IOSR Journal of Engineering (IOSRJEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
PP 47-52

A Survey on Deep Learning Approaches in Retinal Vessel Segmentation for Disease Identification

K.Geethalakshmi [1]

[1] *Research Scholar, Chikanna Government Arts College, Bharathiar University, Combatore, Tamil Nadu,India*

Abstract: *Human retinal image plays a vital role in detection and diagnosis of various eye diseases for ophthalmologist. Automated blood vessel segmentation diagnoses many eye diseases like diabetic retinopathy, hypertension retinopathy, retinopathy of prematurity or glaucoma based on the feature extraction. Automated image analysis tool based on machine learning algorithms are the key point to improve the quality of image analysis. Deep learning (DL) is a subset of machine learning which is completely based on artificial neural network. It helps a machine to analyze the data efficiently. Deep learning is one extensively applied techniques that provides state of the art accuracy. Different types of neural network and platform used for DL also discussed. This paper reviews the different DL approaches for blood vessels segmentation. It concludes that the deep learning methods produces high level of accuracy in disease identification*
Keywords*— Diabetic Retinopathy, Deep Learning, Segmentation, Neural Network*

I. Introduction

Deep learning is an artificial Intelligence function that replicates the human brain functions by processing the given data and producing patterns for decision making. Deep learning operates a hierarchical level of artificial neural networks to bring out the process of machine learning. The artificial neural networks are designed similar to human brain that consists of neuron nodes connected together like a web. The Hierarchical function of deep learning model allows the machine to process data with a nonlinear approach rather than linear way in traditional programs. Deep Learning system is able to learn the unstructured or unlabelled data in a network and it is a subset of Machine Learning in AI.

Deep Learning methods use neural network architectures, which are often referred to as deep neural networks. The total number of hidden layers in the neural network is referred as “DEEP”. Deep networks can have as many as hidden layers. Deep learning models are trained by using large sets of data and neural network architectures that extract features directly from the data without the manual feature extraction. The building blocks of neural networks including neurons, weights and activation functions.

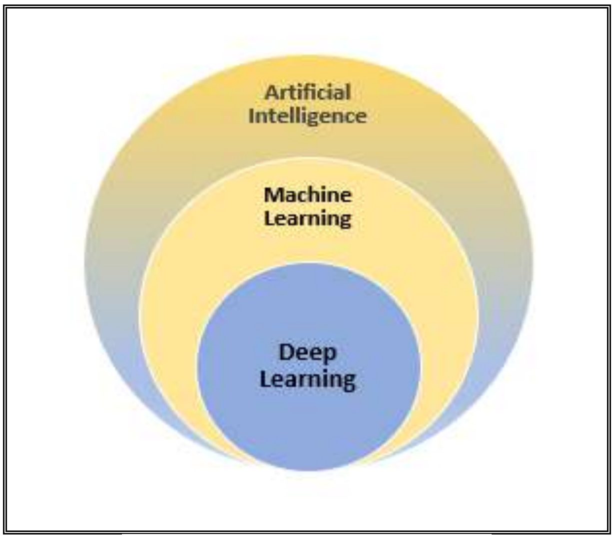

Fig 1: hierarchy of deep learning

A. Difference between Machine and Deep Learning

In machine Learning approach the workflow starts with extracting relevant features from the given image and based on the feature the model is developed to describe or predict the object. In Deep learning approach, the relevant features are automatically extracted from the images and manual feature extraction is evaded. The deep learning models are capable of learning to focus on the right features by themselves, requiring little guidance from the programmer. This makes deep learning an extremely powerful tool for modern machine learning and achieves higher level accuracy than the machine learning models.

Fig 2: traditional machine learning flow

Fig 3: deep learning flow

B. Overview of Deep Learning

Deep learning has developed from cognitive and information theories, seeking to imitate the learning process of human neurons and create complex interconnected neuronal structures. As one of the key concepts of computing neurons and the neural model, the ability for a generic neuron to be applied to any type of data and learn indiscriminately is a powerful concept [2]. There is no singular structure for each application, but instead a generally applicable model for all applications. Computer algorithms that mimic these biological structures are formally called artificial neural networks.

C. Structure of Deep Neural Networks

The Neural Network model [3] consists of three layers called the input layer, hidden layer, and output layer. In Each layer there are one or more nodes. The information flows from one node to another node, which is represented by lines. The input layer nodes are in passive form, do not modify the data. They obtain a single value from input channel and duplicate the value to their multiple outputs. The hidden and output layer nodes are in active form. For example, pixel values from an image, samples from an audio signal, etc.

The input layer value is duplicated and sent to all the hidden nodes. This is referred as fully interconnected structure. Neural networks consist any number of layers and nodes per layer. The three-layer structure with a maximum of a few hundred input nodes are mostly used. The output layer only needs a single node in the case of target detection. The output of this node is thresholded to provide a positive or negative sign of the target existence or absence in the input data.

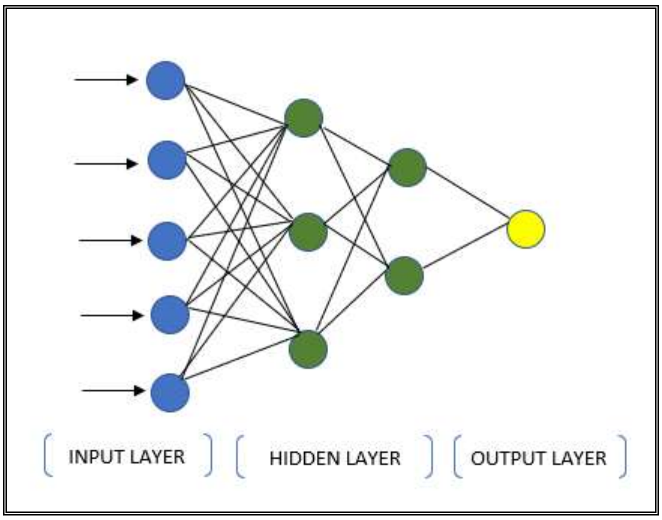

Fig 4: structure of neural network

D. Types of Neural Networks

There are different kinds of artificial neural networks. These type of networks are executed based on the mathematical operations and a set of parameters required to determine the output.[5]

Multilayer Perceptron

. A multilayer perceptron (MLP) is a feedforward artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input and output layers. MLP uses back propagation for training the network.

Convolutional Neural Network

Convolutional Neural Networks are very similar to Neural Networks, they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network still expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other.

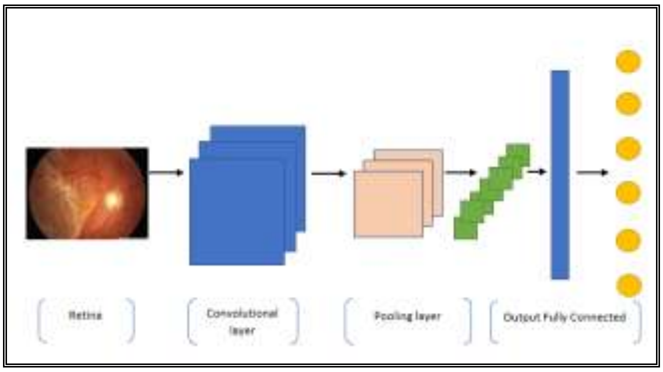

Fig 5: convolutional neural network

Recurrent Neural Network

A recurrent neural network (RNN) is an artificial neural network where connections between nodes form a directed graph along a sequence. This allows it to exhibit dynamic temporal behaviour for a time sequence. Unlike feedforward neural networks, RNNs can use their internal memory to process sequences of inputs.

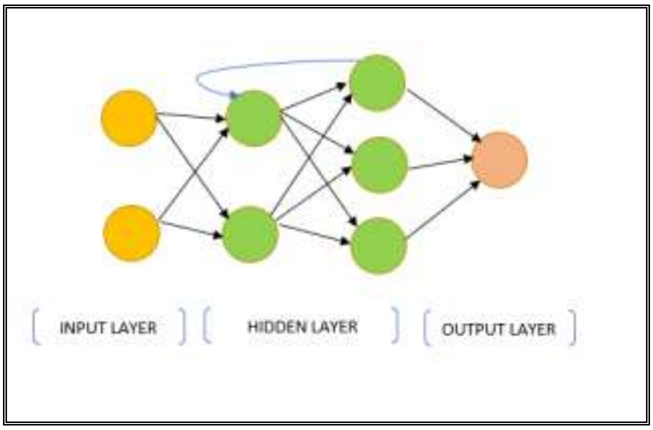

Fig 6: recurrent neural network

Feed Forward Neural Network

A feedforward neural network is an artificial neural network wherein connections between the nodes do not form a cycle. The feedforward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network[23]

Modular Neural Network

A modular neural network is one that is composed of more than one neural network model connected by some intermediary. Modular neural networks can allow for sophisticated use of more basic neural network systems managed and handled in conjunction.[24]

Recursive Neural Network

A recursive neural network (RNN) is a kind of deep neural network created by applying the same set of weights recursively over a structured input, to produce a structured prediction over variable-size input structures, or a scalar prediction on it, by traversing a given structure in topological order.[20]

II. deep learning platforms

Some of the Deep learning platforms are,

A. Tensor Flow

TensorFlow is an open source software library for complex numerical computation. These libraries are very flexibly used in variety of platforms like CPUs, GPUs, TPUs. Originally developed by researchers and engineers from the Google Brain team within Google's AI organization, it support for machine learning and deep learning and the flexible numerical computation[6]

B. Keras

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. Keras allows for easy and fast prototyping through user friendliness, modularity, and extensibility and it supports both convolutional networks and recurrent networks, as well as combinations of the two. It runs seamlessly on CPU and GPU.[7]

C. Theano

Theano is a numerical computation library for python, in theano, computations are expressed using a NumPy-esque syntax and compiled to run efficiently on either CPU or GPU architectures.[8]

D. Microsoft Cognitive Toolkit (CNTK)

CNTK is designed to be easy-to-use and production-ready for use on large production scale data and is supported on Linux and Windows. In CNTK, neural networks are considered as a series of computational steps via directed graphs, and both neural network building blocks and deeper libraries are provided. CNTK has emerged as a computationally powerful tool for machine learning with performance like other platforms that have seen longer development and more widespread use [9].

E. Deeplearning4J

Deep Learning for Java (DL4J) is a robust, open-source distributed deep learning framework for the JVM created by Sky mind, which has been contributed to the Eclipse Foundation and their Java ecosystem. DL4J is designed to be commercial-grade as well as open source, supporting Java and Scala APIs, operating in distributed environments, such as integrating with Apache Hadoop and Spark, and can import models from other deep learning frameworks (TensorFlow, Caffe, Theano) [1]

III. Need of deep learning methods in Retinal image processing

Based on the latest report by the year 2030 there is an epidemic rise of 4.4% in the global prevalence of diabetes. [15] In the present world, Diabetic Retinopathy (DR) is a leading cause of eye disease that occurs due to diabetes mellitus and it has most common cause of blindness in the present world. During the screening process, Fundus images of the retina are taken for the purpose of detection of DR. The presence of Microaneurysm (MA) in retinal image is the early detection of DR. Current treatments for DR are available yet it requires early diagnosis and the constant monitoring of diabetic patient and many methods have proposed by the researchers for blood vessel segmentation by using difference Databases like STARE, DRIVE, CHASE_DBI..

Many medical image diagnosis process needs earlier identification of abnormalities, quantify measurement and changes over time. Automated image analysis tool based on machine learning algorithms are the key enablers to improve the quality of image diagnosis. Deep learning is one extensively applied techniques that provides state of the aft accuracy.[10]

IV. Literature Survey

QiaoliangLi et al [10] presented a wide and deep neural network cross-modality data transformation from retinal image to vessel map with strong induction and this model does not need artificial designed features and preprocessing. This method produces high performance framework for retinal vessel segmentation.

Paweł Liskowski et al [11] presented a supervised segmentation technique that uses a deep neural network trained on a large (up to 400000) sample of examples preprocessed with global contrast normalization, zero-phase whitening, and augmented using geometric transformations and gamma corrections. The networks significantly outperform the previous algorithms on the area under ROC curve measure.

Huazhu Fu et al [12] suggested the vessel segmentation to a boundary detection problem, and utilize the fully convolutional neural networks (CNNs) to generate a vessel probability map and a fully-connected Conditional Random Fields (CRFs) is also employed to combine the discriminative vessel probability map and long-range interactions between pixels.

L.Ngo et al [13] presented a novel max-resizing technique to improve the generalization of the training procedure for predicting blood vessels from the fundus images.
Martina Melinscak et al [14] suggested a Deep Max pooling Convolutional Neural Network to segment the blood vessels.
Debapriya Maj et al [16] suggested an ensemble of deep convolutional neural networks to segment vessel and non-vessel areas of a color fundus image. During inference, the responses of the individual ConvNets of the ensemble are averaged to form the final segmentation.
Jen Hong Tan1 et al [17] presented an algorithm extracted three channels of input from the point's neighborhood and forwarded the response across the 7-layer network. The output layer consists of four neurons, representing background, optic disc, fovea and blood vessels.
Yongliang Chen [18] suggested an approach that allows us to take advantages of supervised learning without labeling and build a naive DCNN model to test it.
BohengZhang et al, [19] presented a novel convolutional neural network which make sufficient use of low-level features together with high-level features and involves atrous convolution to get multi-scale features.
Carson Lam et al, [21] suggested the Deep Learning approach using Image Patches method for retinal Lesion detection.
Leyuan Fang [22] presented the Deep Learning and Graph Search method which identifies age-related macular degeneration (AMD).
Kele Xu [4] suggested Deep Neural network methodology for the automatic classification of diabetic retinopathy using color fundus image.
Harry Pratt et al [25] suggested a Convolution Neural Network and data augmentation to identify the hemorrhages on the retina.

Table 1: performance of different segmentation methods

Existing System	DL Architecture	Technique	Accuracy
QiaoliangLi et al [10]	Five Layer Neural Network	Cross Modality approach	0.9738
Paweł Liskowski et al [11]	Deep Neural Network	Global contrast Normalization, Structure Prediction	0.97
Huazhu Fu et al [12]	Deep Neural Network	Fully connected conditional random field	0.9470
L.Ngo et al [13]	Multi level DNN	Resizing, Multilevel Network	0.9533
Martina Melinscak et al [14]	Convolutional NN	Deep Max pooling of CNN	0.9466
Debapriya Maji et al [16]	Ensemle DNN	SVM Classifier	0.947
Jen Hong Tan1 et al [17]	Convolutional NN	7 layer Network	09268
Yongliang Chen [18]	DNN	Supervised Learning	0.9453
BohengZhang et al, [19]	Multi scale NN	Atrous Convolution	0.9865
Carson Lam et al, [21]	Deep Learning	Sliding Window	0.98
Leyuan Fang [22]	Convolutional NN	Graph Search	--
Kele Xu [4]	Deep Convolutional NN	GBM Classification	0.945
Harry Pratt et al [25]	CNN	Data Augmentation	0.75

V. Conclusion

Deep learning is a subclass of machine learning, which process the unstructured data and predict useful patterns for different applications. Different types of Neural network architecture and platforms are discussed This Paper reviews various Deep Learning approaches like Multilevel DNN, DNN, CNN, Supervised DNN, Ensemble DNN for retinal vessel segmentation for earlier detection of eye diseases like diabetic retinopathy, hypertension retinopathy, retinopathy of prematurity or glaucoma. The performance of the various vessel segmentation based on Deep Neural Networks is measured in terms of Accuracy. The Deep Learning approaches produces the better results than the existing methods. Hence the new methodologies in deep learning to detect blood vessels and the efficient use of already existing methods are the interest of future work.

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