operation

This operation consists of three different operations such as flatten, prediction of features and activation function. The 'Th' flatten is flattening out extracted features from the input image into vector. This vector is feed to a fully connected network such as a neural network for prediction of the input feature vector. Finally, an activation function such as softmax or sigmoid is used to classify the predicted value of the output of the neural network.

3 Deep learning algorithms

In the literature, various types of deep learning algorithms are used for research on image-related applications [9]. These algorithms are convolutional neural networks (CNN), deep autoencoder (DA), recurrent neural network (RNN), deep belief network (DBN), deep neural network (DNN), deep conventional extreme machine learning (DC-EML) available in the literature. For research related to image processing, CNN got a lot of interest and explored by the researcher. The various types of CNN architectures such as Alexnet [16], LeNet [17], Faster R-CNN [18], GoogLeNet [19], ResNet [20], etc. The basic information of these algorithms with its advantages and disadvantages are mentioned in Table 1.

$$\begin{bmatrix} 1 & 1 & 2 & 4 \\ 5 & 6 & 7 & 8 \\ 3 & 2 & 1 & 0 \\ 1 & 2 & 3 & 4 \end{bmatrix} \xrightarrow{\textbf{Average Pool with Filter Mask (2×2)}} \begin{bmatrix} 3 & 5 \\ 2 & 2 \end{bmatrix}$$

Fig. 8 Average pooling operation

Table 1 Basic information of various deep learning algorithms

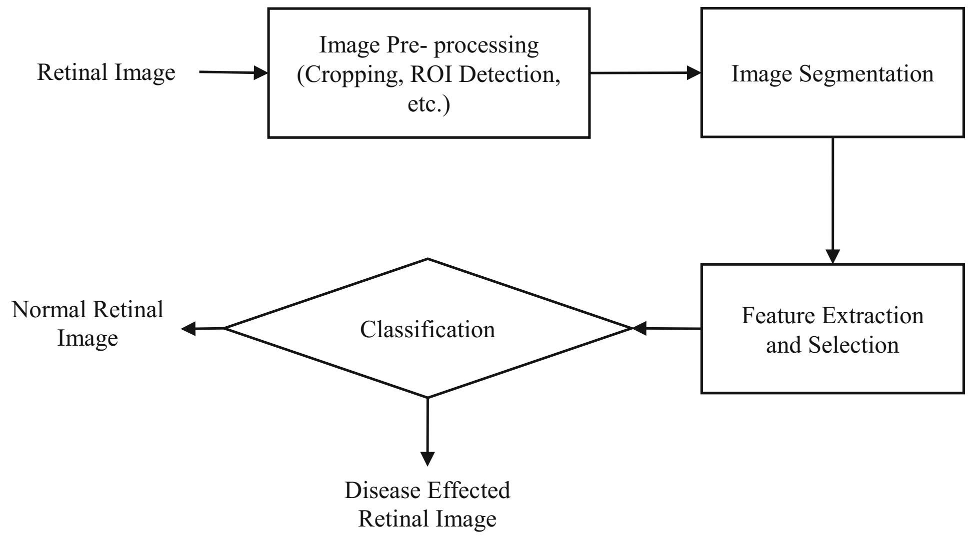
Sr. no.	Deep learning algorithm	Basic information of algorithm	Advantages	Disadvantages
1	Deep neural network (DNN)	It is a simple deep learning algorithm that has more than two hidden layers. Useful in applications related to classification and regression	Widely used with better performance and good accuracy	More time required for the training process
2	Convolution neural network (CNN)	It is a very good algorithm for image-related applications	The learning process of the network is fast and has good accuracy and performance	A lot of training labels required for data in classification related applications
3	Recurrent neural network (RNN)	It is very used for an algorithm for data in sequence format. The weights of the network are shared with all nodes of the network	Used in sequential operation related application. Provide higher accuracy in applications related to recognition	Required big size datasets for better performance
4	Deep belief network (DBN)	It is useful in supervised learning as well as unsupervised learning. The hidden layer of each sub-network is available for the next sub-network	Greedy norms are used in each layer of the network to better prediction of output	Required higher computational complexity in the training process
5	Deep autoencoder (DA)	It is a supervised learning algorithm and used for dimensional reduce of image features. The size of input and output is the same in this algorithm	Not required labeled input data and different kinds of versions for a specific application such as de-noising autoencoder, sparse autoencoder. Provide more robustness to input data	Required pre-training process before using it
6	Deep Boltzmann machine (DBM)	It is worked in unidirectional and based on Boltzmann's family. It is one of the extensions of RNN	More robust against interference and work effectively for discrete predicted value	For the big dataset, optimization, utilization, and analysis of parameters are not possible

4 Related work of machine learning and deep learning for eye disease identification

Up to this point, the discussion of machine learning, deep learning, neural network, the working of a convolution neural network and different types of deep learning algorithms are covered. In this section, the discussion of various machine learning and deep learning schemes for eye disease identification using retinal images are covered. The block diagram of eye disease identification using the retinal image is given in Fig. 9. This process is divided into various sub-steps such as image pre-processing, feature extraction and classification which are given in subsection.

- Image pre-processing: This is the first step in the glaucoma detection scheme. In this step, various image processing operations such as cropping, extraction of a region of interest (ROI), histogram equalization, etc. are applied on input retinal image to extract ROI or enhance the quality of the image. This step is necessary for better extraction of optic disk and cup in a given input image.
- Image segmentation: After improving the quality of input image, image segmentation is applied to the enhanced image to segment image into various parts such as the optic disk, optic cup, and optic nerve. For segmentation of the image, the various types of algorithms such as thresholding, edge detection, split and/or merge region and region growing are used.
- Feature extraction and selection: In this step, features are extracted from the segmented retinal image. The information like the diameter of the optic disk and/or optic cup, the length of the optic nerve and thick of optic nerve can be used as features of the retinal image. After the extraction of features, the selection of a feature is one of the important tasks. In most of the existing schemes, the features like cup-to-disk ratio (CDR) and ISNT rule are used for the identification of glaucoma in the given input image.
- Classification: Finally, various types of classifiers are used to classified retinal images using given features. The classifiers such as thresholding, support vector machines (SVM), neural network (NN), random forest, etc. are used for this purpose. The output of the classifier is that the input image is normal or eye disease effect.

Fig. 9 Basic steps for eye disease identification and classification using retinal image



The lots of schemes based on machine learning schemes are available in the literature particularly for detection glaucoma-based eye disease [21] but few schemes are available in the literature for another eye disease. The various schemes based on machine learning proposed by various researchers for the detection of eye disease using retinal images with its pre-processing method, feature extraction method, and the classification method are summarized in Table 2.

The literature review in Table 2 indicated that more schemes based on data learning need to improve the performance of detection of eye disease in the retinal image. One of the approaches is deep learning based which is recently popular in the detection of eye disease in the retinal image [64]. The few schemes based on deep learning algorithms are recently published by the various researchers which are given below.

Chen et al. [64] proposed a glaucoma detection scheme using deep learning-based classifiers. In this scheme, the Deep convolution neural network (CNN) algorithm was used for classification of the retinal image based on CDR features. This scheme was tested using standard retinal dataset such as online retinal fundus image dataset for glaucoma analysis (ORIGA). They have achieved performance accuracy of the scheme around 0.83–0.90% for glaucoma detection in the retinal images. Chandrakumar et al. [65] proposed deep learning architecture for classification of diabetic retinopathy disease using retinal images. In this approach, the CNN algorithm was used for classification of the retinal image based on convolved features. This scheme was tested using standard retinal datasets such as Kaggle [66], DRIVE [67] and STARE [68]. They have achieved performance accuracy of approach around 94–96% for the classification of retinal images.

Dong et al. [69] proposed deep learning architecture for the identification and classification of cataract disease using retinal images. They were used convolved features and wavelet features of retinal images for classification purposes. The performance accuracy of the approach for convolved features was 94.07% and for wavelet features was 81.91%, respectively. Lam et al. [70] proposed deep learning architecture for detection of diabetic retinopathy using retinal images. They have used CNN architecture for detection of diabetic retinopathy stages in the image. They have achieved detection accuracy of around 95% for this approach. Raghavendra et al. [71] proposed deep learning architecture for the accurate diagnosis of glaucoma in the retinal image. The CNN architecture with different learning rates was used for this purpose.

5 Limitations of existing techniques and future research direction for detection of eye disease

After this study of learning based various techniques for detection of eye disease, the following points are indicated as limitations of it:

- Most of the techniques were implemented using their own database. Therefore, it is less standardization in existing techniques.
- A small database of retinal images was used in many techniques. The performance of existing techniques is questionable when they were implemented for large size of the database.
- There is no standardization in the calculation of the cup to disc ratio (CDR) in many existing techniques.
- The fewer techniques are available based on a deep learning model for detection of eye disease.

Table 2 Machine learning based approaches for eye disease identification using retinal image

Authors	Proposed method	Pre-processing methods	Feature extracted	Classifiers	Maximum accuracy (%)
Nagarajan et al. [22]	Glaucoma detection	NR	Multi-focal visual evoked features	NN	94
Bizios et al. [23]	Glaucoma detection	NR	Optic disk features	ANN and clustering	93.5 and 87.9
Bock et al. [24]	Glaucoma classification	Homomorphic surface fitting	Transform coefficients of image	Naïve Bayes, K-nearest neighbours, and SVM	84, 82 and 86
Kolar et al. [25]	Fractal dimension reduction	Fractal analysis	Power spectrum	SVM	74.9
Nyul et al. [26]	Glaucoma detection	Contrast enhancement and removal of nerve vessel	PCA	SVM	80
Balasubramanian et al. [27]	Glaucoma detection	NR	Optic disk features	SVD and L2 norm	94
Nayak et al. [28]	Glaucoma detection	Morphological operations and thresholding	CDR, ONHS and ISNT Features	Analysis of CDR, ONHS, and ISNT	90
Bock et al. [29]	Texture analysis for glaucoma detection	Image normalization	Transform coefficients of image	GPS, CDR, and GRI	78, 68 and 80
Huang et al. [30]	Glaucoma detection	NR	Entropy-based features	LDA and ANN	95 and 97
Acharya et al. [31]	Retinal image diagnosis	Histogram equalization and randon transform	Higher-order spectra (HOS) features	Random Forest	91
Madhusudhan et al. [32]	Glaucoma detection	Illumination correction, blood vessel removal, and normalization	CDR	Multi-thresholding, snakes, and region growing	88.89, 94.44 and 100
Mookiah et al. [33]	Retinal image classification	Histogram equalization and randon transform	HOS feature entropy and wavelet features	SVM	95
Dua et al. [34]	Glaucoma classification	Histogram equalization	Wavelet features	LibSVM, random forest and Naïve Bayes	91.67, 88.33 and 90.00
Pruthi et al. [35]	CDR calculation	Anisotropic diffusion filter	CDR	ANFIS, SVM and back propagation	97.77, 98.12 and 97.35
Krishnan et al. [36]	Glaucoma detection using DWT and texture analysis	Histogram equalization and randon transform	HOS features and wavelet energy features	SVM	91.67
Suh et al. [37]	Glaucoma Detection	NR	Optical coherence tomography features	Categorical classification	NR
Anusorn et al. [38]	Glaucoma detection	Morphological operations, edge detection, and ellipse fitting	CDR	K-mean clustering	89
Patil et al. [39]	Glaucoma screening	NR	CDR	SVM	NR
Guerre et al. [40]	Glaucoma detection	Color channel selection, low pass filtering, histogram equalization, Otsu's segmentation	CDR	SVM	89
Agarwal et al. [41]	Glaucoma detection using thresholding	Color channel extraction	Mean and standard deviation of CDR	Thresholding	90
Acharya et al. [42]	Glaucoma detection using Gabor filter	Histogram equalization	Gabor features	SVM and Naïve Bayes	93.1 and 90.14

Table 2 continued

Authors	Proposed method	Pre-processing methods	Feature extracted	Classifiers	Maximum accuracy (%)
Virk et al. [43]	Glaucoma Screening	NR	CDR	SVM	98.12
Gopalakrishnan et al. [44]	Optical disk segmentation	Gaussian smoothing filter	CDR	Least square minimization	68
Sakthivel et al. [45]	Histogram-based segmentation	Gabor filter	LBF	Euclidean distance	95.45
Singh et al. [46]	Glaucoma screening	Thresholding and morphological operation	CDR	Thresholding of CDR	90
Issac et al. [47]	Glaucoma detection and classification	Color channel extraction	CDR	ANN and SVM	89.6 and 94.11
Claro et al. [48]	Glaucoma detection	ROI extraction and thresholding	Texture features using gray level co-occurrence matrix (GLCM) method	Multi-layer perceptron (MLP), random committee, random forest and radian basis function	93.03, 88.60, 85.44 and 83.54
Soman et al. [49]	Glaucoma classification	NR	Wavelet features	SVM, SVO, random forest, Naïve Bayes, and ANN	85.66, 85, 86, 81 and 91.1
Ayub et al. [50]	K-mean clustering for segmentation of optic disk and cup	Histogram equalization and morphological operations	CDR	K-mean clustering	92
Dey et al. [51]	NR	NR	NR	SVM	96
Maheshwari et al. [52]	Empirical wavelet transform (EWT) and correntropy features based glaucoma detection	Color channel extraction	EWT and correntropy features	LS-SVM	98.33
Singh et al. [53]	Glaucoma detection	Color channel extraction	Pixel values of color channels	KNN, Bayes, and SVM	92, 89 and 97
Vijapur et al. [54]	Glaucoma detection	Color conversion, Weiner filters, correlation filter and Isotropic Wavelet Transform	Vessel risk index feature	Fuzzy logic	NR
Sevastopolsky et al. [55]	Glaucoma detection	Cropping and contrast limited adaptive histogram equalization (CLAHE)	CDR	Neural network	NR
Sarkar et al. [56]	Glaucoma detection	Color conversion, median filtering, multilevel thresholding, and biogeography based optimization	CDR	Thresholding	97.58
Dey et al. [57]	Glaucoma detection	Color conversion, image resize, gaussian filter and adaptive histogram equalization	Statistical feature	SVM	97
Nawaldgi et al. [58]	Glaucoma detection	Color channel extraction, adaptive thresholding, morphological operation	CDR	Adaptive thresholding and ISNT rule	99
Septiarini et al. [59]	Glaucoma detection	Localization, segmentation, histogram equalization	Texture features	Naïve Bayes, MLP, SVM, and K-NN	92.90, 94.00, 92.90, and 95.12

Table 2 continued

Authors	Proposed method	Pre-processing methods	Feature extracted	Classifiers	Maximum accuracy (%)
Zou et al. [60]	Glaucoma detection	Illumination correction, contrast enhancement, radon transform, DWT, and PCA	Hybrid features	SVM and random forest	86.15, 77.10 and 74, 78
Manju et al. [61]	Glaucoma detection	Binarization and morphological operations	CDR	Analysis of CDR and thresholding	73
Puthren et al. [62]	Glaucoma detection	Cropping, resizing, morphological operation, and Gaussian filter	CDR	Back propagation neural network	84.6
Devasia et al. [63]	Glaucoma detection	OD localization, ROI extraction, channel selection, blood vessel removal	LMeP feature using FCM clustering	CDR, analysis of CDR, RDR, ISNT rule, NN, and cascade correlation NN	91.14, 92.41, 91.77 and 92.41

Some future research needs to perform for detection of eye disease are as below:

- Developed more techniques based on a deep learning model for detection of eye disease.
- Need to make standardization of available techniques in terms of implementation steps, required accuracy for detection of eye disease.
- Developed effective models that can be used for any size of retinal images dataset.

6 Conclusions

This paper gives a review of deep learning, algorithms of deep learning, working of convolution neural network and application of deep learning in the area of image processing. This paper is also describing various machine learning and deep learning algorithms that are used for detection of eye disease using the retinal image. Nowadays, there is a lot of research work is going on solved medical science-related problems using deep learning. In this research, researchers are trying to improve the performance of detection of disease for the given case study. But the performance of every scheme is differed due to the different input datasets. Therefore, the selection of a scheme or algorithm for a given case study is the changeling task for any researchers. It is also seen that few research works are done for eye disease detection using deep learning in the literature. Thus, it is one of the open researcher areas for eye disease identification using deep learning architecture.

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