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Original Research Paper

Engineering

EVOLUTIONARY REVOLUTION OF DEEP LEARNING MODEL IN DIABETIC RETINOPATHY

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KEYWORDS :

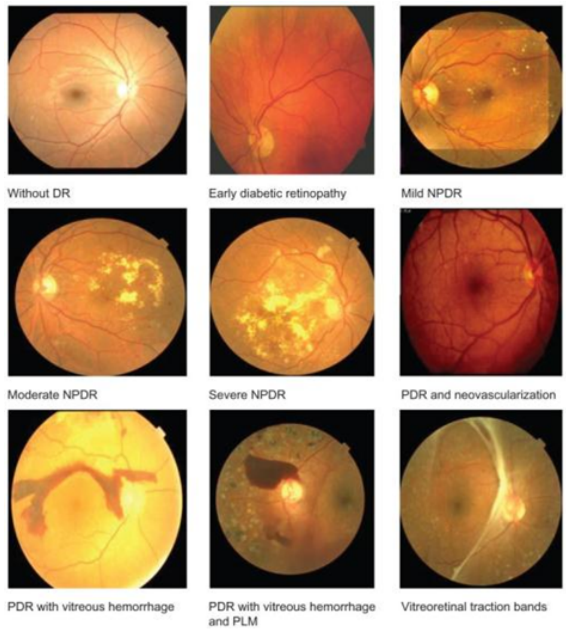
INTRODUCTION

Diabetic retinopathy is a condition that occurs in people who have diabetes. It causes progressive damage to the retina, the light-sensitive lining at the back of the eye. Diabetic retinopathy is a serious sight-threatening complication of diabetes. Diabetes interferes with the body's ability to use and store sugar (glucose). The disease is characterized by too much sugar in the blood, which can cause damage throughout the body, including the eyes. Over time, diabetes damages the blood vessels in the retina. Diabetic retinopathy occurs when these tiny blood vessels leak blood and other fluids. This causes the retinal tissue to swell, resulting in cloudy or blurred vision. The condition usually affects both eyes. The longer a person has diabetes, the more likely they will develop diabetic retinopathy.[1] It is a leading cause of blindness among working-age adults. Early detection of this condition is critical for good prognosis.[2] Often the early stages of diabetic retinopathy have no visual symptoms. That is why the American Optometric Association recommends that everyone with diabetes have a comprehensive dilated eye examination once a year. Early detection and treatment can limit the potential for significant vision loss from diabetic retinopathy.Treatment of diabetic retinopathy varies depending on the extent of the disease. People with diabetic retinopathy may need laser surgery to seal leaking blood vessels or to discourage other blood vessels from leaking.[1]

Inventors have long dreamed of creating machines that think. This desire dates back to at least the time of ancient Greece. The mythical figures Pygmalion,Daedalus, and Hephaestus may all be interpreted as legendary inventors and Galatea, Talos, and Pandora may all be regarded as artificial life (Ovid and Martin,2004; Sparkes, 1996 and Tandy, 1997). When programmable computers were first conceived, people wondered whether such machines might become intelligent, over a hundred years before one was built (Lovelace, 1842). Today, artificial intelligence(AI) is a thriving field with many practical applications and active research topics. We look to intelligent software to automate routine labor, understand speech or images, make diagnoses in medicine and support basic scientific research.

In the early days of artificial intelligence, the field rapidly tackled and solved problems that are intellectually difficult for human beings but relatively straight-forward for computers—problems that can be described by a list of formal, mathematical rules. The true challenge to artificial intelligence proved to be solving the tasks that are easy for people to perform but hard for people to describe formally—problems that we solve intuitively, that feel automatic, like recognizing spoken words or faces in images.[3]

This solution is to allow computers to learn from experience and understand the world in terms of a hierarchy of concepts, with each concept defined through its relation to simpler concepts. By gathering knowledge from experience, this approach avoids the need for human operators to formally specify all the knowledge that the computer needs. The hierarchy of concepts enables the computer to learn complicated concepts by building them out of simpler ones. If we draw a graph showing how these concepts are built on top of each other, the graph is deep, with many layers. For this reason, we call this approach to AI **deep learning. [3]**Developed from artificial neural networks, deep learning-based algorithms show great promise in extracting features and learning patterns from complex data.[1] A supervised classification is based on classifying the test image dataset from the training data with a labeled classes. In general, classification is done by extracting the features from the images followed by identifying the categorized classes based on the trained data with labeled classes.



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Some of the popular methodologies well utilized to do feature extraction and classifica-tion of diabetic retinopathy analysis are :

1. Wang, [1], using convolutional neural network performs as a trainable hierarchical feature extractor and Random Forest(RF) as a trainable classifier. It has 6 stacked layers of convolution and followed by subsampling layers for feature extraction. Random Forest algorithm is utilized to for classifier ensemble method and introduced in the retinal blood vessel segmentation. This architecture is used in the DRIVE,STARE databases and achieved around 0.98 and 0.97.
2. Haloi *et al*[2], a new deep learning based computer-aided system for microaneurysm detection. Comparing other deep neural network, it required less preprocessing, vessel extraction and more deep layers for training and testing the fundus image dataset.It consists of five layers which includes convolutional, max pooling and Softmax layer with additional droput training for improving an accuracy.It achieved low false positive rate. And the performance measured as 0.96 accuracy with .96 specificity and .97 sensitivity.
3. Melinscak *et al*[3], an automatic segmentation of blood vessels in fundus images. It contain a deep max-pooling convolutional

neural networks to segment blood vessels.It is deployed 10-layer architecture for achieving a maximum accuracy but worked with small image patches. It contain a preprocessing for resizing and reshaping the fundus images. It carried around 4-convolutional and 4-max pooling layer with 2 additional fully connected layer for vessel segmentation. Also, this method achieved an accuracy around 0.94.

4. Gardner *et al*[4], a pioneer method of diabetic retinopathy screening tool using artificial neural network with preprocessing techniques. This method learned features from the sub-images. It heavily relied on back propagation neural network. It contains set of diabetic features in fundus images and compare against the ophthalmologist screening set of fundus images.Its a wholistic approach of recognition of vessels, exudates and haemorrhages were 91.7%, 93.1% and 73.8%.
5. Roychowdhury *et.al*[5] proposed a novel two stage hierarchical classification algorithm for automatic detection and classification. For automated detection, novel two-step hierarchical binary classification is used. For classification of lesions from non-lesions purposed GMM, SVM, KNN and ADABOOST methods are used. They take 30 top features like are, variance of Ired channel, Igreen channel, I sat of object, major and minor axis length, Mean pixels for Igreen, Ired and intensity, solidity etc. The DREAM system 100 percent sensitivity, .5316 specificity achieved. Also, carried out average computation time for DR severity per image from 59.54 to 3.46s. overall feature reduction effects the average computation time.
6. Lachure *et* al[6], retinal micro-aneurysms, hemorrhages, exudates, and cotton wool spots are the abnormality find out in the fundus images. Detection of red and bright lesions in digital fundus photographs. Pre- processing, morphological operations performed to find microaneurysms and features are extracted such as GLCM and structural features for classification. This SVM classifier optimized to 100 percent and 90 percent sensitivity.
7. Priya and Aruna [7], to diagnostic retinopathy used two models like Probabilistic Neural network(PNN) and Support Vector Machines. The input color retinal images are pre-processed using grayscale conversion, adaptive histogram equalization, discrete wavelet transform, matched filter and fuzzy C-means segmentation. The classification of pre- processed images features were extracted.It achieved an accuracy of 89.6 percent and SVM of around 97.608 percent.
8. Giraddi *et al*[8], detection of the exudates in the color variability and contrast retinal images. Comparative analysis made for SVM and KNN classifier for earliest detection. They utilized the GLCM texture features extraction for obtaining the reduced number of false positives. Eventually the true positive rates for SVM classifier around 83.4 and KNN classifier around 92%.As a result, KNN outperforms SVM with color as well as texture features.
9. Srivastava *et* al[9], a key idea of randomly drop units along with their connections during the training. His work significantly reduces the over fitting and gives improvements over other regularization techniques. Also, improves the performance of neural networks in vision, document classification, speech recognition etc.

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. It is an aspect of artificial intelligence that is concerned with emulating the learning approach that human beings use to gain certain types of knowledge. At its simplest, deep learning can be thought of as a way to automate predictive analytics.[9] While traditional machine learning algorithms are linear, deep learning algorithms are stacked in a hierarchy of increasing complexity and abstraction.

How Deep Learning Works

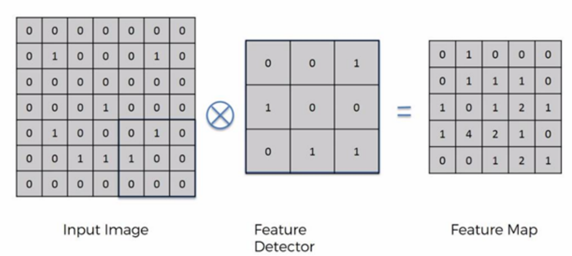
The success of traditional methods for solving computer vision problems heavily depends on the feature extraction process. But Convolutional Neural Networks (CNN) have provided an alternative for automatically learning the domain specific features. Now every problem in the broader domain of computer vision is re-examined from the perspective of this new methodology. Therefore, it is essential to figure-out the type of network specific to a problem. In this work, we have done a thorough literature survey of Convolutional Neural Networks which is the widely used framework of deep learning.[10]

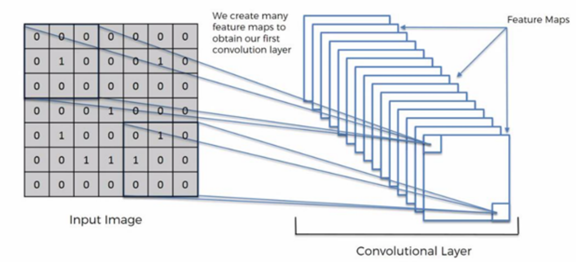
In Deep Learning, each algorithm in the hierarchy applies a nonlinear transformation on its input and uses what it learns to create a statistical model as output. Iterations continue until the output has reached an acceptable level of accuracy. The number of processing layers through which data must pass is what inspired the label deep. Convolutional Neural Network is the widely used deep learning framework which was inspired by the visual cortex of animals. Initially it had been widely used for object recognition tasks but now it is being examined in other domains as well like object tracking, pose estimation , text detection and recognition, visual saliency detection, action recognition, scene labeling and many more.

Convolution Neural Networks

ConvNets are very similar to normal neural networks which can be visualized as a collection of neurons arranged as an acyclic graph. The main difference from a neural network is that a hidden layer neuron is only connected to a subset of neurons in the previous layer. Because of this sparse connectivity it is capable to learn features implicitly. The deep architecture of the network results in hierarchical feature extraction i.e. the trained filters of first layer can be visualized as set of edges or color blobs, of second layer as some shapes, the next layer filters might learn object parts and the filters of final layers can identify the objects.

This layer forms the basic unit of a ConvNet where most of the computation is involved. It is a set of feature maps with neurons arranged in it. The parameters of the layer are a set of learnable filters or kernels. These filters are convolved with the feature maps to produce a separate 2-dimensional activation map which when stacked together along the depth dimension, produce the output volume. Neurons that lie in the same feature map shares the weight (parameter sharing) thereby reducing the complexity of network by keeping the number of parameters low.[11]



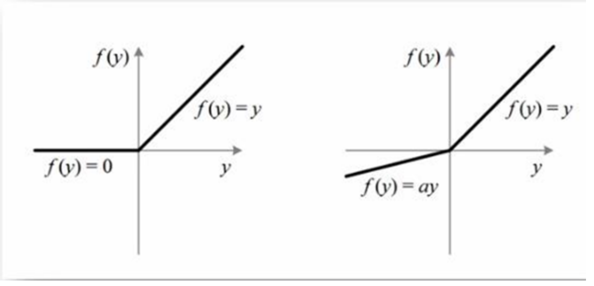


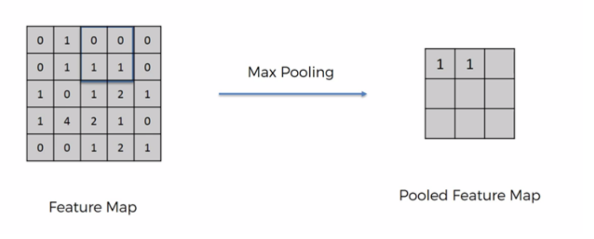
2. ReLU

This is the rectified linear unit function on Convolution layer to break the linearity of con-volution. Images are non-linear and thus a non linear function works more effectively on them. The convergence of gradient descent can be accelerated on applying ReLU.[17]

3. Max Pooling

Pooling layers function to reduce the spatial dimension of the activation maps (without loss of information) and the number of parameters in the net and thus reducing the overall compu-tational complexity. This controls the problem of overfitting. [18]



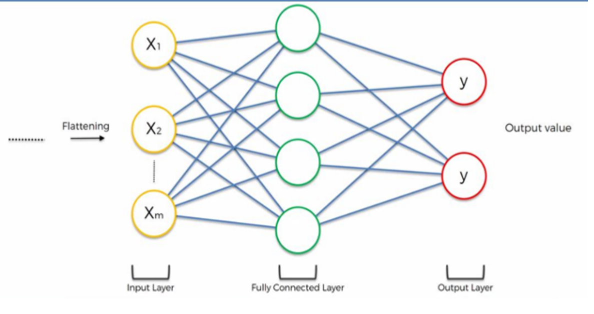


4. Flattening

Flattening is the process of converting all the resultant 2 dimensional arrays into a single long continuous linear vector. The flattening step is needed so that you can make use of fully connected layers after some convolutional layers

5. Fully connected layer

Neurons in this layer are fully connected to all neurons in the previous layer, as in a regular Neural Network. High level reasoning is done here. The neurons are one dimensional so there cannot be a convolved layer after a fully connected layer.



FUTURE OF DEEP LEARNING IN MEDICINE

It is a rapidly growing industry and the evolution of it has just begun in true senses. It is a boon indeed in the field of medicine. It is a mechanism which is one step closer to the patient in diagnosing his/her health status and providing with a decisive opinion. Deep learning models are bridging the gap between a doctor and his/her patient. It is a positive approach which will have even more revolutionising developments in the coming times. It's improving the healthcare indus-try and building socioeconomic environment making it much more accessible for individuals.

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