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A STUDY OF DEEP LEARNING METHODS AS AN AID FOR GLAUCOMA DETECCTION

[1]Marie Fernandes

[1]Research Scholar

School of Computer Science

Renaissance University, Indore, India

ABSTRACT: In recent era and research studies, the deep learning apart from being a subpart of the most technological advance area of the machine learning that believes in learning from example for producing result with higher emphasis on accuracy same as human instinct.

Glaucoma is a silent and neuro-degenerative eye disease which is irreversible and is considered as the primary reason of vision loss. As per World Health Organization (WHO), glaucoma is affecting more than 65 million people in the world ans so its early detection and treatment are far much more important so as to prevent vision loss. This eye disease has a major setback of optic nerve fibre loss that is due to increased intraocular pressure (IOP) or can be said in simple words that due to loss of blood flow to the optic nerve. It has been noted that IOP measurement is cannot be specific nor it is sensitive to be an effective indicator or highly noted measured valued as it has been noted that visual damage can also occur even without increased IOP.
So, the early detection of glaucoma through machine learning, artificial intelligence application of deep learning is highly one of the computer aids available that can help ophthalmologists in this area.

In this paper, we present study of the deep learning technique with different CNN architectures which can be used for glaucoma assessment.

Keywords: Glaucoma, machine learning, artificial intelligence, deep learning, convolution neural network

1. INTRODUCTION

Deep learning algorithms have the potential to significantly improve diagnostic capabilities in glaucoma, but their application in clinical practice requires careful validation, with consideration of the target population, the reference standards used to build the models, and potential sources of bias.

Despite the availability of effective treatments, glaucoma remains the leading cause of irreversible blindness worldwide.[1] Current projections estimate that 111.8 million people will have glaucoma by the year 2040, with people in Asia and Africa disproportionately affected. The early detection and intervention can help prevent vision loss from glaucoma, but a majority of patients do not know they have the disease[2,3] because it is generally asymptomatic in early stages.[4–6] Thus early detection of glaucoma is important and may be improved by introducing novel approaches for screening, diagnosis, and detection of change over time.

Glaucoma is regularly related to a build-up of strain or pressure within the eyes. Glaucoma has a tendency to run in households and one typically doesn't get it till later in life. The improved strain in eyes, known as intraocular strain, can harm the optic nerve, which sends images to the brain. If the harm worsens, glaucoma can purpose everlasting imaginative and prescient loss or maybe general blindness inside some years. Most humans with glaucoma haven't any early signs or pain. One have to go to the attention physician frequently in order to diagnose and deal with glaucoma before one has long-time period imaginative and prescient loss. If someone loses his imaginative and prescient, it can't be added back. But, decreasing eye strain can assist maintain the sight that he has. Most humans with glaucoma who comply with their remedy plan and feature ordinary eye tests are capable of maintain their imaginative and prescient. An optic disc and cup are found in all people however an extraordinary length of the cup with appreciate to the optic disc is a feature of a glaucoma inflamed eye. Traditional strategies of detecting glaucoma consist of an eye fixed physician analysing the pics and locating the abnormalities in it. This approach may be very time ingesting and now no longer usually correct due to the fact the photograph consists of noise and different elements which make it hard for correct evaluation. Also, if a gadget skilled for evaluation it turns into greater correct than human evaluation.

Most of the literature works gift especially awareness on optic cup and disk segmentation and a few awareness on Cup/Disk ratio. Through our evaluation we've located the use of Convolution Neural Network version to be higher than different literature works proposed. Convolution neural networks are one of the maximum famous deep mastering strategies for photograph evaluation. In this method, schooling information units of formerly labeled pics are used to increase the system. This deep mastering method means that computer systems can perform function mastering and category simultaneously. In deep mastering algorithms, a version is shaped the use of many layers which transform the given enter information to an output.

2. ARTIFICIAL INTELLIGENCE, MACHINE LEARNING AND DEEP LEARNING

Artificial intelligence (AI) is a branch of computer science dealing with the simulation of intelligent behav ior in computers, but in practice, and particularly in the popular press, "AI" has been used to describe any cutting-edge machine capability. Machine learning is a subset of AI that is concerned with setting up computer algorithms to recognize patterns in data, without human programmers having to dictate all aspects of this recognition.

In its most traditional form, machine learning algorithms still require human-designed code to transform raw data into input features, as these algorithms are not particularly good at learning features directly from raw data. Examples of these more traditional algorithms include logistic regression, k-Nearest Neighbor, decision trees, random forests, support vector machines (SVMs), among others (Fig. 1). The process of creating these initial features, however, can be a highly specialized task, requiring substantial subject-matter expertise, and there is no guarantee that the human-extracted features are optimal for use by the classifier. As an example, previous studies have used SVMs to improve detection of glaucoma damage from imaging data.[6-8] The SVMs used features such as learning algorithms that use "representation learning" (Fig. 1).

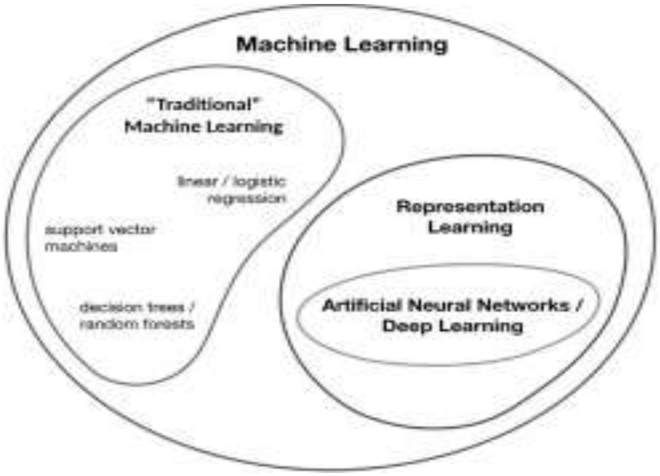

Figure. 1

These algorithms learn features (representations) from data automatically, as long as enough data are given to them. A primary benefit of deep learning is that it eases the requirement for subject matter expertise. Instead of manually trying to curate relevant features from the data, one can feed the raw data directly to a deep leaning model, which will then automatically learn the most relevant features from the data. These features may be more subtle and comprehensive than those that would have been manually curated. As a trade-off, however, these automatically learned features may not be as straightforward to understand or explain, leading to the perception that deep learning models are a “black-box.”

Deep learning models are a type of artificial neural network composed of several layers of artifi cial “neurons.” These neurons are simple algorithms inspired by biological brain cells, in the sense that they receive input from other neurons, perform compu tations, and produce an output (Fig. 2). An artifi cial neural network is a collection of interconnected artificial neurons. Data are fed to the network and processed in some way with the goal of producing a desired outcome. Neural networks have been known for decades. Goldbaum et al.22 used them to inter pret perimetry results in glaucoma almost 30 years ago. However, only recently the advances in computational power have allowed the buildup of networks of several layers, that is, deep learning networks, which are able to process much more complex data, resulting in far better performance compared to the shallow artificial neural networks.

A type of deep learning network called convolutional neural network (CNN) has been the main one responsible for the explosion of deep learning applications as shown in Figure 2.

In Figure 2 : a schematic representation of “neurons” on an artificial neural network is shown. The input data corresponds to the data one it trying to classify. The number of neurons in the input layer will depend on the input data (e.g., number of pixels in an image). These input neurons are then connected to neurons in hidden layers. There may be many hidden layers, which can be quite complex depending on the type of model. For convolutional neural networks, the hidden layers are of the convolutional type, specializing in spatial patterns. Finally, all calculations will converge to a final model prediction in the output layer.

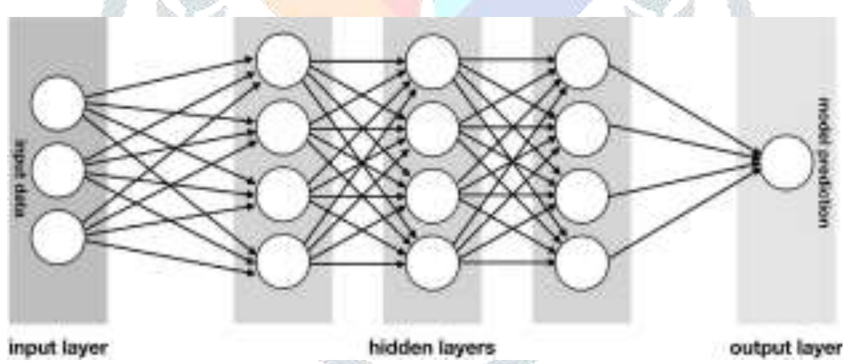

Figure 2

CNNs have one or more convolutional layers, which consist of sets of filters, and are ideally suited to process spatial patterns and perform tasks such as image classification and object detection. These filters can be used to automatically extract features from images, obviating the need for manual labor in crating relevant features, a major limitation of traditional machine learning algorithms, as described above. As one of the medical fields that is highly dependent on ancillary imaging tests, ophthalmology has been a prime area to witness the application of CNN algorithms to help analyze data coming from these tests.

3. DEEP LEARNING MODELS: TRAINING, VALIDATION, AND TESTING

Before a deep learning network can be used for a specific task, it needs to be trained, so that the specific computations needed at each artificial neuron (i.e., weights) and their interconnections can be determined to produce the desired result. In general terms, this training process involves feeding the network with data, observing the results, making modifications to the model, and repeating the process iteratively, until a desired level of accuracy is achieved.

There are essentially three ways to train a deep learning algorithm: supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning has training of the algorithm with a completely labeled dataset.

For example, if an algorithm is being used to identify glaucoma on fundus photographs, it can be initially trained by feeding the network with labeled photos of glaucoma and normal eyes. The network then “learns” the best features and the combination of them that will lead to the best discrimination of a glaucomatous from a normal photo. This learning process is done by comparing the algorithm’s predictions to the actual labels and readjusting the weights of the artificial neurons, in a process known as backpropagation.[9] There are various studies which have been done for using supervised learning algorithms to improve glaucoma detection.10-12 ,17–21 Unsupervised learning, on the other hand, involves training the algorithm with unlabeled data. The goal is to have the model discover some hidden underlying structure or pattern in the data, without being told a priori what the task should be. For example, one can train a model to identify patterns of visual field damage in glaucoma with a large unlabeled set of visual fields from patients with the disease, in the hope that the model will “learn” the different patterns in those fields. This approach has previously been used to classify fields in glaucoma, as well as to detect progressive change over time.13–15,25–27 Finally, semisupervised learning uses a combination of the two approaches, where one has a relatively small set of labeled data and generally a much larger amount of unlabeled data. The labeled dataset is used to obtain a reasonable initial model, which is then used to perform predictions on the unlabeled dataset. Such new predictions can then be used to retrain the model and the process is repeated until a final satisfactory model is obtained. This situation can occur, for example, when the process of data labeling is time-consuming or expensive. Application of semisupervised models in glaucoma has been rare,[16] but this is a promising approach that deserves more investigation.

The process of training requires the investigator to have an amount of data that will be used to train the model and a separate dataset that will be used to check the model’s predictions (i.e, validation). If the predictions are unsatisfactory, then certain parame ters of the model can be changed—for example, the number of hidden layers of neurons—and the training is repeated. It is important to note that this process of training and validating the model is highly iterative and time-consuming and still requires substantial human input.

One challenge to the development of a deep learning algorithm is the general requirement of very large datasets for training, which can be on the order of thousands or even millions of images. This occurs because of the very large number of parameters in these models. Some state-of-the-art CNNs have dozens of layers, resulting in millions of parameters that need to be trained. Ophthalmic image datasets of this size are not typically available, especially labeled datasets.

However, transfer learning techniques have been applied to overcome this limitation.[30] In transfer learning, a CNN (e.g., ResNet, Inception) [31,32] previously trained on a very large general image dataset can be used as a general feature extractor and undergo additional training so it can be refined to perform a more specific task (e.g., distinguishing glaucoma from non-glaucoma) using a much smaller dataset. Transfer learning techniques are now ubiquitously applied to train CNNs that detect glaucoma on imaging datasets of more limited size.

4. CNN: THE DEEP LEARNING METHODS

Convolutional network architectures were initially designed for image recognition tasks. The primary design goal of CNNs was to create a network where the neurons in the early layer of the network would extract local visual features, and neurons in later layers would combine these features to form higher-order features. There are three main types of layers which can be seen in almost every CNNs ; convolutional layer, pooling layer, and fully connected layer. Over the years, there are many CNN architectures which have been developed to solve various problems in here are many variants of CNN architectures have been developed to solve real-world problems.

However, there are some architectures which have been popular among researchers. We will discuss each architecture and its applications.

A). AlexNet is a convolutional neural network (CNN) architecture which was designed by Alex Krizhevsky in collaboration with Ilya Sutskever and Geoffrey Hinton. The architecture includes of eight layers , five convolutional layers and three fully connected layers [37]. AlexNet have some of the features which are new approaches to convolutional neural networks. AlexNet is a leading architecture for any object-detection task and It has many applications.

AlexNet[33] consists of eight layers. Input images go through five convolutional layers and then three fully connected layers. Images are convolved with 96 filters of size 11×11 in the first convolution layer. After, the output of the first convolutional layer is used as input to the second convolutional layer. Then the pooling is performed on the output of the second convolutional layer. This input is filtered with 256 kernels of size 5×5 in the second convolutional layer. This convolution process is done for third and fourth and fifth convolutional layers. After, fully connected layers are constructed.

B). GoogLeNet is a convolutional neural network architecture and it is based on the Inception architecture. It utilizes Inception modules, which permit the network to choose between multiple convolutional filter sizes in each block. An Inception network stacks these modules on top of each other, with occasional max pooling layers with stride 2 to halve the resolution of the grid . The GoogLeNet architecture is very different from previous state-of-the-art architectures such as AlexNet . It uses many different methods such as global average pooling and 1×1 convolution and that enables it to create deeper architecture. [38]

GoogleNet [35,36] consists of 20 layers. This deep learning model is based on inception modules. Inception modules allow parallel filtering of the layers. This is network is much deeper than VGG and AlexNet deep learning models.

C). VGGNet is a CNN architecture which was proposed by Karen Simonyan and Andrew Zisserman. It was developed in University of Oxford in 2014. It focuses on the outcome of the convolutional neural network depth on its accuracy. The input of the VGG based convNet is a 224*224 RGB image. RGB image is taken by preprocessing layer pixel values in the range of 0–255 and subtracts the mean image values which is calculated over the entire ImageNet training set. The input images after preprocessing are processed through these weight layers. The training images are processed through a stack of convolution layers. There are total of 3 fully connected layers and 13 convolutional layers in VGG16 architecture. VGG has smaller filters (3*3) with more depth instead of having large filters [4]. VGGNet has another variation which has 19 weight layers consisting of 16 convolutional layers with same 5 pooling layers and 3 fully connected laters. In both variation of VGGNet there consists of two Fully Connected layers with 4096 channels each which is followed by another fully connected layer with 1000 channels to predict 1000 labels. However, the there are some drawbacks in VGGNet architecture. One is that it is very slow to train, And the network architecture weights themselves are quite large in terms of disk/bandwidth. [39] Thus, VGG Net [34] consists of 16 and 19 layers. The input images pass through two 64 filters with 3×3 sizes. Then, another two 128 sets of filters of 3 × 3 sizes are utilized to process the output of the first filtering. This convolution process is utilized with 256 and 512 sets of filters. Finally, fully connected layers are created.

D). ResNet, short for Residual Network is a type of neural network that was porposed in 2015 by Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun in their research paper “Deep Residual Learning for Image Recognition”. According to the paper it can learn residual functions with reference to the layer inputs, without learning unreferenced functions. Instead of hoping each few stacked layers directly fit a desired underlying mapping, residual nets let these layers fit a residual mapping. They stack residual blocks ontop of each other to form network: e.g. a ResNet-50 has fifty layers using these blocks.

ResNet-18, ResNet-32, ResNet-50, and ResNet-1527 are the mainly used models for medical image classification. These models are based on the residual learning method. Residual learning does not allow error accumulation on the convolution layers but enables a better representation of the content in the convolution layers.

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