# Machine Learning Techniques for Diabetic Retinopathy Detection: A Review

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## Abstract

Diabetic retinopathy is a threatening complication of diabetes, caused by damaged blood vessels of light sensitive areas of retina. DR leads to total or partial blindness if left untreated. DR does not give any symptoms at early stages so earlier detection of DR is a big challenge for proper treatment of diseases. With advancement of technology various computer-aided diagnostic programs using image processing and machine learning approaches are designed for early detection of DR so that proper treatment can be provided to the patients for preventing its harmful effects. Now a day machine learning techniques are widely applied for image processing. These techniques also provide amazing result in this field also. In this paper we discuss various machine learning and deep learning based techniques developed for automatic detection of Diabetic Retinopathy.

***Keywords:*** *Convolutional neural network, Deep Neural Network, Diabetic retinopathy, k-Nearest Neighbor , Support Vector Machine.*

## 1. Introduction

The population of diabetic patients has been growing day by day against total population of world. According to a recent survey, approximately 382 million people of total world population are suffering from this diseases and this population is expected to reach 592 million in upcoming years. Diabetes is long life disease that affects persons of every age. It is a very common disease that occurs due to the high ratio of glucose or sugar buildup in body. As the level of sugar increases uncontrollable, it starts to create various complications in body and affects various parts of body and causes disease like Alzheimer's disease, Cardiovascular disease, Eye damage (retinopathy), Nerve damage (neuropathy), Kidney damage (nephropathy), Foot damage, Skin conditions, Hearing impairment [1]. Diabetic retinopathy is one of these complications that affects eyes badly and may lead to visual loss. It is caused by damaged blood vessels of light sensitive areas of retina. This is a long term complication of diabetes that develops gradually and does not give any sign at initial stages.

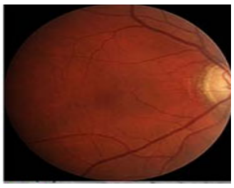

**Fig. 1(a) Normal**

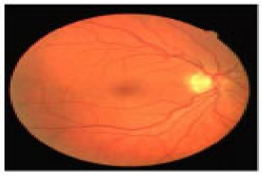

**Fig. 1(b) Mild NPDR**

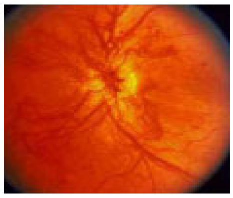

**Fig. 1(c) Moderate NPDR**

**Fig. 1(d) Severe NPDR**

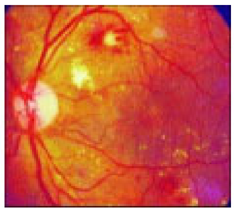

**Fig. 1(e) PDR**

**Fig 1. Stages of Diabetic Retinopathy**

DR is of two types: Nonproliferative diabetic retinopathy and proliferative diabetic retinopathy. Fig. 1 shows the stages of DR Nonproliferative DR is early stage of DR in which new blood vessels stops growing. In this type blood vessels wall of retina become weak and tiny bulges (microaneurysms) starts diffusing from the walls of small blood vessels. Sometime starts leaking fluid and blood into tissues of retina. Larger blood vessels start to dilate and become irregular in diameter. Sometimes swelling (macular edema) starts to occur in the central part of the retina (macula) [2]. DR can progress from mild to severe if damaged retinal vessels

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close off and starts growing new and abnormal blood vessels in light sensitive tissues of the retina, this is the **Advanced severe stage DR and** known as proliferative diabetic retinopathy. In this stage new or abnormal blood vessels starts to leak a jelly like substance that fills center of retina called Viterous. New blood vessels start interfering with normal flow of fluid and can damage the nerves that take images from retina to brain results in glaucoma [3]. Sometimes scar tissues generated by the growth of new and abnormal vessels may cause the retina to detach from the back of eye. [1] [4] DR is a long term complication of diabetes that develops gradually and does not give any sign at initial stages. Therefore it is very essential to diagnose this at early stage to reduce its harmful affects on eyes.

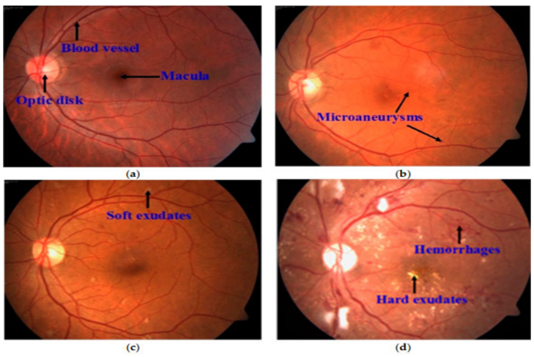


**Fig. 2 symptoms of DR** [1]

Various studies show that presence of hemorrhages, soft/hard exduates and microaneurysms in retina are symptoms of DR shows in Fig. 2. Hemorrhages are red deposits caused by the leaking of weak capillaries. Soft/hard exduates are small size white/yellowish-white spots that occur due to the leakage of proteins from vessels and microaneurysms are bulges of thin blood vessels on retina, these bulges appears as red spots of sharp and small borders. Based on these signs various computer-aided diagnostic programs are designed for early detection of DR so that proper treatment can be provided to the patients for preventing its harmful effects.

The aim of this paper is to review the existing machine learning and deep learning methods for automatic detection of diabetic retinopathy and discuss future research direction for automated detection of diabetic retinopathy.

The rest of this paper is structured as followed. In Section 2 various machine learning techniques used to classify DR in Retinal images are discussed. Section 3 we introduce deep learning and CNN, a most popularly image analysis technique and describes various deep learning models that are used to detect DR in Retinal datasets. In Section 4, various DR detection technique are discussed. In last section of the paper conclusion and references are given.

## 2. Diabetic Retinopathy Detection Using Machine Learning Algorithms

Machine learning is effectively accepted as an efficient tool for predicting outcomes in almost every domain. In lieu of hand designed rules, machine learning algorithms are able to learn from dataset to discover unknown patterns and support decisions. The type of machine learning technique a researcher chooses depends upon type of data they want to classify. These are categorized by how they learn to become more accurate in predictions [5] and basically classified in four categories: **Supervised machine learning algorithms** a researcher supply labelled training data and define variables he want algorithm to be used for prediction. In these algorithms both input and output are specified. **Unsupervised machine learning** algorithms, training is performed on unlabeled data. These algorithms scan dataset for any meaningful connection to discover information and patterns that are previously undetected. **Semi-supervised machine learning** algorithms combine both supervised and unsupervised approaches to predict data. Training is performed mostly on labeled data, but after this algorithm itself explore the data and develop its own understanding of the data. **Reinforcement learning** algorithms train a machine for completing a multi-step process on clearly defined rules. A researcher programs a model to complete a particular task and provides it positive or negative cues as it works. But for the most part, the model itself decides what steps to perform during processing.

Several researchers applied different machine learning approaches for diabetic retinopathy detection. In this section we discuss some of the machine learning based techniques employed to built the DR classification model.

In some of the primary studies based on ML approaches, researchers have implemented different kinds of ML alg

**Support Vector Machine :**

SVM is basically a supervised machine learning algorithm which provides amazing results for both classification and regression of data. SVM has a distinctive way of classification as compared to other ML classifiers. It creates a hyperplane near the extreme points called support vectors in the dataset. The main objective of SVM is to find a maximum marginal hyperplane that divide the dataset into two classes. For this SVM first generates hyperplanes iteratively which separate the classes in best ways. Then, it chooses the hyperplane that segregates the classes correctly [5] several research works employed SVM algorithm for detection of diabetic retinopathy in retinal datasets S. A. G. Naqvi [6]proposed a model for the detection of hard exudates in fundus images. This model combine different machine learning techniques like K-means Clustering Scale Invariant Feature Transform (SIFT), Support Vector Machine (SVM) and Visual Dictionaries. The model was tested on Back Propagation Neural Network as a classifier. R. Chand CP and J Dheeba *et. al.* [7] proposed an automatic CAD system to detect the DR in retinal OCT images. This paper considered Analysis mainly three stages, first stage removal optic disc was done then normalization was performed using histogram processing after that texture information was extracted by applying Gray Level Co-Occurrence Matrix (GLCM) and classification was done using SVM. Image preprocessing techniques were applied initially to improve the contrast of low quality images. Then optic disc segmentation was done to avoid the miss interpretation of optic disc as lesions. Then GLCM method was applied to extract different texture features so that SVM classifier provides better outcome for exudate lesions detection. E. V. Carrera *et.al.*[8] proposed a automatic DR detection technique using SVM classifier. in this technique initially blood vessels , hard exudates and micronureysms were isolated to extract features that were used by SVM to further classify the images in DR and NDR. A decision tree classifier were used to contrast the results of SVM classifier.

**Random Forest:**

RF is one of the most widely used powerful ML classification algorithms. RF makes forests with decision tree. In this algorithm for classifying a new model each tree provides a classification vote and algorithm is save that tree with the label. At last model chooses the class which has highest numbers of votes [5]. D. Xiao, *et al* [9] proposed a novel automatic DR detection model for identification of hemorrhages in fundus images. The proposed model was based on rule-based and random forest machine learning algorithm. Model was designed to focus on detection of the hemorrhages that were close to and connected with blood vessels in retina, along with the detection of independent hemorrhage regions.

**k-Nearest Neighbor:**

KNN is a popularly used supervised machine learning algorithm for classification purpose. It employed 'feature similarity' concept to predict the labels of new datapoints. In KNN new data points are assigned a value based on how closely it matches the points in a training set [5]. Several researchers applied KNN algorithm for DR detection and provide better results. SS. Rahim et al. [10] Presented a automatic diabetic retinopathy screening system that focused on microaneurysms . microaneurysms are the earliest visible signs of diabetic retinopathy.The proposed system employed circular Hough transform Several and fuzzy histogram equalisation method for feature extraction methods. Later KNN technique was applied to classify microaneurysms. This system provided better results in microaneurysms detection. P. Nijalingappa and B. Sandeep [11] proposed a automatic DR detection system using kNN classification algorithm at severity levels. S. Wang *et al.* [12] proposed a novel approach for automated detection of microaneurysms. In this method first a dark object filtering process was applied to locate Candidate objects. Then cross-section profiles along with multiple directions were processed using singular spectrum analysis. Then a scale factor for each correlation coefficient and a microaneurysms profile was computed. This was used to increase the difference between true microaneurysms and other non microaneurysms candidates. features of those profiles was extracted through KNN classifier.

**Local Linear Discrimination Analysis:**

LLDA is a commonly used dimensionality reduction and classification technique. It is basically used for multiclass discrimination. Local Linear Discrimination Analysis projects to a line that intrinsically preserves directions which is heplful in data prediction and classification. It projects to a line, so that partition of samples in different classes is done efficiently. Wu JY, et al [13] proposed a new hierarchical based computing-aided diagnosis method for the for locating microaneurysms. This approach employed the multi-scale and multi-orientation sum of matched filter for features extraction of each candidate. For classification purpose LLDA and SVM were used and provides better performance on ROC curve.

**Artificial Neural Network :**

ANN generally contains three layers named input layer, hidden layer and output layer consist of many nodes. Input layer is used to take the input from user and hidden layer process this for classification. Output layer of the network contains only one node which provides output to user. Different structures of ANN were applied by authors to built classification for DR. In 2013 V. Hanúsková [14] proposed an

algorithm which identified severe diabetic retinopathy in early phase. This method was based on three primary modules namely image preprocessing, feature extraction and after that feature classification. In first step contrast enhancement, luminance normalization and optical disk removal was performed using image processing techniques. Then Feature extraction process includes two steps: localization of bright lesions candidates and feature extraction step. multilayer perceptron (MLP) layer was used for classifying features with one hidden layer. Then in 2014. K. Ganesan *et al.* [15] presented a retinal vessel segmentation technique for identifying DR and NDR images. This technique first classifies each pixel of the image into vessel or non-vessel structures. Then a multilayer perceptron (MLP )neural network algorithm was employed for identifying and segmenting blood vessels. are, for which in MLP the inputs was derived by making use of three primary color components, i.e., red, green and blue. In 2017, Al-Jarrah and H. Shatnawi [16] proposed a novel approach for detecting retinal lesions -based on morphology algorithm. this method first identified the three diabetic retinopathy lesions, microaneurysms haemorrhages, and exudates. Then extracted features from these lesions.

After that a selected ser of features imitate what a physician checks for, in classifying a Non PDR case. Finally, they used an artificial neural network classifier which consists of three layers to classify NPDR stage. ANN used resilient backpropagation and Bayesian regularisation algorithms for training purpose. T. Bui et al.[17] proposed an automatic segmentation technique for detection of cotton wool spots in the retinal images. Early detection of cotton wool is essential to avert the dangerous effect to eyes which may cause vision loss and permanent blindness. In this method a preprocessing technique was applied to improve quality of images subsequently OD removal. Afterward a feature extraction method was applied to obtain useful elements from the retinal images for improving accuracy. At last ANN model was applied for learning task and testing was performed using k-fold cross validation.

**TABLE I. Studies containing machine learning Techniques**

| Method | Database | Accuracy | Images |
|---|---|---|---|
| SIFT, K-mean,SVM[6] | Mixed Database | 0.87 | 1154 |
| SVM [7] | e-optha database | 0.92 | 164 |
| SVM [8] | Messidor | 0.85, 95(sensitivity) | 400 |
| Rule Based, RF [9] | DIARETDB1 and DR database | 93(sensitivity) | 578 |
| KNN[11] | Messidor and DIARETDB1 | .95 | 169 |
| KNN[12] | Public Dataset | .464(ROC) | - |
| MLP[14] | MESSIDOR | .93 | 1200 |
| MLP(SVM with quadratic, polynomial, radial basis function kernels and probabilistic neural network)[15] | DRIVE database | .95 | - |
| ANN[16] | DIARETDB1 | .94 | 89 |
| ANN[17] | DIARETDB1 public data | .85 | - |

## 3. Diabetic Retinopathy Detection Using Deep Learning Algorithms

**Overview of deep learning methods:** Deep learning is a subarea of machine learning that is emerged from the concept of neural network. It is inspired by and resembles the human nervous system and the structure of the brain. It is an application of Artificial Neural Network in which number of hidden layer is one but as number of hidden number of hidden layer increases network goes deeper and it refers to deep neural network. Deep learning can be applied in almost every machine learning problem. The layers in DNN are divided into three categories broadly input layer, multiple hidden layer and output layers. Input layer is used to give input to the network, hidden layer process the input provided and output layer generates output to the system. Input in hidden layers processed a distributed representation and the main driving variables of the input data. Deep learning working model is organized into two phases, training and testing. In training phase of model, model parameters with random numbers are introduced and the pre-train some models are done. After first iteration completes then next step is to read and processes the training data and training errors are calculated by comparing the obtained output with expected output. Then parameters are upgraded according to training error through error back propagation. Then testing phase is performed to find if conditions of the iterative training are met for termination or continue the iterative process of training. For designing a complex deep neural network requires complex and high level resources for computation along with large amount of training data. Deep learning models have automatic feature extraction capability that make it different from traditional machine learning algorithms, means user need not to specify the feature to the model, neural network architecture itself find out important feature required for desired results. Deep learning network provides high level of abstraction; even developer does not know how neurons in the network are connected and how data is processed within the network. For solving problems deep learning uses end to end process. Suppose we have a task of multiple object detection, when we solve this problem with earlier machine learning model then whole task is divided into two phases in first phase we apply bounding box detection algorithm to find all the objects on a image and then we apply a recognizer algorithm like support vector machine to detect a particular object on the image. Whereas deep learning performs whole task in one go. We apply euro net deep learning algorithm in which we pass image to the model it gives the location along with the name of the object. As deep neural network is very complex, it requires Graphics processing units for processing large matrix multiplication and other complex operations. Deep learning requires large amount of data to train the machine so that it can generate accurate results so training time of DNN is more than traditional machine learning models.[18][19]

Deep learning is ideal to use where we have to predict results from large amount of data.

Deep learning is applied to solve those complex problems that are very expensive to solve with human decision making.

**Convolutional Neural Network[20][21]:**

***CNN:*** is a feedforward neural network that is generally used to analyse the image data and is also known as ConvNet. In CNN, whole architecture is divided into three layered structure as shown in Fig. 3. In image identification, CNN take the input image, process it, and classify it in a certain category eg. NPDR, PDR,. In computer image is stored as an array of pixels. Like the traditional machine learning architecture, CNN also have to train for data to solve a particular problem. For this first architecture of Neural network is decided like how many layers are used in network, how we arrange the layers, which layer to use, and how many neuron to be used in a layer. Various CNN architectures are AlexNet, GoogleNet, Inception ResNet, VGG. Once network architure is decided after that various biases and parameters for the network are selected bases on the problem. At first these are selected randomly but further they are changed through back propagation. Objective of this phase is to find the best possible values of network parameters and data features so that further identification of data can be accurately done. For eg when we try to build a classifier for DR and NDR images then we are looking to find the parameters that gives the probability of DR 1 or higher than NDR and for all the images of NDR it provides 0 or less than DR images. Whole CNN process is divided into two parts feature learning and classification. In feature learning there are three steps performed many times for different feature detection. These are convolutional operation, ReLu and Pooling. In classification image is classification is performed. In this phase three operation is performed flattened, fully connected and softmax operations.

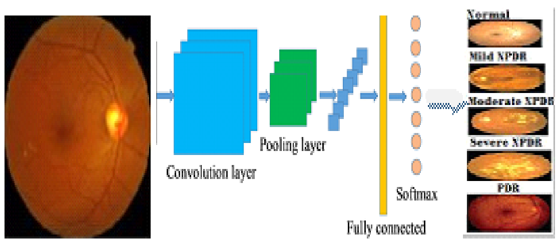


**Fig. 3 CNN Architecture** [1][20]

***Convolutional layer:*** in this layer filter works on every part of the image. And search same feature everywhere in the image. This layer involves shift, multiply and sum operations. The purpose of this layer is to identify the basic pattern of which the object in the image is made up of. Output of this layer is a new modified filtered image. In this layer features are identified. In training phase this layer identified the most accurate feature for image classification[21].

***ReLU layer:*** is rectified linear unit. Once features are extracted using convolutional layer then next step is to move them to ReLU layer. This layer mainly performs element wise operations, sets all the negative values to zero and introduces non linearity in the network. At this layer sigmoid function are applied. This function removes all the black elements from the images.

***Pooling layer***: provides the down sampling to the output that reduces the dimension of the feature map. This layer reduces size of each feature map by 2. Two types of pooling can be applied in CNN, Average pooling and max pooling. In average pooling feature map is patched with average value and in max pooling feature map is patched by maximum value of the matrix.

These three steps are applied multiple times to find best features of the data.

***Flattening layer***: this layer transforms the matrix into a vector form so that it can be fed into a fully connected NN classifier.

***Fully connected layer**:* at this layer data is in one dimensional structure. This layer helps in classifying the input pattern with high-level features extracted by previous layer. This layer gives a probability that a certain feature belongs to a label. Softmax activation function is used to provide probability to each label.

Extensive research efforts have been devoted to solve the problem of early detection of diabetic retinopathy. First, researchers try to use classical and traditional methods of computer vision and machine learning to provide a suitable solution to this problem. In 2011 H. F. Jelinek *et. al.* [22] presented a model to identify retinal pathology using visual dictionary. In this approach retinal images were analyzed without preprocessing. Points of interest and a local descriptor around each point of interest of human retinal images were calculated using the Speeded-Up Robust Features (SURF). And important features obtained were stored in data structure and visual dictionary were created from these. Final classification of training images was done by SVM. Then a automated segmentation technique for identification of intraretinal cystoid fluid in optical coherence tomography was developed[23]. Further Y. Zheng and others developed a Computerized Assessment technique for identify Intraretinal and Subretinal Fluid Regions in Spectral-Domain of OCT Images[24]. But as the concept of neural network introduced, machine learning is revolutionized completely. After the success of deep learning in other real world applications, it is also providing amazing results in this field also. Many reserchers applied convolutional neural networks approach of deep learning to solve this problem and find better results than previous methods. Table 1 shows some CNN based methods that were developed to early detection of DR. in this table accuracy and Dataset name and size used are displayed. In 2016 P. Liskowski and K. Krawiec [25] Proposed a supervised segmentation technique that was trained using Deep Neural Network for detecting problems of blood vessels in fundus images. Before training DNN preprocessing of images was done Global Contrast Normalization was performed for local brightness and contrast normalization, Zero Phase Component Analysis was used for removal of universal correlation so that higher order correlation can be focused then augmentation was performed for generating additional examples by transforming existing training examples. Than A CNN network model was implemented for segmenting blood vessel features. In this model authors applied three convolutional layers followed by three fully connected layers to extract features accurately and their model provided better results when compared with previous algorithms on the area under ROC curve. In 2017 Pedro Costa and Aur elio Campilho [26] proposed a convolutional neural network architecture that generalizes BoVW(Bag-of-Visual-Words) model for detecting Diabetic Retinopathy images from fundus image. The BoVW model first extract local features using SURF anf CNN from these images then it create a visual dictionary and mid-level representations of the fundus images using this dictionary after that learn a classifier using the mid-level representations for classifying images in DR and normal. This model was good but did not perform well in the case of the DR1 dataset. Then Di Nui et. al. [27] proposed a cascading method of deep learning for enhancing accuracy of Optic Disc localization. In this method saliency map was used to locate most salient region yhrough intensity. In this method CNN was used to classify OD region or non OD region. J. Hamwood *et. al.* [28] applied Deep learning CNN architecture, to find patterns in images for DR and non DR. The model was used to detect retinal boundary locations in retinal images and further used to segment these images. they also evaluate the performance of CNN by using by increase/ decrease patch size. . In 2018 A. Vahadane *et. al* [29] proposed a model for detecting presence of Diabetic Macular Edema in OCT frames. This was done by locating fluid filled region and hard exudates. First image processing technique was applied for detecting potential candidates having patches in OCT frames and classify them into Fluid Filled Region and Hard Exdutes using CNN approach of deep learning. Then they used rule based approach for classifying an OCT scan as indicative of DME or not. Performance of this architecture was compared with other method and experimental results are better than previously used methods. J. Kim, E. Y. Chew, *et. al* [30] proposed a CNN based model to automatically detect Optic Disc Region. The model was built of two convolutional layers, two MaxPooling Layers and two Fully connected layer with one output layers. Authors also used same CNN model for segmenting blood Vessels from fundus images.. In 2019 P. Seebock *et. al* [31] proposed a Bayesian Deep Learning technique that was based on the assumption that epistemic uncertainities from training set were correlated with anatomical derivations. DNN was trained to detect Biomarkers in Retinal OCT that helps in diagnosing various diseases and planning treatment. First a Bayesian U-Net model was trained on normal cases for segmenting retinal layers. For this Graph based segmenting approach was used. Then Monte Carlo Dropout is applied to this model for obtaining pixel-level epistemic uncertainity. Finally Majority Ray casting was performed for transforming uncertainty map into compact segmentation of anomalies. This model was validated on retinal OCT images by using weak labels of anatomy. This approach provided high accuracy for retinal vein occlusion, diabetic macular edema and dry geographic atrophy. J. Orlando *et. al.* [32] proposed a bayseian deep learning model for identification of pathological OCT scans. This model used the epistemtic map for detecting pathological error. This method was evaluated on the OCT scan of DME, AME and vein occlusion. This technique provides better result in compared to UNET model. . N. Motozawa *et. al.* [33] developed two computational deep-learning models one for differenciating A from normal OCT images, and second for classifying Age related Macular Degeneration based on the presence or absence of exudative changes. CNN technique of deep learning was used for classification purpose. This model utalized only OCT images that pass through the fovea of the cross scan and radial scan.

Z. Wang *et. al.*[34] Proposed a deep learning based framework to locate the optic cup and optic disk jointly. This technique directly estimates parameters of ellipse of optic disk and optic cup region for computing optic to disc ratio. REFUGE dataset was used for training and GS1 dataset was used to test the model. Z. Wang and J. Yang [35] proposed a regression activation map (RAM) using deep learning technique. RAM localizes the discriminative regions of interest of retinal images. RAM is applied after global averaging pooling layer of CNN. Kappa score was used to measure the performance of the model. Model provides better results on large dataset. B. Tymchenko, P. Marchenko *et.al.* [36] proposed a multistage deep learning transfer approach for detection diabetic retinopathy stages by single photography of retinal fundus images. In this model, 3 CNN architectures were ensemble and transfer learning was applied for ultimate solutions. Weighted kappa score of this model was 0.925466 that was good on large dataset.

**Deep learning approaches using novel deep learning architectures**

Several authors developed their own novel deep learning based technique for detecting diabetic retinopathy using distinctive number of layers and classifiers in the architecture. Most of the authors applied Softmax classifier for retinal images classification. Some researchers applied random forest, pixel-wise classification and decision tree for classifying images. Yang, Li *et. al.*[40] proposed an automatic diabetic retinopathy detection technique based on two-stage deep DCNN named local CNN and global CNN. First Lesions were detected using the Local CNN. The Local CNN used a ten layer CNN architecture while the global CNN consist of 26 layers and used for improving DCNN. Yu, Xiao [41] proposed novel deep learning technique for DR detection. a sixteen layers deep CNN architecture for exudates detection. They applied softmax classifier to locate exudates on pixel-wise classification. In this technique initially data preprocessing was performed to standardize exudate patches. Then, region of interest localization was applied to localize exudates featuers. Furthermore transfer learning was used to extract feature using pretrained CNN architectures. After that fused features from fully connected layers were fed into the softmax classifier to classify exudate. Gargeya and Leng [42] proposed a noval deep CNN based technique that classified the retinal OCT images into two classes namely normal retinal images or diabetic retinopathy affected images. In this technique authors used a Deep CNN architecture for feature extracting and applied softmax layer for initially classification and decision tree classifier for final classification.

**Combination of machine learning and deep learning approaches:**

Various researchers used combination of machine learning algorithms and deep learning approaches for DR detection. Orlando and Prokofyeva [45] applied a combination of deep CNN and machine learning techniques for identifying red lesions. In this technique authors combined CNN architecture with LeNet architecture with 10 layers to get better performance. The features extraction was based on the shape and intensity of OCT images. A. kumar and K. kumar [46] applied

Deep Belief Network and support vector machine techniques for DR detection. In this approach features extracted using DBN were summarized using generalized regression neural network and then support vector machine was applied for image classification.

**TABLE II. STUDIES CONTAINING DEEP LEARNING ARCHITECTURE**

| Method | Database | Accuracy | Images |
|---|---|---|---|
| Convolution Neural Network[25] | DRIVE, STARE AND CHASE | 0.97 | 60 |
| BoVW using CNN model. [26] | DR1, DR2 and MESSIDOR. | 0.94 | 2712 |
| Salient map and CNN[27] | ORIGA and MESSIDOR | 0.98 | 1850 |
| Convolutional Neural Network (CNN) and graph-search method. [28] | Retrospective dataset of OCT images | - | 328 |
| Deep CNN and Dijkstra's shortest path algorithm [29] | Heidelberg Spectralis OCT Scanner database | - | 532 |
| Bayseian U-Net [31] | Heidelberg Spectralis OCT Scanner database | - | 580 |
| Bayseian U-2Net[32] | Spectralis OCT Scanner database | - | 2500 |
| CNN and Transfer Learning Model [33] | spectral domain (SD)-OCT images | 0.94 | 1621 |
| Fully Convolutional Network[38] | Dataset from Tongren Hospital | 0.94 | 5620 |
| Deep CNN and STSF [39] | AFIO and Retinal OCT | 0.93 | 39000 |
| CNN [40] | DATAset Kaggle | 0.95 | 35126 |
| CNN [41] | e-Ophtha and DIARETDB1 | .95 | 117 |
| CNN [42] | public MESSIDOR 2 and E-Ophtha | .94 | 75137 |
| CNN with SVM classifier. [43] | OCT images dataset | 0.97 | 400 |
| FCNN with U-Net architecture[44] | RIGA and MESSIDOR | 0.98 | 750 |
| CNN and LeNet[45] | DIARETDB1, e-ophtha and Messidor | .93 | 1670 |
| CNN with SVM[46] | ARIA dataset | .96 | 146 |

## 4. Discussion

In this paper we presented the review of various machine learning and deep learning approaches employed to construct the diabetic retinopathy classification model. For research, researchers have either used publicly available datasets or exclusive datasets like DRIVE, MESSIDOR and DIARETDB1etc. In numerous studies, authors have implemented many machine learning algorithms like CNN-SVM, SIFT- K-mean-SVM, Deep CNN-STSF and FCNN with U-Net etc. to extract features for classification models and compared the results on the used datasets. In addition, various researchers implemented only single machine learning algorithm to construct a classification model. But there is no single algorithm suitable for all types of images. The automated blood vessel segmentation system uses matching filters and SVM technique to identify blood vessel under pathological condition. But this technique does not work well when the non-vessel structures are connected to the vessel structures upon MFFDOG segmentation. The C-BoVW for Diabetic Retinopathy Detection from Fundus Images model first extract local features using SURF and CNN from the images then creates a visual dictionary and mid-level representations of the fundus images using this dictionary after that learn a classifier using the mid-level representations for classifying images in DR and normal. But this technique does not work well in case of large data sets. A cascading method of deep learning model is used for optic disc localization to locate most salient region. This method provides high accuracy than previously used method but fails when brightness of image is low or some bright lesion can create confusion to locate optic disc region. A Bayesian Deep Learning technique that is based on the assumption that epistemic uncertainties from training set are correlated with anatomical derivations. In this, DNN was trained to detect Biomarkers in Retinal OCT that helps in diagnosing various diseases and planning treatment. But performance of this model relies on additional post processing that make it complex for applications. A transfer based deep learning approach used for the Automatic detection of Diabetic Macular Edema have high accuracy than other techniques but it can only be used for detection of DME and can not be applied to AME and vascular occlusions. A bayseian U2 net deep learning model used to scan OCT pathology. This technique provides better results but sometime misinterprets the area as layer thinning. Therefore, detection of this disease is still challenging research work due to multimodality of data and a wide range of confusing factors.

## 5. Conclusion

Diabetic retinopathy is a dangerous complication of diabetes. Anyone having diabetes is at a high risk of DR. It is a serious vascular disorder which may lead to complete vision loss. This disease does not give any sign or symptoms at early stages so it is very difficult to diagnoses it. In this paper, we discussed various machine learning and deep learning based techniques used for detection of diabetic retinopathy. Earlier Manual inspection methods are used to diagnose diseases but these methods are time consuming and demands skilled professionals for the diagnosis. As the information technology advanced various Automatic Diabetic Retinopathy diagnosis systems are developed that reduces both time and manual labor. But diagnosing this disease is still challenging research work due to multimodality of data and a wide range of confusing factors.

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