Machine Learning Algorithms for Optic Pathway Disease Diagnostics: A Review

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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
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 exudus, and macular edema.

3.1 Supervised Learning

Convolutional 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.
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].

Kanungo 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 1. Supervised Machine Learning Method for Glaucoma Detection

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

### 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 et al [45] | 2019 | Diabetic Retinopathy | Kaggle | 94.23% |
| 22 layers of CNN following GoogleNet CNN model | Lam et al[46] | 2018 | Diabetic Retinopathy | Kaggle | 96% |
Dutta et al. [47] 2018  Diabetic Retinopathy  Kaggle  72.5%

Deep CNN adding Softmax at the last layers.  Xu et al [48] 2017  Diabetic Retinopathy  Kaggle  94.5%

Inception V3 CNN model (Test on different size of batch size, epoch and dataset)  Kanungo et al [49] 2017  Diabetic Retinopathy  Kaggle  88%

Inception V3 CNN model  Zeng et al [50] 2016  Diabetic Retinopathy  Kaggle (EyePACs)  82.9%

8 layers Deep CNN using Keras Model (Theano)  Pratt et al [51] 2016  Diabetic Retinopathy  Kaggle  75%

Iowa Detection Program (IDP) + CNN  Abramoff et al [52] 2016  Diabetic Retinopathy  Kaggle  96.8%

Deep CNN Inception V3  Gulshan et al [6] 2016  Diabetic Retinopathy  Kaggle (EyePACS & Messidor)  98.1%  98.5%

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 et al [26]  | 2017 | Cataract     | 7851 fundus image        | 90.82%    |
| Caffe+SVM                    |                  |      |              |                          | 84.17%    |
| Wavelet+CNN                  |                  |      |              |                          | 84.94%    |
| Wavelet+SVM                  |                  |      |              |                          | 84.7%     |
| Convolution-recursive Neural Network(CRNN)  | Gao et al [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 obtain 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 et al[54]           | 2019 | Glaucoma Disease    | Anterior chamber OCT images  | 81.0%    |
| PCA                         | Monturo et al[55]        | 2017 | Macular edema       | 20 000 OCT images            | 78%      |
| GEM & VIM                   | Yousefi et al[56]        | 2016 | Glaucoma Disease    | Visual field images          | 93.8%    |
| GEM                         | Yousefi et al[57]        | 2014 | Glaucoma Disease    | Visual field images          | 97.0%    |
| VIM                         | Bowd et al[2]            | 2014 | Glaucoma Disease    | 1190 fundus images           | 93.1%    |
| PNN                         | Bayesian classification   | 2013 | Diabetic retinopathy| 350 fundus images            | 89.6%    |
| SVM                         | Priya & Arjuna[58]       |      |                     |                              | 94.4%    |
|                             |                          |      |                     |                              | 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.
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.

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