

PAPER • OPEN ACCESS

Machine Learning Algorithms for Optic Pathway Disease Diagnostics: A Review

To cite this article: M Abu *et al* 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **767** 012067

View the [article online](#) for updates and enhancements.

You may also like

- [An optimized content-aware image retargeting method: toward expanding the perceived visual field of the high-density retinal prosthesis recipients](#)
Heng Li, Yajie Zeng, Zhuofan Lu *et al.*
- [Two degree-of-freedom robotic eye: design, modeling, and learning-based control in foveation and smooth pursuit](#)
Sunil Kumar Rajendran, Qi Wei and Feitian Zhang
- [Artificial intelligence techniques in inherited retinal diseases: a review](#)
Han Trinh, Jordan Vice, Zahra Tajbakhsh *et al.*



The Electrochemical Society
Advancing solid state & electrochemical science & technology



249th
ECS Meeting
May 24-28, 2026
Seattle, WA, US
Washington State
Convention Center

Spotlight Your Science

**Submission deadline:
December 5, 2025**

SUBMIT YOUR ABSTRACT

Machine Learning Algorithms for Optic Pathway Disease Diagnostics: A Review

M Abu¹, N A H Zahri¹, A Amir¹, M I Ismail²

¹Advanced Communication Engineering Centre (ACE), School of Computer and Communication Engineering, Universiti Malaysia Perlis, Malaysia

²School of Mechatronic Engineering, Universiti Malaysia Perlis, Malaysia

adilahhanin@unimap.edu.my

Abstract. Most of people are unaware that some of the indicators of optic pathway diseases such as stroke or tumor can be detected from the loss part of human vision, or referred as visual field defect. Ophthalmologist will manually examine the site, size and margin of the lesion from patient's visual field points mapped by Humphrey Field Analyzer. Different site, size and margin of lesion indicates different type of defects and disease that associated with it. Therefore, an effective automated detection mechanism of multi class visual field defect is in demand to help decision making by ophthalmologist. In this paper, we review multiple techniques of supervised and unsupervised learning method for detection of optic pathway disease.

1. Introduction

Studies on optic pathway disease detection have been conducted for many years not only by medical researchers but also by researchers from the engineering field. Many people are unaware that some of these optic pathway disease are one of many indicators of serious illness such as stroke and tumors. An optic pathway consists of a series of cells and synapses that carry visual information from the environment to the brain for processing [1], and the defect to the optic pathway caused by tumors or any other brain related illness can interrupt the higher order processing of visual input. Other than detection of abnormalities in retina structure, researchers are developing a diagnosis system for specific eye disease such as glaucoma [2]–[5], diabetic retinopathy [6]–[8], and age-related macular degeneration [9], [10].

Most of the previous works are working on automated detection of eye disease in order to provide more accurate and consistent mechanism to aid ophthalmologists to diagnose and prioritize based on the severity of the patient's conditions. Therefore, effective decision making mechanism for medical diagnostic can be produced to deal with currently rapid growing medical data and improve patient healthcare.

In this work, existing machine learning methods for eye disease detection (using visual field data, fundus images and OCT images as a dataset) will be reviewed, analysed from a different perspectives and finally concluded to summarize the current advancement of detection mechanism for eye disease.

2. Existing Machine learning Algorithms



Content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](https://creativecommons.org/licenses/by/3.0/). Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Machine learning is a part of an Artificial Intelligent application that provides systems ability to learn automatically and improve from experience without being explicitly programmed [11]. Machine learning also learns the information directly from data without relying on a predetermined equation as a model. The performance of machine learning can be improved by adding more data [12], [13]. Machine learning has several main categories, for example, supervised, semi-supervised, unsupervised, deep hierarchical learning/ deep structured learning, reinforcement and active learning algorithms [14], [15].

2.1. *Supervised Learning*

There are two types of feature learning frequently used to train data set for example supervised learning and unsupervised learning. Supervised learning is the machine-learning procedure of deriving a function from supervised training data. Training data in supervised learning include a set of model that match input subjects and desired output. A supervised learning algorithm analyses the training data and produces a deriving function, which is called classifier or a regression function. The function should predict the correct output value for any valid input object. This requires the learning algorithm, to sum up from the training data to concealed circumstances in a sensible manner [15], [16]. For supervised learning, the inputs data for the training process will be labeled in different classes using classification methods. Then, the trained system generates actions that allocate hidden inputs to these classes. This process is called multi-labeling process in supervised learning [14], [15], [17].

2.2 *Unsupervised Learning*

For unsupervised learning, it is different compared to supervised learning because it will not label the data into any class. Therefore, the systems are intended to outline information to itself with the purpose of the systems to learn better features by themselves. This is called feature or representation learning [14], [18]. One advantage of this approach is there is no need to manually label the data and as the consequences, the networks can be trained with a large number of unlabelled data compare to supervised learning that only can train a small amount of data [18]. Besides that, this method also can suffer from misprediction in some regions that have various conditions [19].

2.3 *Deep Learning*

Neural network works a similar way as the human brain performs a given task [20]–[23]. Deep learning is an advanced phase of machine learning that utilized in neural networks for learning and prediction of data [14], [24]. It a procedure that avoids most predictive features to learn directly from the data in the large data set [6], [12]. For image classification, feature extractors obtained from a pre-trained deep learning model perform well on different types of tasks, including tasks that are very different from the original task for which the feature extractors were trained [25]. Deep Learning performed very well in terms of accuracy and time processing to process a mass amount of information compared to human. However, as the samples and parameter increase, the artificial selection of features will restricted the performance of classification. Therefore, deep learning is used to find the most distinguished features from thousands of parameters automatically [26]. There are several types of neural network models that had been used for deep learning [27].

- Multilayer Perceptron (MLP): It is a feed-forward neural network and it has multiple hidden layers between the input layer and output layer.
- Autoencoder (AE): An unsupervised model, it reconstruct the input data in the output layer. The middle layer is used as a salient feature that represent the input data. Types of autoencoder are denoising autoencoder, marginalized denoising autoencoder, sparse autoencoder, contractive autoencoder and variational autoencoder [28], [29].
- Convolutional Neural Network (CNN): A feed forward neural network, which build with convolution layers and pooling operations. It can capture the global and local features. It significantly enhancing the efficiency and accuracy. It performs well in processing data with grid-like topology. [14], [19], [30]–[32]

- Recurrent Neural Network (RNN): Suitable for modelling sequential data. RNN has loops and memories so it can remember former computations different from feedforward neural network. Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) network is used to overcome the vanishing gradient problem [33]–[35].
- Restricted Boltzmann Machine (RBM): A two layer neural network consisting of a visible layer and a hidden layer. Restricted here means that there are no intra layer communications in visible layer or hidden layer [36].
- Neural Autoregressive Distribution Estimation (NADE): An unsupervised neural network built atop autoregressive model and feedforward neural networks. It is a tractable and efficient estimator for modelling data distribution and densities.
- Adversarial Networks (AN): A generative neural network which consists of a discriminator and a generator. The two neural networks are trained simultaneously by competing with each other in a minimax game framework.
- Attentional Models (AM): Differentiable neural architectures that operate based on soft content addressing over an input sequence. Attention mechanism is typically ubiquitous and was incepted in Computer Vision and Natural Language Processing domains. However, it has also been an emerging trend in deep recommender system research.
- Deep Reinforcement Learning (DRL): Reinforcement learning operates on a trial-and-error paradigm. The whole framework mainly consists of the following components: agents, environments, states, actions and rewards. The combination between deep neural networks and reinforcement learning formulate DRL, which have achieved human-level performance across multiple domains. Deep neural networks enable the agent to get knowledge from raw data and derive efficient representations without handcrafted features and domain heuristics.

3. Detection of Eye Disease by Using Different Machine Learning Algorithm

There are many existing reviews and surveys on some diseases and techniques such as CNN, SVM, GEM, VIM, PNN and Bayesian classifier [14], [37]–[39]. In this paper, we highlight the works published on supervised and unsupervised techniques. We divide all these algorithms into categories of eye disease detection, which are glaucoma, diabetic retinopathy, cataract, hard exodus, and macular-edema.

3.1 Supervised Learning

Convolution Neural Network is a popular algorithm that had been used in supervised deep learning. Li *et al.*, 2018 had build 22 layers of CNN, which contain Inception-V3 CNN model to detect GON in 48116 fundus images, 8000 from the images is used for validation. The accuracy is 92.9%[40]. Raghavendra *et al.*, 2018 used eighteen layers of CNN to detect glaucoma. The accuracy is 98.13% by using 1426 (589: normal and 837: glaucoma) fundus images [41]. Abbas, 2017 using ORIGA and SCES dataset and the accuracy obtained is 99% for both ORIGA and SCES datasets. The method used by Abbas, 2017 is Glaucoma-deep, which is the integration of CNN, DBN and Softmax deep-learning classifiers [42]. Asaoka *et al.*, 2016 used deep feed-forward neural network (FNN) classifier to detect glaucoma in 279 visual field images and the accuracy obtained is 92.6%[43]. Chen *et al.*, 2015a and 2015b had built six layers deep CNN for their research. The dataset used by them is ORIGA and SCES. For the ORIGA dataset, the training set contains a random selection of 99 images from the whole 650 images, and the remaining 551 images are used for testing. For the SCES dataset, 650 from the ORIGA dataset will be used for training and 1676 is used for testing. The accuracies for 2015a are 83.1% for ORIGA dataset and 88.7% for SCES dataset and for 2015b are 83.8% for ORIGA dataset and 89.8% for SCES dataset [30], [44]. The summarization of works on glaucoma diseases is shown in **Table 1**.

Table 1. Supervised Machine Learning Method for Glaucoma Detection

Machine Learning Techniques	Author	Year	Disease	Dataset	Accuracy
Deep CNN with Inception-V3 architecture	Li <i>et al</i> [40]	2018	Glaucomatous Optic Neuropathy Disease	48116 fundus images	92.9%
Deep CNN 18 layers	Raghavendra <i>et al</i> [41]	2018	Glaucoma Disease	1426 fundus images	98.13%
Glaucoma-deep(CNN,DBN and Softmax deep learning)	Abbas [42]	2017	Glaucoma Disease	ORIGA & SCES	99%
Deep Feed Forward Neural Network	Asaoka <i>et al</i> [43]	2016	Glaucoma Disease	PPGVFs	92.6%
Deep CNN with 6 layers- 5 multilayer perceptron layer,1 fully-connected layer	Chen <i>et al</i> [44]	2015b	Glaucoma Disease	ORIGA SCES	83.8% 89.8%
Deep CNN with 6 learned layer- 4 convolutional layer,2 fully-connected layer	Chen <i>et al</i> [30]	2015a	Glaucoma Disease	ORIGA SCES	83.1% 88.7%

For diabetic retinopathy, many of the supervised learning algorithms used Kaggle/ Messidor/Eyepacs images as training dataset. Liu et al had proposed WP-CNN method, where this method applies multiple weighted path into CNN. In WP-CNN, multiple path weight coefficients are optimized by back propagation, and the output features are averaged for redundancy reduction and fast convergence. The dataset they used is taken from Kaggle and the accuracy obtain are 94.23%[45]. Lam *et al.*, 2018 used 22 layers GoogleNet CNN model and Kaggle's dataset to perform their research. They also do transfer learning pre-trained for the model to improve the classification. The high accuracy achieve in this research is 96%[46]. Dutta et al, 2018 also used Kaggle's dataset. The dataset will undergoes some image processing process and Fuzzy C-Means to identify the proper class of severity of the dataset. Then, it will be trained and classified using CNN model(VGGNet) and obtain accuracy 72.5%[47]. Xu *et al.*, 2017 also using Kaggle's dataset. The method they used is CNN and Softmax layer is added at the end of their CNN layers. The accuracy they obtain is 94.5%[48].

Kanungoet *et al.*, 2017 used Inception V3 CNN model techniques to evaluate different number of batch size, epoch and dataset. The highest accuracy they obtain are 88% by using 128 batch size, 200 epoch and 40,000 DR dataset that obtain from Kaggle[49]. Zeng et al, 2016 used EyePACS dataset that obtain from Kaggle. It contains 35126 high resolution fundus photographs taken under a range of imaging conditions. Inception V3 CNN model will be used as their method to automatically detect RDR. The accuracy of their research are 82.9% [50]. Pratt *et al.*, 2016 used Kaggle's dataset, 80000 images for training and 5000 images for validation. They using eight layers CNN for detection by using Keras model (Theano) to build their CNN. The accuracy obtained is 75% [51]. Abramoff *et al*, 2016 compare performance of a deep-learning enhanced algorithm for automated detection of diabetic retinopathy (DR), to the previously published performance of that algorithm, the Iowa Detection Program (IDP) without deep learning components on Messidor taken from Kaggle. It was shown that the algorithm with CNN, a deep learning method can achieve a high performance of 96.8% [52]. Gulshan *et al*, 2016 used 9963 images from EyePACs and 683 images from Messidor as their dataset taken from Kaggle. The method they used Inception V3 CNN model to detect diabetic retinopathy. The accuracy for EyePACs is 98.1% and for Messidor is 98.5% [6]. The summarization of works on diabetic retinopathy is shown in **Table 2**.

Table 2. Supervised Machine Learning Method for Diabetic Retinopathy Detection

Machine Learning Techniques	Author	Year	Disease	Dataset	Accuracy
WP-CNN (applies multiple weighted path into CNN)	Liu <i>et al</i> [45]	2019	Diabetic Retinopathy	Kaggle	94.23%
22 layers of CNN following GoogleNet CNN model	Lam <i>et al</i> [46]	2018	Diabetic Retinopathy	Kaggle	96%

FCM+CNN(follow VGGNet CNN model)	Dutta <i>et al</i> [47]	2018	Diabetic Retinopathy	Kaggle	72.5%
Deep CNN adding Softmax at the last layers.	Xu <i>et al</i> [48]	2017	Diabetic Retinopathy	Kaggle	94.5%
Inception V3 CNN model (Test on different size of batch size, epoch and dataset)	Kanungo <i>et al</i> [49]	2017	Diabetic Retinopathy	Kaggle	88%
Inception V3 CNN model	Zeng <i>et al</i> [50]	2016	Diabetic Retinopathy	Kaggle (EyePACs)	82.9%
8 layers Deep CNN using Keras Model (Theano)	Pratt <i>et al</i> [51]	2016	Diabetic Retinopathy	Kaggle	75%
Iowa Detection Program (IDP) + CNN	Abramoff <i>et al</i> [52]	2016	Diabetic Retinopathy	Kaggle	96.8%
Deep CNN Inception V3	Gulshan <i>et al</i> [6]	2016	Diabetic Retinopathy	Kaggle (EyePACS & Messidor)	98.1% 98.5%

Dong *et al.*, 2017 had split 7851 fundus images into 70% for training and 30% for testing. They compared a deep learning method with classic machine learning. For feature learning, Dong *et al* 2017 compare Caffe and Wavelet feature. They combined this feature learning with classification method, SVM and deep learning classifier, softmax classifier to detect cataract on the eyes. In their research, the highest accuracy is 94.07% by using Caffe as feature learning and Softmax as classifier [26]. Gao *et al.*, 2015 used 5378 images from the ACHICO-NC dataset. The dataset is categorised based on grade 1=94 images, 2=1874 images, 3=2476 images, 4=897 images, and 5=37 images for training and the remaining will be used as testing. The method used in their research is Convolution-recursive Neural Network. In this method, the patches will be randomly selected using the pre-training convolutional neural network (CNN), then, feeding the filters into a CNN layer by generating local representations of each image, and lastly, multiple recursive neural networks (RNNs) with random weight will learn hierarchical feature representations. The result obtained are 99.0% when the decimal grading error less than one [33].

Table 3 shows the supervised machine learning method to detect cataracts.

Table 3. Supervised Machine Learning Method to detect Cataract

Machine Learning Techniques	Author	Year	Disease	Dataset	Accuracy
Caffe+CNN	Dong <i>et al</i> [26]	2017	Cataract	7851 fundus image	90.82%
Caffe+SVM					84.17%
Wavelet+CNN					82.94%
Wavelet+SVM					84.7%
Convolution-recursive Neural Network(CRNN)	Gao <i>et al</i> [33]	2015	Grade nuclear cataract	ACHICO-NC	99%

3.2 Unsupervised Learning

For unsupervised learning, Amil *et al.*, 2019 used a large database of anterior chamber OCT images. The algorithm used is t-SNE with the Helinger technique as feature extraction. The accuracy obtained is 81.0% [54]. Montuoro *et al.*, 2017 used 20,000 OCT B-scans from 100 scans of patients. The method used to detect macular edema in OCT images is the PCA method. The accuracy achieved is 78.0% [55]. Yousefi *et al.*, 2016 and Yousefi *et al.*, 2014 used 999 visual field images as their dataset. They had compared two methods in their research, Gaussian Mixture Model with Expectation Maximization (GEM) and Variational Bayesian Independent Components Analysis Mixture Model (VIM) in 2016 and only using GEM in 2014 to cluster the dataset. The accuracy is 93.8% for GEM and 97.0% for VIM in

2016 and the accuracy of GEM is 93.8% for 2014 [56], [57]. Bowd *et al.*, 2014 used 1190 eyes with normal FDT and 786 eyes with abnormal FDT. The algorithm used is VIM and the accuracy obtained for normal is 93.1% and for abnormal is 82.8% [2]. Priya & Arjuna, 2013 used 350 fundus images to detect diabetic retinopathy, 100 images used for training and 250 images used for testing. In their research, three methods will be used to detect glaucoma in fundus images. The methods used are probabilistic Neural Network (PNN), Bayes classifier and SVM. The accuracy obtained are 89.6% for PNN, 94.4% for Bayes Classifier and 97.6% for SVM [58]. **Table 4** shows the unsupervised machine learning method for multiple eye disease detection.

Table 4. Unsupervised Machine Learning Method for Eye Diseases Detection

Machine Learning Techniques	Author	Year	Disease	Dataset	Accuracy
t-SNE+Helinger technique	Amil <i>et al</i> [54]	2019	Glaucoma Disease	Anterior chamber OCT images	81.0%
PCA	Montuoro <i>et al</i> [55]	2017	Macular edema	20 000 OCT images	78%
GEM & VIM	Yousefi <i>et al</i> [56]	2016	Glaucoma Disease	Visual field images	93.8%
GEM	Yousefi <i>et al</i> [57]	2014	Glaucoma Disease	Visual field images	97.0%
VIM	Bowd <i>et al</i> [2]	2014	Glaucoma Disease	1190 fundus images	93.1%
PNN					89.6%
Bayesian classification	Priya & Arjuna[58]	2013	Diabetic retinopathy	350 fundus images	94.4%
SVM					97.6%

4. Discussion and Analysis of Machine Learning Algorithm

For the diagnosis of glaucoma, diabetic retinopathy, cataract, and macular edema, several machine-learning algorithms are observed to perform very well. From existing literature, it shows that deep learning is the most frequent method used in recent researches to detecting eye disease. By using this technique, the performance of the systems detected have improved significantly. By using the CNN method, the accuracy of the system can be improved by increasing the layer of CNN model. In addition, there also other researchers build their CNN by following the existing CNN model, for example, VGG, ResNet, Inception-V3 and GoogleNet and combine CNN algorithm with other deep learning algorithm for example RNN. In this review paper, there are seventeen works used deep learning as their method. 11 from those works achieved accuracy above 90% and others achieved accuracy that varies between 80% to 90%. For unsupervised learning, most method used to build this system is Bayesian classifier. It shows that the performance of unsupervised learning can also achieved high accuracy. There are six works of unsupervised learning have been reviewed. Three works using Bayesian Classifier, and achieve above 90% and another three works used PCA, Gaussian and t-SNE with Helinger techniques and achieve accuracy 78% above. Figure 1 shows the performance of previous works mentioned in the above regardless the type of disease, dataset used and experimental parameters. This figure is constructed to generally illustrate the effectiveness of deep learning method, supervised and unsupervised learning that have been studied and experimented in many previous works of eye disease detection.

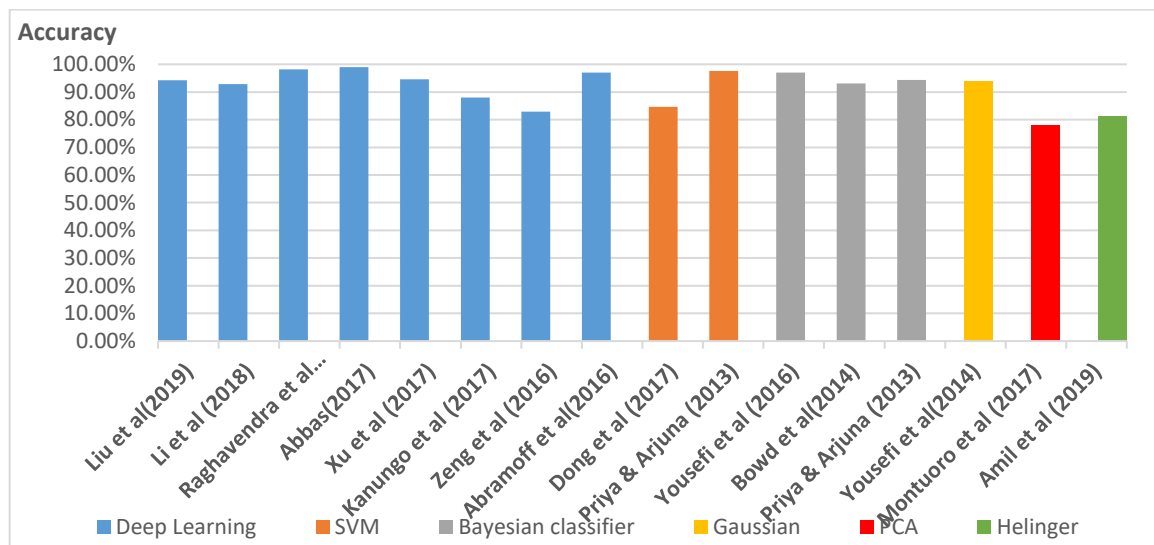


Figure 1. Accuracy of Machine Learning techniques

5. Conclusion

Machine Learning had been used in many applications, for example, image detection, data mining, natural language processing, and disease diagnostics. This paper provides a survey/review of different machine learning techniques (algorithm) for diagnosing eye diseases such as glaucoma, diabetic retinopathy, cataract, hard exodus, and macular edema. Many algorithms have shown good results because they identify the attribute accurately. From Figure 1, we can conclude that eye disease detection performs well on deep learning regardless of its dataset and method used. From our investigation, it has shown that by using deep learning, the lowest accuracy achieved are 75% and can reach maximum accuracy of 99%. Abbas, 2017 had integrates CNN with DBN and adds the Softmax layer in his algorithm to improve their accuracy. For the unsupervised method, the Bayesian classification are mostly used for detecting multiple eye diseases. From examination of the previous works, the accuracy of using Bayesian classifier method achieved above 90%. It had shown by Yousefi *et al*, 2016, by using Bayesian Classifier, they have improved previous work that used Gaussian method and increase the performance from 93.8% to 97.0%. This paper have reviewed many of detection techniques to aid the diagnosis process of many types of eye disease. From our observation, many of recent works are focused on enhancing hyper parameter of deep learning method to improve accuracy and the obtained result are significantly high and promising for many types of eye disease detection.

Acknowledgement

This research was supported by Fundamental Research Grant Scheme (FRGS 1/2018). We are thankful to our colleagues who provided expertise that greatly assisted the research, although they may or may not agree with all of the interpretations provided in this paper. We are also grateful to Advanced Communication Engineering Centre (ACE) under School of Computer and Communication Engineering, Universiti Malaysia Perlis, which has provided laboratory facilities during the course of this research.

References

- [1] L. A. Remington, *Clinical Anatomy and Physiology of the Visual System*, Third Edit. 2012.
- [2] C. Bowd et al., “Glaucomatous patterns in Frequency Doubling Technology (FDT) perimetry data identified by unsupervised machine learning classifiers,” *PLoS One*, vol. 9, no. 1, 2014.
- [3] S. Verma et al., “Visual Field Progression in Patients with Primary Angle-Closure Glaucoma Using Pointwise Linear Regression Analysis,” *Ophthalmology*, vol. 124, no. 7, pp. 1065–1071, 2017.
- [4] E. Atalay et al., “Pattern of Visual Field Loss in Primary Angle-Closure Glaucoma Across Different Severity Levels,” *Ophthalmology*, vol. 123, no. 9, pp. 1957–1964, 2016.
- [5] S. Yousefi et al., “Detecting glaucomatous change in visual fields: Analysis with an optimization framework,” *J. Biomed. Inform.*, vol. 58, pp. 96–103, 2015.
- [6] V. Gulshan et al., “Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs,” *Am. Med. Assoc.*, vol. 316, no. 22, pp. 2402–2410, 2016.
- [7] S. S. Rubini and A. Kunthavai, “Diabetic retinopathy detection based on eigenvalues of the hessian matrix,” *Procedia Comput. Sci.*, vol. 47, no. C, pp. 311–318, 2015.
- [8] J. Amin, M. Sharif, and M. Yasmin, “A Review on Recent Developments for Detection of Diabetic Retinopathy,” *Scientifica (Cairo)*, vol. 2016, 2016.
- [9] A. García-Floriano, Á. Ferreira-Santiago, O. Camacho-Nieto, and C. Yáñez-Márquez, “A machine learning approach to medical image classification: Detecting age-related macular degeneration in fundus images,” *Comput. Electr. Eng.*, vol. 75, pp. 218–229, 2019.
- [10] A. Wood, T. Margrain, and A. M. Binns, “Detection of early age-related macular degeneration using novel functional parameters of the focal cone electroretinogram,” *PLoS One*, vol. 9, no. 5, pp. 1–9, 2014.
- [11] D. S. W. Ting et al., “Deep learning in ophthalmology: The technical and clinical considerations,” *Prog. Retin. Eye Res.*, no. December 2018, pp. 1–24, 2019.
- [12] A. Fourcade and R. H. Khonsari, “Deep learning in medical image analysis : A third eye for doctors,” *J. Stomatol. Oral Maxillofac. Surg.*, 2019.
- [13] D. S. W. Ting et al., “Progress in Retinal and Eye Research Deep learning in ophthalmology : The technical and clinical considerations,” *Prog. Retin. Eye Res.*, no. April, pp. 1–24, 2019.
- [14] J. Latif, C. Xiao, A. Imran, and S. Tu, “Medical Imaging using Machine Learning and Deep Learning Algorithms : A Review,” *2019 2nd Int. Conf. Comput. Math. Eng. Technol.*, pp. 1–5, 2019.
- [15] M. Maliha, A. Tareque, and S. S. Roy, “Diabetic Retinopathy Detection Using Machine Learning,” 2018.
- [16] S. Guo, K. Wang, H. Kang, Y. Zhang, Y. Gao, and T. Li, “BTS-DSN : Deeply supervised neural network with short connections for retinal vessel segmentation,” *Int. J. Med. Inform.*, vol. 126, no. March, pp. 105–113, 2019.
- [17] Y. Pu et al., “Variational autoencoder for deep learning of images, labels and captions,” *Adv. Neural Inf. Process. Syst.*, no. Nips, pp. 2360–2368, 2016.
- [18] H. F. Pardede, E. Suryawati, R. Sustika, and V. Zilvan, “Unsupervised Convolutional Autoencoder-Based Feature Learning for Automatic Detection of Plant Diseases,” *2018 Int. Conf. Comput. Control. Informatics its Appl.*, pp. 158–162, 2018.
- [19] Y. M. Kassim and K. Palaniappan, “Extracting Retinal Vascular Networks Using Deep Learning Architecture,” pp. 1170–1174, 2017.
- [20] O. Isaac, A. Jantan, and A. Esther, “State-of-the-art in artificial neural network applications : A survey,” *Heliyon*, no. June, p. e00938, 2018.
- [21] M. S. Solanki, “Diabetic Retinopathy Detection Using Eye Images,” vol. 8, no. 12419, p. 12419, 2015.
- [22] T. Erić, S. Ivanović, S. Milivojša, and N. Smiljković, “Voice Control for Smart Home Automation : Evaluation of Approaches and Possible Architectures,” pp. 140–141, 2017.

- [23] J. Schmidhuber, "Deep Learning in Neural Networks : An Overview," vol. 61, pp. 1–88, 2015.
- [24] A. S. Ahuja and L. S. Halperin, "Understanding the advent of artificial intelligence in ophthalmology," vol. 31, pp. 115–117, 2019.
- [25] Y. Kim, "Convolutional Neural Networks for Sentence Classification," 2011.
- [26] Y. Dong, Q. Zhang, Z. Qiao, and J. Yang, "Classification of Cataract Fundus Image Based on Deep Learning," *IEEE Instrum. Meas. Soc.*, pp. 1–5, 2017.
- [27] S. Zhang, L. Yao, A. Sun, and Y. i Tay, "Deep Learning based Recommender System : A Survey and New Perspectives," vol. 1, no. 1, pp. 1–35, 2018.
- [28] Y. Bengio, A. Courville, and P. Vincent, "Unsupervised Feature Learning and Deep Learning : A Review and New Perspectives," pp. 1–30, 2012.
- [29] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, "Neurocomputing A survey of deep neural network architectures and their applications," *Neurocomputing*, vol. 234, no. December 2016, pp. 11–26, 2017.
- [30] X. Chen, Y. Xu, D. Wing, and K. Wong, "Glaucoma Detection based on Deep Convolutional Neural Network," pp. 715–718, 2015.
- [31] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," *Insights Imaging*, vol. 9, no. 4, pp. 611–629, 2018.
- [32] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," 2015.
- [33] X. Gao, S. Lin, and T. Y. Wong, "Automatic Feature Learning to Grade Nuclear Cataracts Based on Deep Learning," *IEEE Trans. Biomed. Eng.*, pp. 1–9, 2015.
- [34] O. Irsoy and C. Cardie, "Deep Recursive Neural Networks," pp. 1–9, 2014.
- [35] M. Langkvist, L. Karlsson, and A. Loutfi, "A Review of Unsupervised Feature Learning and Deep Learning for Time-Series Modeling," vol. 42, pp. 11–24, 2014.
- [36] G. Litjens et al., "A survey on deep learning in medical image analysis," vol. 42, no. December 2012, pp. 60–88, 2017.
- [37] E. Pead et al., "Automated detection of age-related macular degeneration in color fundus photography : a systematic review," *Surv. Ophthalmol.*, vol. 64, no. 4, pp. 498–511, 2019.
- [38] Y. Hagiwara et al., "Computer Methods and Programs in Biomedicine Computer-aided diagnosis of glaucoma using fundus images : A review," *Comput. Methods Programs Biomed.*, vol. 165, pp. 1–12, 2018.
- [39] N. Salamat, M. M. S. Missen, and A. Rashid, "Diabetic retinopathy techniques in retinal images : A review," *Artif. Intell. Med.*, vol. 97, no. January 2018, pp. 168–188, 2019.
- [40] Z. Li, Y. He, S. Keel, W. Meng, and R. T. Chang, "Efficacy of a Deep Learning System for Detecting Glaucomatous Optic Neuropathy Based on Color Fundus Photographs," *Ophthalmology*, pp. 1–8, 2018.
- [41] U. Raghavendra, H. Fujita, S. V Bhandary, and A. Gudigar, "Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images," *Inf. Sci. (Ny).*, vol. 441, pp. 41–49, 2018.
- [42] Q. Abbas, "Glaucoma-Deep: Detection of Glaucoma Eye Disease on Retinal Fundus Images using Deep Learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 6, 2017.
- [43] R. Asaoka, H. Murata, A. Iwase, and M. Araie, "Detecting Preperimetric Glaucoma with Standard Automated Perimetry Using a Deep Learning Classifier," *Ophthalmology*, pp. 1–7, 2016.
- [44] X. Chen, Y. Xu, S. Yan, D. W. K. Wong, T. Y. Wong, and J. Liu, "Automatic Feature Learning for Glaucoma Detection Based on Deep Learning," in *Springer International Publishing Switzerland*, 2015, vol. 9351, pp. 669–677.
- [45] Y. Liu, Z. Li, C. Xu, J. Li, and R. Liang, "Referable Diabetic Retinopathy Identification from Eye Fundus Images with Weighted Path for Convolutional Neural Network," *Artif. Intell. Med.*, 2019.
- [46] C. Lam, D. Yi, M. Guo, and T. Lindsey, "Automated Detection of Diabetic Retinopathy using Deep Learning," *AMIA Jt. Summits Transl. Sci. proceedings. AMIA Jt. Summits Transl. Sci.*, pp. 147–155, 2018.

- [47] S. Dutta, B. C. S. Manideep, S. M. Basha, R. D. Caytiles, and N. C. S. N. Iyengar, "Classification of diabetic retinopathy images by using deep learning models," *Int. J. Grid Distrib. Comput.*, vol. 11, no. 1, pp. 89–106, 2018.
- [48] K. Xu, D. Feng, and H. Mi, "Deep Convolutional Neural Network-Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image," 2017.
- [49] Y. S. Kanungo, B. Srinivasan, and S. Choudhary, "Detecting Diabetic Retinopathy using Deep Learning," *Int. Conf. Recent Trends Electron. Inf. Commun. Technol.*, pp. 801–804, 2017.
- [50] X. Zeng, H. Chen, Y. Luo, and W. Ye, "Automated Diabetic Retinopathy Detection Based on Binocular Siamese-like Convolution Neural Network," *IEEE Access*, vol. 4, pp. 1–10, 2016.
- [51] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng, "Convolutional Neural Networks for Diabetic Retinopathy," *Int. Conf. Med. Imaging Underst. Anal.*, no. July, pp. 1–6, 2016.
- [52] M. D. Abramoff et al., "Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning," *Investig. Ophthalmol. Vis. Sci.*, vol. 57, no. 13, 2016.
- [53] N. Ayuni, M. Asyraf, W. Mimi, and D. Wan, "An automated glaucoma screening system using cup-to-disc ratio via Simple Linear Iterative Clustering superpixel approach," *Biomed. Signal Process. Control*, vol. 53, p. 101454, 2019.
- [54] P. Amil et al., "Unsupervised feature extraction of anterior chamber OCT images for ordering and classification," *Sci. Rep.*, vol. 9, no. 1, pp. 1–9, 2019.
- [55] A. Montuoro, S. M. Waldstein, B. S. Gerendas, U. Schmidt-Erfurth, and H. Bogunović, "Joint retinal layer and fluid segmentation in OCT scans of eyes with severe macular edema using unsupervised representation and auto-context," *Biomed. Opt. Express*, vol. 8, no. 3, p. 1874, 2017.
- [56] S. Yousefi et al., "Unsupervised Gaussian mixture-model with expectation maximization for detecting glaucomatous progression in standard automated perimetry visual fields," *Transl. Vis. Sci. Technol.*, vol. 5, no. 3, 2016.
- [57] S. Yousefi, M. H. Goldbaum, L. M. Zangwill, F. A. Medeiros, and C. Bowd, "Recognizing patterns of visual field loss using unsupervised machine learning," *Med. Imaging 2014 Image Process.*, vol. 9034, no. March 2014, p. 90342M, 2014.
- [58] R. Priya and P. Aruna, "Diagnosis of Diabetic Retinopathy Using Machine Learning Techniques," vol. 6956, no. July, pp. 563–575, 2013.