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AN EFFECTIVE DIABETIC RETINOPATHY DETECTION SYSTEM USING DEEP BELIEF NETS AND ADAPTIVE LEARNING IN CLOUD ENVIRONMENT

PRAVEEN MODI* AND YUGAL KUMAR†

Abstract. The major reason behind the blindness of the diabetes patients is diabetic retinopathy. It can be characterized as an eye disease that affects the retina of eye due to diabetes mellitus. The detection of diabetic retinopathy in early stage is a challenging task to ophthalmologists. This paper presents a diabetic retinopathy detection system for accurate detection of DR in the patients. The proposed diabetic retinopathy detection system is the combination of several preprocessing technique and deep belief nets. The aim of preprocessing technique is to enhance the images, edge detection, and segmentation. Further, the deep belief nets are adopted for the accurate detection of DR. But, the parameter tuning of weight, bias and learning rate have significant impact on the performance of deep belief nets. This work also addresses these issues of deep belief nets though an adaptive learning strategy for learning rate and updated mechanism for weight and bias issues. The proposed system is implemented in cloud environment. It is utilized to store the information regarding DR and communication between doctors and patients. Further, the efficacy of the proposed diabetic retinopathy detection system is tested over an image dataset and it comprises of three thousand two hundred eye images include with diabetes retinopathy and no diabetes retinopathy. The results are evaluated using accuracy, sensitivity, specificity, F1-Score and AUC parameters. The results of proposed system are compared with KNN, SVM, ANN, InceptionV3, VGG16 and VGG19 techniques. The results showed that proposed diabetic retinopathy detection system obtains 91.28% of accuracy, 93.46% of sensitivity, 94.84 of specificity and 94.14 of F1-Score rates than other techniques using 10-cross fold validation method. Hence, it is stated that proposed system detects diabetes retinopathy more accurate than other techniques.

Key words: Adaptive learning, Deep Belief Nets, Image, Diagnosis, Diabetes, Diabetic Retinopathy

1. Introduction. Diabetes mellitus (DM) can be characterized as chronic disease throughout worldwide and fourth foremost reason of people death [28]. A recent study showed that presently in the world, 336 million people are affected form diabetes mellitus and 7.7% more people will be affected with diabetes mellitus up to 2030 [33]. Further, the diabetic retinopathy (DR) can be defined as condition of DM that is responsible for blindness in diabetes patients [36]. It is related with type-1 and type-2 diabetes. The symptoms of DR can be visible for type-1 diabetes patients after fifteen years of diabetes, and 75%-90% of patients are suffering from DR symptoms. While, 60% of type-2 diabetes patients having symptoms of DR that are affected with diabetes more than 16 years. The contribution of DR into eye related disease up to 80%, especially patients that are diagnosed eye related disease more than ten years [1, 25]. The main points regarding the incremental growth of DR are lack of prior symptoms of DR, severely vision loss and untimely diagnosis. However, the existence of DR can be reduced with timely diagnosis and screening, proper medical treatment, and medication. The initial treatment for DR can be described in terms of fundus photography through ophthalmoscopy and grading the fundus images. Further, these retinal fundus images are examined by ophthalmologists for detecting the DR in manual order. The ophthalmologists examine the presence of cotton wool spots, retinal swellings, and hemorrhages [9]. Sometimes, the process of capturing the retinal fundus images can reveal irrelevant illuminations, blurred and darkened candidate regions, and non-uniformity of light distribution [38]. But, the high precision is required for detecting the DR, otherwise it will lead to the wrong decision and responsible for serious problems and sometimes permanent blindness in patients. If the image obtained through the fundoscopic test is highly saturated, then it is quite a tough task for ophthalmologists to proper visual investigation of diabetic retinopathy. It is also found that the occurrence of non-uniform illuminations can lead to bias prediction of DR [30]. Hence in pre-processing task, luminosity normalization is one of important aspect for generating the diverse set of retinal images [7].

*Department of Computer Science and Engineering and Information Technology, Jaypee University of Information Technology, Waknaghat, Solan, Himachal Pradesh, India (modi.240289@gmail.com)

†Department of Computer Science and Engineering and Information Technology, Jaypee University of Information Technology, Waknaghat, Solan, Himachal Pradesh, India (yugalkumar.14@gmail.com)

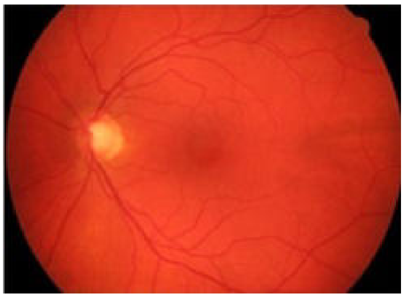

Fig. 1.1: Depicts the healthy retinal fundus images

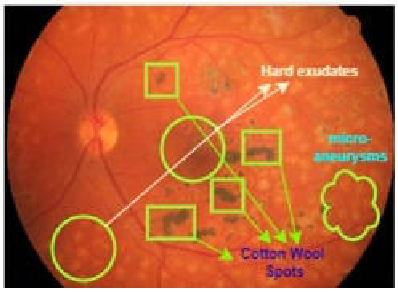

Fig. 1.2: Depicts diabetic retinal fundus images with retina complications

Fig. 1.1 shows the healthy retinal fundus image and Fig. 1.2 shows the diabetic retinal fundus images with retinal complications. Through the literature on diabetic retinopathy, it is found that diabetic retinopathy is divided into two categories- (i) binary classification of DR disease, and (ii) multiclass classification of DR disease. In literature, several techniques have been presented for accurate detection of DR disease based on eye fundus images. These techniques describe the candidate regions in terms of exudates, cotton wool spots, blood vessels, micro aneurysms and hemorrhages etc. Further, these techniques also consider the uniform features and extract the features manually [31, 11]. In turn, the detection rate of DR is not up to significant level.

1.1. Motivation and Contribution of the Work. This subsection presents the motivation and contribution of the work. Through literature, it is identified that CNN, MLP and several popular ML algorithms have been explored to find the more accurateand earlier detection of DR disease [35]-[37].However, the problems of non-uniform reflectance, over fitting, over saturation and biased solution are still remaining.Hence, the main focus of this work is to handle aforementioned issues related with accurate detection of DR disease based on eye fundus images.This work presents an automatic diabetic retinopathy detection system for accurate prediction of DR. The proposed system comprises of various pre-processing technique for handling the non-uniform reflectance and over saturation issues of fundus images.Further, the deep belief nets are integrated into proposed detection model as predictive classifier. It is also noticed that the performance of the deep belief nets is dependent on learning rate, weight and bias parameters. If, learning rate is not optimal, then it can not achieve contrastive divergence as well as optimal training of the model. Hence, to alleviate this issue, an adaptive learning strategy is incorporated into beep belief nets. The main contributions of the work are highlighted as below.

- To developed an automatic diabetic retinopathy detection system for accurate detection of DR disease through eye retinal fundus images.
- To handle the issue of non-uniform illumination and color of fundus images through threshold and luminosity function through processing of image step in the proposed diabetic retinopathy detection system.The color component(R,G,B) are extracted from the images and threshold function is designed to improve the RGB. The distribution of light is also adjusted through luminosity function.

- The statistical and spatial features are computed using the histogram and edge detection techniques. Further, k-means based segmentation technique is utilized for obtaining the appropriate clusters.
- A deep belief nets with adaptive learning strategy is integrated into proposed diabetic retinopathy detection system for accurate detection of DR disease.
- The performance of the proposed detection model is tested over fundus image dataset comprising of 3200 images and results are evaluated using accuracy, AUC, sensitivity, specificity and F1-Score parameters.
- The results of proposed model are compared with Incpetion V3, VGG16, VGG19, ANN, SVM,and KNN techniques. The efficacy of simulation results are also assessed though training/testing (70%-30%), training/testing (80%-20%), 5-cross fold validation and 10-cross fold validation methods.The results revealed that proposed diabetic retinopathy detection system is efficient to recognize the DR disease.

2. Related Works. This section summarizes the recent work reported on diabetic retinopathy diagnosis. Gao et al.[8] considered the diabetic retinopathy as one the major concern among the diabetes affected patients and it is also responsible for the blindness in diabetes. In this work, an automated diagnosis model is presented for prediction of diabetic retinopathy and this system is also capable for providing the suggestions to diabetic retinopathy patients. In the proposed system, deep convolutional neural network is utilized for prediction of DR. Furthermore, a diabetic retinopathy dataset is constructed using the retinal fundus images and severities of DR is divided into four classes. The performance of the proposed model is evaluated using accuracy parameter and results showed that proposed model achieves 88.72% of accuracy rate. The proposed model is also deployed into several hospitals and authors claimed that proposed model obtains 91.8% of accuracy with ophthalmologists.

Kandhasamy et al. [17] developed a diagnosis system for finding the severity of DR. The proposed diagnosis system is the combination of multi-level segmentation and SVM with GA. Some morphological operations are also applied to determine the clusters in the retinal images. The multi-level segmentation is employed on these clusters for extracting features. Further, a local binary pattern is also adopted for extracting the texture features of retina images. The effectiveness of the diagnosis system is evaluated using accuracy, sensitivity and specificity parameters. It is found that proposed diagnosis system achieves 99.3% accuracy rate, 97.14% of sensitivity rate and 100% specificity rate.

Qureshi et al. [22] presented an automatic recognition model of DR severity. The proposed recognition model is based on multilayer architecture of active learning, called ADL. In ADL, CNN is adopted for computing the features in automatic manner. Further, an excepted gradient length method is applied as active learning method for multilayer architecture, called ADL-CNN. The proposed ADL-CNN is in two folds– (i) consider the informative patches and ground truth label of images to train the model, and (ii) prognostication the image into five severity-levels of diabetic retinopathy. The results of the ADL-CNN model are evaluated using accuracy, sensitivity, specificity and F1-Score. It is noticed that proposed ADL-CNN achieves higher results than other methods in terms of accuracy, sensitivity, specificity and F1-Score.

Qiao et al. [21] considered the deep convolutional neural network to determine the presence of micro aneurysm in fundus. Further, GPUs are adopted for acceleration of CNN. In this study, fundus images are segmented using semantic segmentation algorithm and this algorithm divides the images in binary class- (i) normal, and (ii) infected. It is seen that CNN predicts the diabetic retinopathy as early NPDR, moderate NPDR, and severe NPDR. The performance of the CNN model is evaluated through sensitivity, specificity and average accuracy. It is seen that proposed CNN based model achieves higher accuracy rate.

Jebaseeli et al. [16] designed an IOT based Sustainable Diabetic Retinopathy Diagnosis System for effective treatment of DR. In the proposed system, the glucose level of diabetes patients is collected through Dexcom G4 Platinum sensors. After classification of diabetes, the retinal fundus images of patients are captured through smart camera. Further, the segmentation is performed on the captured images and a modified fuzzy c-means algorithm is employed for predicting the diabetic retinopathy. The results showed that IOT based diabetic retinopathy diagnosis system obtain higher accuracy, sensitivity and specificity rates than other existing models.

Mansour [19] developed CAD based diabetic retinopathy model for early detection and diagnosis of DR disease. The proposed retinopathy model contains an Alexnet DNN technique which is a variant of CNN to find the optimal solution for DR. The Gaussian mixture model is adopted to determine the region segmentation.

LDA based feature selection technique is employed for computing relevant features. It is observed that proposed retinopathy model obtains more than 0.7% classification accuracy rate. With spatial features, the proposed model having 94.4% accuracy rate.

Kaushik et al. [18] considered the reflectance properties issue of the fundus images as one of potential issue for accurate detection of diabetic retinopathy. In this work, gray world color constancy algorithm is utilized for the luminosity normalization of the images. The fundus images are diagnosed using stacked deep learning technique. The performance of the Stacked DNN is assessed over peak signal to noise ratio (PSNR), mean squared error (MSE), accuracy, F-measure, sensitivity, specificity, recall and precision. The simulation results showed that Stacked DNN obtains 87.45% accuracy rate for multiclass classification. To determine the abnormality in retinal images,

Hemanth et al. [13] presented a modified Hopfield neural network (MHNN) for diagnosis of diabetic retinopathy. In modified Hopfield neural network, weights are optimized using an updated mechanism and changed in each iteration instead of fixed weights. The novelty of the proposed MHNN is tested over five hundred forty retinal images and results are evaluated using sensitivity, specificity and accuracy parameters. The MHNN obtains 99.25% of accuracy rate than HNN. In continuation of their work,

Hemanth et al. [14] presented a hybrid method for improving the diagnosis rate of diabetic retinopathy. The hybrid method is the combination of the image processing and deep learning method. The histogram equalization method is utilized for image processing. For the prediction task, convolutional neural network technique is adopted. The efficacy of the hybrid method is investigated over four hundred retinal images taken from MESSIDOR database. The results are evaluated using accuracy, sensitivity, specificity, F-Score and G-mean. It is noticed that hybrid model provides 97% of accuracy rate than existing methods. To alleviate the problems of misdiagnosis, reducing time, cost and effort,

Alyoubi et al. [2] developed two deep learning based model for effective diagnosis of diabetic retinopathy. These models are CNN512 and YOLOv3. The proposed model divides the retinal fundus image dataset into five severity class. Further, CNN512 considers the entire image as an input and predicts into five stages such as no-DR, mild, moderate, severe and proliferative DR. CNN512 model obtains 84.1% of accuracy rate. YOLOv3 model is adopted for detecting and localizing the DR lesions. Finally, both models are integrated into a single model and it is seen that combination of both models achieves higher accuracy rate of 89%.

Sharafeldeen et al. [24] designed a computer assisted diagnostic model for early detection of diabetic retinopathy. This work considers the optical coherence tomography scan for detecting DR. In the proposed diagnostic model, the segmentation approach is adopted for separating the retinal layers. Further, morphological and reflective markers are extracted from each layer and cumulative distribution function is applied for extracting the image driven markers. The SVM with linear kernel is utilized for diagnosis of diabetic retinopathy at each layer. The novelty of diagnostic model is examined over two hundred sixty OCT images and experimental results are evaluated using sensitivity, specificity, F1-score, and accuracy parameters. The experimental results showed that 96.15% of sensitivity, 99.23% of specificity, 97.66% of accuracy, and 97.69% of F1-score rates. Most of the works reported in literature on diabetic retinopathy are considered the high resolution images.

Wang et al. [32] considers the low resolution retinal fundus images for detecting the diabetic retinopathy. This work adopts the CNN technique to joint learning of multi-level tasks for grading of the DR, named it DeepMT-DR. The aim of DeepMT-DR is to handle low-level task of ISR, mid-level task of lesion segmentation and high-level task of disease severity classification. The efficiency of DeepMT-DR are tested over three image datasets and experimental results are evaluated using accuracy parameter. It is found that DeepMT-DR obtains 83.6% of accuracy rate.

Skouta et al. [26] designed an automated method for screening of diabetic retinopathy. The proposed automated method consists of modified CNN UNet architecture to determine retinal hemorrhages in fundus images. In this work, IDRiD dataset is adopted for evaluating the efficacy of automated model. In automated model, UNet is applied for training task and detecting the possible symptoms of DR. The experimental results are assessed through sensitivity, specificity and accuracy parameters. It is found that the proposed automated model achieves 80.49% of sensitivity, 99.68% of specificity, and 98.68% of accuracy rates. The selections of relevant features have significant impact on the performance of the classifiers especially with image dataset.

Vijayan et al. [29] considered the feature selection issue of image dataset and presented the simple color histogram filter as feature selection method for retinal fundus images. KNN and J48 techniques are adopted for diagnosis of the diabetic retinopathy in fundus images. The performance of the proposed feature selection technique with J48 and KNN is evaluated using accuracy and ROC parameters. The results showed that KNN with feature selection method obtains 81.99% accuracy rate.

Gurcan et al.[12] presented an automated system for identification of diabetic retinopathy. The proposed system considers the retinal images for detection of diabetic retinopathy. The features are extracted from retinal images based on InceptionV3 including the transfer learning. The simulated annealing is utilized for selecting the relevant features. Finally, the diabetic retinopathy is detected using the XGBoost technique. The performance of the proposed automated model is evaluated using Messidor-II dataset. The results showed that proposed automated model obtains more than 92% of accuracy rate.

Gundluru et al.[10] considered the several issues like feature selection, optimization etc., of the existing diabetic retinopathy systems and presented a deep learning model for accurate detection of diabetic retinopathy. In the proposed model, PCA method is utilized for dimensionality reduction of the given dataset. While, harris hawks optimization algorithm is adopted for optimizing the feature extraction and classification processes. The proposed model is implemented on Diabetic Retinopathy Debrecen dataset and simulation results are evaluated using specificity, precision, accuracy, and recall parameters. The findings stated that proposed model obtains satisfactory results compared to existing systems.

Yue et al. [34]considered the limited capability to extract lesion-aware information and manual lesion annotations issues of diabetic retinopathy process. To handle aforementioned issues of DR, an end-to-end Attention-Driven Cascaded Network (ADCNet) is presented for grading of the diabetic retinopathy. In the proposed cascade network, the lesion-aware information is extracted using the hybrid attention module at shallow layer. The hybrid attention module is the combination of the multi-branch spatial attention and a loss-based attention. An aggregation strategy based on attention driven is also designed to get relevant features for DR. The APTOS and EyePACS datasets are chosen for examining the performance of the proposed cascade network. The results showed that proposed cascade network provides superior results than existing state of art methods.

To reduce the error rate and computational time, Chandran et al. [6] designed an auto-metric graph neural network (AGNN) for grading the diabetic retinopathy. Further, the noise in the images are eliminated throughAPPDRC filtering method. The features are extracted from retinal images based on GLCM based method. The weight of the AGNN is optimized using Capuchin search optimization algorithm. The performance of the AGNN model is evaluated using two popular eye retinal datasets i.e. ISBI 2018 and Messidor based on f-measure, execution time and accuracy metrics. The results showed that proposed model obtains more accurate results with both of datasets.

Canayaz [4]applied the wrapper method for selecting the more relevant features to detect the diabetic retinopathy. In their work, author explore the five hundred twelve features by using the EfficientNet and DenseNet models. Finally, two hundred fifty features are extracted based on the wrapper method. These method comprises of several popular meta-heuristic algorithms like binary bat algorithm (BBA), equilibrium optimizer (EO), gravity search algorithm (GSA), and gray wolf optimizer (GWO). The efficacy of the model is evaluated using the APTOS dataset based on the accuracy and kappa parameters. It is observed that proposed model obtains higher accuracy (96.32%) and kappa rate (0.98) compared to other algorithms.

To improve the detection accuracy of diabetic retinopathy Ragab et al. [23] developed a deep learning enable computer diagnosis model, called MDL-CADDR. In the proposed MDL-CADDR model, the image quality is enhanced in the pre-processing phase by applying filter and image contrast. Further, the region of interest is determined using Archimedes optimization algorithm (AAO) and relevant features are chosen based on Chimp Optimization Algorithm with DenseNet. Finally, detection of diabetes retinopathy is accomplished through skipping neural network. The well-known MESSIDOR dataset is utilized for evaluating the efficiency of MDL-CADDR model. The findings stated that MDL-CADDR model obtains the higher accuracy rate compared to other existing diabetic retinopathy model.

To early detection and diagnosis of diabetic retinopathy. Modi and Kumar[20] presented and efficient model for accurate detection of DR. The proposed model comprises of reprocessing, feature extraction, feature selection and classification. The noise are eliminated using the median filter and images are enhanced using

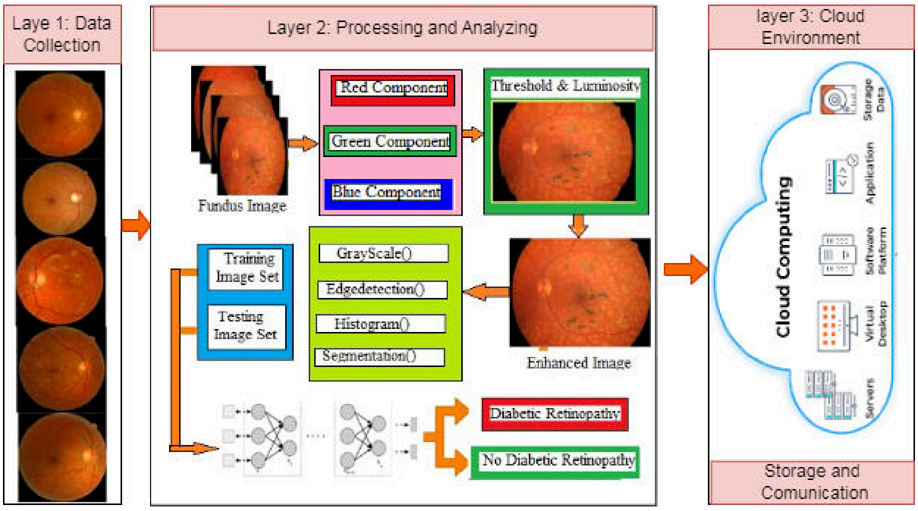

Fig. 3.1: Schematic Diagram of proposed diabetic retinopathy detection system

CLAHE algorithm. The k-Mean based segmentation technique is utilized for extracting the lesion region. The features are extracted using multi grained scanning technique, while relevant features are identified using bat based optimization algorithm. The classification task is performed using the DeepForest cascade technique. The efficacy of the proposed model is evaluated using two well-known diabetic retinopathy datasets based on accuracy, F-score, sensitivity and specificity. The results confirmed that proposed model obtains superior results for diabetic retinopathy compared to existing models. Table 2.1 summarizes the existing work of diabetic retinopathy detection in terms of segmentation method, feature selection method, classification model and potential parameters.

3. Proposed Diabetic Retinopathy Detection System. This section presents the proposed diabetic retinopathy detection system. The proposed diabetic retinopathy detection model is illustrated into Fig 3.1. The proposed detection system comprises of three layer-(i) data collection layer, (ii) processing and analyzing layer, (iii) cloud environment. The data collection layer is responsible for collection of data and working of this layer is explained in subsection 3.1. The second layer is the processing and analyzing Layer. The main activities of this layer is to perform the pre-processing activities, feature creation, and detection of diabetic retinopathy. The working of this layer is discussed in subsection 3.2. The third layer of the proposed model corresponds to cloud environment and working of this layer is discussed in subsection 3.3.

3.1. Data Collection Layer. This layer is responsible to collect the data regarding the diabetic retinopathy. In this work, a total a total of three thousand two hundred retinal images are considered for evaluating the performance of the proposed detection system. These images are downloaded from IEEE data portal (https://ieee-dataport.org). Further, two hundred twenty-four images are related to diabetic retinopathy symptoms and rest of the images have not any DR symptoms.

3.2. Processing and Analyzing Layer. The task of this layer is to process the images and analyze the performance of the proposed DR detection system. The image quality is enhanced based on resizing, extracts the feature and perform segmentation. The occurrence of DR is detected using adaptive deep belief network and performance of model is analyzes using well defined performance measures.

3.2.1. Processing of Image. Initially, the colored images are downloaded, stored in the folder on local system. The first step corresponds to enhance the retinal fundus images as processing of the images. In this step, the R, G, and B component of the images are extracted and further, threshold and luminosity mechanism are adopted for enhancing the quality of images.In turn, an enhanced quality images are obtained that contains high luminance and information instead of weak luminance and little information. In the next step, imresize()

Table 2.1: Summary of recent survey papers on diabetic retinopathy

Author	Segmentation Method	Feature Selection Method	Classification Method	Potential Parameter
Gao et al.[8]	*	*	Deep CNN	Detection Accuracy
Kandhasamy et al.[17]	*	Multi-level Segmentation and LBP	SVM Classifier	Sensitivity, Specificity and Accuracy
Qureshi et al.[22]	*	*	ADL	Sensitivity, Specificity, F1-Score and Accuracy
Qiao et al.[21]	Semantic Segmentation Method	MSSIM Maximization	CNN	Sensitivity, Specificity and Average Accuracy
Jebaseeli et al.[16]	*	Dexcom G4 Platinum sensors	Modified Fuzzy C-Means Algorithm	Sensitivity, Specificity and Accuracy
Mansour[19]	E-GMM	PCA & LDA	Alexnet DNN technique	Accuracy, Specificity, and Sensitivity
Kaushik et al.[18]	Gray World Color Constancy Algorithm	Gaussian Convolutional Deep Belief Network with Dwarf Mongoose Optimization Algorithm	Stacked DNN	Accuracy, Specificity, and Sensitivity
Hemanth et al.[13]	*	CNN	Modified Hopfield Neural Network	Sensitivity, Specificity and Accuracy
Hemanth et al.[14]	*	*	CNN	Specificity, Precision, Accuracy, and Recall
Alyoubi et al.[2]	YOLO V3	PCA	CNN512 and YOLO V3	Accuracy, Specificity, and Sensitivity
Sharafeldeen et al.[24]	Fuzzy C-means Clustering	*	SVM With Linear Kernel	Sensitivity, Specificity, F1-Score and Accuracy
Wang et al.[32]	*	*	CNN	Specificity, Precision, Accuracy, and Recall
Skouta et al.[26]	Semantic Segmentation Method	*	CNN UNet	Sensitivity, Specificity, F1-Score and Accuracy
Vijayan et al.[29]	*	*	KNN and J48	Accuracy and ROC
Gurcan et al.[12]	*	Simulated Annealing	InceptionV3, XGBoost	Accuracy
Gundluru et al.[10]	*	*	DNN-PCA-HHO	Sensitivity, Specificity, Recall, Precision
Yue et al.[34]	*	HAM	ADCNet	Specificity, Precision, Accuracy, and Recall
Chandran et al.[6]	*	*	AGNN Optimized with Capuchin Search Optimization	Accuracy, ROC
Canayaz[4]	*	GSA & GWO	SVM	Accuracy and Kappa-Score
Ragab et al.[23]	Archimedes Optimization	Chimp Optimization Algorithm	Spiking Neural Network	Accuracy
Modi and Kumar[20]	K-Mean	BAT Optimization Algorithm	Deep- Forest Cascading Technique	Accuracy, Precision, Recall, and Sensitivity

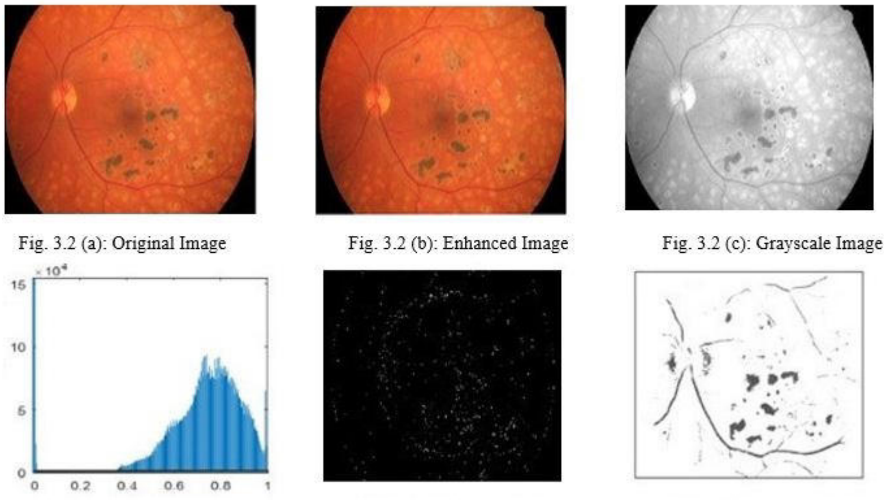

Fig. 3.2 (a): Original Image
Fig. 3.2 (b): Enhanced Image
Fig. 3.2 (c): Grayscale Image
Fig. 3.2 (d): Histogram
Fig. 3.2 (e): Edge Detection
Fig. 3.2 (f): Segmented Image

Fig. 3.2: (a-f) Depicts the processing of the image, Fig.3.1(a) shows the original retinal fundus image, Fig.3.1(b) illustrates the enhanced image in terms of RGB component of original image, Fig.3.1(c) shows the grayscale image of enhanced image, Fig.3.1(d) shows the histogram of corresponding grayscale image, Fig.3.1(e) shows the edge detection of grayscale image and Fig.3.1(f) shows the segments/clusters using CLAHE.

function is applied for resizing the images into 64×64 size and further, the RGB images are converted into grayscale as these images are represented through 8 bits and having pixel information in the range of 0 to 255. Further, it is observed that retinal layer is not of gray color and conversion into grayscale can be used to examine the image quality in normalization phase. This work considers the statistical and spatial features of detection of diabetic retinopathy. So, a hist() function is applied on the image for computing the statistical feature. Further, the edge of the grayscale images is detected through canny() function. The aim of edge detection is to determine the feature of images and check whether there are significant changes in the feature during the grayscale and also computing spatial features. Finally, the image segmentation is performed on grayscale images through imsegkmeans() function and number of K is set to 2. The aforementioned process is illustrated in the Fig 3.2 (a-f).

3.2.2. Deep Belief Nets With Adaptative Learning Strategy. Deep Belief Nets can be described as an improved variant of deep neural network [15] [3]. It contains multiple restricted Boltzmann machines (RBMs) which are stacked to each other. Further, the greedy approach is utilized for training of the stacked RBMs, and the stacked RBMs network is connected to a deep layer for final outcome, called deep belief nets. In DBN, an RMB is designed on the basis of two sequential hidden layer and input layer is characterized as output layer of the previous RBM, called visible layer. The distribution probability of visible input layer (VI) and hidden layers (HI) is described into equation (3.1a and 3.1b) and the hidden layers (HI) can be given as $HI_a =\in (a = 1, 2, 3....n)$ $HI_0 =$ VI.

$$DistProb(HI_1, HI_2, ..., HI_n/VI) = Prob\left(\frac{HI_n}{HI_{n-1}}\right) Prob\left(\frac{HI_{n-1}}{HI_{n-2}}\right) ...Prob\left(\frac{HI_1}{VI}\right) \tag{3.1a}$$

$$= \Pi_{a=1}^{n} Prob\left(\frac{HI_a}{HI_{a-1}}\right) \tag{3.1b}$$

The probability of bottom Prob(HI_1/ VI)with respect to visible layer (VI) and hidden layer (HI_a) is given using equation (3.2).

$$Prob(HI_a/HI_{a-1}) = \sigma\left(bi_j^a + \sum_{j=1}^{m} W_{i,j}^a \times Prob_j^{a-1}\right) \tag{3.2}$$

The probability of top inference (Prob($HI_a/HI_(a-1)$)) with respect to visible layer (VI) and hidden layer (HI_a) is given using equation (3.3).

$$Prob(HI_a/HI_{a-1}) = \sigma\left(bs_j^{a-1} + \sum_{j=1}^{m} W_{i,j}^{a-1} \times Prob_j^{a}\right) \tag{3.3}$$

Prior to precede the training of the deep belief nets, firstly, the concept of RBM is discussed as it can be worked like baseline method for deep belief nets. RBM can be defined as restricted Boltzmann machine (RBM) an extension of generative neural network [5]. Furthermore, it trains the network through the probability distribution function on given input set. RBM is more precisely described in terms of input layer and hidden layers. The hidden layers are utilized for learning the input data. An RBM consists of visible layer (VI) and hidden layer (HI) with values belong to 0, 1. A weight matrix ($W_{p\times q}$) can be defined to store the weight of connection among visible layer (VI) and hidden layer (HI) and the weight of j^{th} hidden layer (HI) and I^{th} visible layer (VI) is denoted as ($(w)_{(i,j)}$). Further, the bias of the j^{th} hidden and the i^{th} visible layers are also computed to minimize the error and can be represents as bi_j and bs_i respectively. An energy function among the j^{th} hidden and the i^{th} visible layers is computed using equation (3.4).

$$ef(VI,HI) = \sum_{i=1}^{k} bs_i VI_i - \sum_{j=1}^{m} bi_j HI_j - \sum_{i=1}^{k}\sum_{j=1}^{m} W_{i,j} \times VI_i \times HI_j \tag{3.4}$$

In equation (3.4), $bs_i \in (i = 1, 2, \ldots, k)$ denotes the bias related visible layer (VI), $bi_j \in (j = 1, 2, \ldots, m)$ denotes the bias related to hidden layer (HI) and $w_{(i,j)} \in (i = 1, 2, \ldots, k$ and $j = 1, 2, \ldots, m)$. These are the learning parameters of RBM, while k and m denotes the number of features in visible and hidden layers. Hence, the configuration probability of visible and hidden layers is described using equation (3.5).

$$Prob(VI,HI) = \frac{1}{M} e^{-ef(VI,HI)} \tag{3.5}$$

In equation (3.5), M can be described as normalization term and it can be computed using equation (3.6).

$$M = \sum_{HI,VI} e^{-ef(VI,HI)} \tag{3.6}$$

Finally, the visible layer probability can be described in terms of hidden layer and it is computed using equation (3.7)

$$Prob(VI) = \frac{1}{M}\sum_{HI} e^{-ef(VI,HI)} \tag{3.7}$$

The independence probability of data distribution is easier to compute as neurons on same layer are not connected to each other. Hence, for randomly chosen neuron on visible layer (VI), the probability of j^{th} hidden layer (HI_j) is computed using equation (3.8).

$$Prob\left(HI_j = \frac{1}{VI}\right) = \sigma\left(bi_j + \sum_{i=1}^{k} W_{i,j} \times VI_j\right) \tag{3.8}$$

In equation (3.8), σ can be defined as linear sigmoid function. In similar manner, the probability of i^{th} visible layer (VI_i) with respect to hidden layer (HI) can be computed using equation (3.9).

$$Prob\left(VI_i = \frac{1}{HI}\right) = \sigma\left(bs_i + \sum_{j=1}^{m} W_{i,j} \times HI_j\right) \tag{3.9}$$

Further, a threshold function (ω) is employed for assessing the probability of hidden and visible layers. The computed probability is compared with threshold function(ω) as summarized into equations (3.10-3.11).

$$HI_j = \begin{cases} 1, \text{if } Prob(HI_j = 1/VI) > \omega \\ 0, \text{otherwise} \end{cases} \tag{3.10}$$

$$VI_i = \begin{cases} 1, \text{if } Prob(VI_i = 1/HI) < \omega \\ 0, \text{otherwise} \end{cases} \tag{3.11}$$

The probability of training can be enhanced through optimized values of weight and bias parameters. The weight and bias are updated using equations (3.12-3.14).

$$\triangle W_{k,l} = \varphi(\langle VI_{j,k}, HI_{j,m}\rangle_{data} - \langle VI_{j,k}, HI_{j,m}\rangle_{model}) \tag{3.12}$$

$$\triangle a_k = \varphi(\langle VI_{j,k}\rangle_{data} - \langle VI_{j,k}\rangle_{model}) \tag{3.13}$$

$$\triangle b_1 = \varphi(\langle HI_{j,m}\rangle_{data} - \langle HI_{j,m}\rangle_{model}) \tag{3.14}$$

3.2.3. Adaptive Learning Strategy. It is found that presence of multiple RBMs in deep belief nets architecture make the training process tedious and complex. In turn computational time of model is also significantly increased. Hence, there should be an appropriate mechanism for learning of training data. Such mechanism also helps to achieve contrastive divergence. It is also noticed that the training process become unstable due to higher learning rate, slightly lesser learning rate results in higher training time and slower convergence rate [27]. To deal with such issues, this work also presents an adaptive learning strategy for computing the learning rate. This strategy compute local learning rate (learning rate for each connection) instead of a single learning rate throughout an epoch. The independent learning rate parameter is obtained for each weight connection instead of a global learning rate to achieve the satisfactory training speed. The computation of learning parameter is summarized into equations (3.15-3.16)

$$\mu\varphi^a_{i,j}, if((VI_iHI_j)_k - (VI_iHI_j)_M)((VI_iHI_j)^a_K - ((VI_iHI_j))^{a-1}_m) > 0 \tag{3.15}$$

$$\vartheta\varphi^a_{i,j}, if((VI_iHI_j)_k - (VI_iHI_j)_M)((VI_iHI_j)^a_K - ((VI_iHI_j))^{a-1}_m) < 0 \tag{3.16}$$

The adaptive learning strategy for visible layer (VI) and hidden layer (HI) is illustrated in algorithm 1 and algorithm 2. In equation (3.15-3.16), $\mu > 0$ and $\vartheta < 0$ correspond to the increment and decrement factors of learning rate. The learning rate will be increased with two consecutive updates in similar direction; otherwise, it will be decreased. So, a uniform step size is introduced in the training process, in turn convergence speed can be improved. Further, the objective function for deep belief nets is described as error rate(ER(E)) and it is mentioned in equation (3.17).

$$ER(E) = \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{m}(\hat{y}_{i,j} - y_{i,j})^2 \tag{3.17}$$

Further, the process of training phase of deep belief nets with adaptive learning strategy is mentioned in Algorithm 3, while Algorithm 4 summarizes the testing phase process of deep belief nets.

3.3. Cloud Environment. The cloud environment is responsible for storing the data related to DR and communication among doctors and patients. It consists of large storage space to store data and this data can easily access at any time. The patients and family members can access health data of individual and also provide the feedback regarding the treatment. Other side, doctors access the patient data for treatment. A message facility is also enable in this environment regarding the health checkup, appointment and medical test.

Algorithm 1 Adaptive Learning Strategy for visible layer (VI)

for each visible layer (VI), i=1 to k **do**
  for each hidden layer (HI), j=1 to m **do**
    Compute the value of $\mu\phi_{(i,j)})^a$ using equation 3.15.
    if ($\mu > 0$) **then**
      Learning rate $\phi_{(i,j)})^a$ is increased using previous value for two consecutive steps.
    end if
  end for
end for

Algorithm 2 Adaptive Learning Strategy for hidden layer (VI)

for each visible layer (VI), i=1 to k **do**
  for each hidden layer (HI), j=1 to m **do**
    Compute the value of $\mu\phi_{(i,j)})^a$ using equation 3.16.
    if ($\vartheta > 0$) **then**
      Learning rate $\phi_{(i,j)})^a$ is decreased using previous value for two consecutive steps.
    end if
  end for
end for

Algorithm 3 Deep Belief Network with Adaptive Learning Strategy // Training Phase

Input: Training image dataset, number of epoch, number of RBM, number of visible layer, number of hidden layer.
Output: Diabetic Retinopathy Detection either presence or absence

Initialize the bias of visible and hidden layers (bs_i and bi_j), weight matrix($w_(p \times q)$), learning rate (φ), number of training data (N) and number of epoch (Max_Epoch).
while ($currentepoch \leq Max\_Epoch$) **do**
  for each training data (c)=1 to N **do**
    for each visible layer (VI) i=1 to k **do**
      Compute the probability of hidden layer (HI) using equation 3.8.
    end for
    for each hidden layer (HI) j= 1 to m **do**
      Compute the probability of visible layer (HI) using equation 3.9.
    end for
    Assessed the hidden and visible layers probability using equation 3.10-3.11.
    Invoke the adaptive learning strategy (Algorithm 1)
    Update the parameters of RBM ($bi_j, bs_i, andw_{(i,j)}$) using equations 3.12-3.14.
  end for
  Training phase of RBM is completed and obtained the optimum tuning of parameters (bi_j, bs_i, and $w_{(i,j)}$) and learning rate (ϕ).
  Evaluate the objective function using equation 3.17 on output layer of deep belief nets.
  Back propagation method is adopted for computing diabetes in forward direction and weight in backward direction.
end while
Training of beep belief nets is completed and obtained the training accuracy.

4. Experimental Results. The section presents the effectiveness of the proposed diabetic retinopathy detection system. The efficacy of the proposed detection system is tested over retinal fundus images. In this, work, a total of three thousand two hundred retinal images are utilized for evaluating the performance of the

Algorithm 4 Deep Belief Network with Adaptive Learning Strategy // Testing Phase

Input: Test image dataset, number of epoch, number of RBM, number of visible layer, number of hidden layer.
Output: Diabetic Retinopathy Detection either presence or absence

```
Initialize the bias of visible and hidden layers (bs_i and bi_j), weight matrix(w_(p × q)), learning rate (φ),
number of training data (N) and number of epoch (Max_Epoch).
while (currentepoch ≤ Max_Epoch) do
   for each testing data (c)=1 to N do
      for each visible layer (VI) i=1 to k do
         Compute the probability of hidden layer (HI) using equation 3.8.
      end for
      for each hidden layer (HI) j= 1 to m do
         Compute the probability of visible layer (HI) using equation 3.9.
      end for
      Assessed the hidden and visible layers probability using equation 3.10-3.11.
   end for
   Evaluate the objective function using equation 3.17 on output layer of deep belief nets.
   Back propagation method is adopted for computing diabetes in forward direction and weight in backward
   direction.
end while
Training of beep belief nets is completed and obtained the training accuracy.
```

proposed detection system in which two hundred twenty-four images having diabetic retinopathy symptoms and the rest of the images with no symptoms. The performance of the proposed diabetic retinopathy detection system is tested over a set of performance parameters. These parameters are accuracy, sensitivity, specificity, F1-Score and AUC. The training and validation accuracy along with loss rate are also investigated for over fitting issue of data. The abovementioned parameters are computed using the confusion matrix. The confusion matrix can be described in terms of true positive, true negative, false positive, and false negative. The proposed system is implemented in MATLAB 2016b environment using corei7 processor with 16GB RAM on window 10 operating system.

4.1. Results and Discussion. This subsection discusses the simulation results of the proposed model. Fig 4.1 shows the confusion matrix of the proposed diabetic retinopathy detection system and other techniques like InceptionV3, VGG19, VGG16, SVM, ANN and KNN. The confusion matrix is utilized to compute the other performance parameters such as accuracy, sensitivity, specificity, F1-score and AUC. Table 4.1 illustrate the experimental results of proposed diabetic retinopathy detection system and other techniques using accuracy and F1-score parameters.Further, these results are evaluated using Training/Testing (70%-30%), Training/Testing (80%-20%), 5-CrossFold Validation, and 10-CrossFold Validation methods. In Training/Testing (70%-30%), the entire data is divided into 70% and 30%. The seventy percent data is considered for training set and adopted for train the model, while thirty percent dataset is used as validation set and applied for evaluating the performance of the model.

In Training/Testing (80%-20%), eighty percent of entire data is adopted for training set, while twenty percent data is considered for validation set and can be used to evaluate the performance of model. In 5-cross fold validation, the entire dataset is divided into five equal sized set and out of five, four sets are applied to train the model as training set, rest one is used to evaluate the performance of model as validation set. This process is repeated up to five times, but every time validation set is different. In 10-cross fold validation, the data is divided into ten equal sized sets in which nine sets are used as training set and tenth set is employed for evaluating the performance of model as validation set. This process is repeated up to ten times and every times validation set is different. It is found that proposed diabetic retinopathy detection system achieves better results than other techniques like InceptionV3, VGG19, VGG16, SVM, ANN and KNN in terms of accuracy and F1- Score parameters using all aforementioned methods. The accuracy and F1-score rates of proposed diabetic retinopathy detection system using Training/Testing (70%-30%), Training/Testing (80%-20%), 5-CrossFold

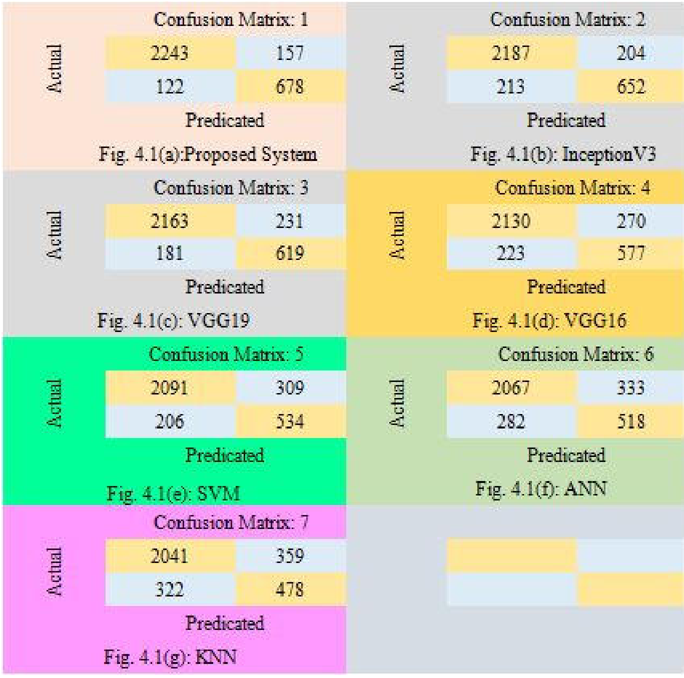

Fig. 4.1: (a-g) Depicts the Confusion Matrix of proposed diabetic retinopathy detection system and other techniques.

Table 4.1: Results of proposed model and other techniques for diabetic retinopathy using accuracy and F1-score parameters.

Technique	Training/Testing (70%-30%)		Training/Testing (80%-20%)		5- Cross Fold Validation		10-Cross Fold Validation	
	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score
KNN	69.21	71.23	73.21	76.06	76.46	82.95	78.72	85.72
ANN	70.93	72.06	75.64	79.26	77.09	84.88	80.78	87.04
SVM	73.24	76.76	77.52	80.03	80.41	85.73	82.03	87.91
VGG16	74.67	77.18	78.97	81.12	82.94	87.81	84.59	89.63
VGG19	77.03	78.73	81.53	83.05	85.91	89.56	86.94	91.31
Inception V3	79.89	81.78	84.93	86.53	87.09	90.14	88.72	91.38
Proposed System	85.91	87.48	87.41	89.11	90.46	92.5	91.28	94.14

Validation, and 10-CrossFold Validation methods are (85.91 and 87.48), (87.41 and 89.11), (90.46 and 92.5), (91.28 and 94.14) respectively. It is analyzed that proposed system having higher accuracy and F1-score rate than other techniques using all possible training/testing and cross fold validation methods. It is also observed that KNN technique provides less efficient results for detecting of the diabetic retinopathy in terms of accuracy and F1-score as (69.21 and 71.23) with training/testing (70%-30%), (73.21 and 76.06) with training/testing (80%-20%), (76.46 and 82.95) with 5-cross fold validation, and (78.22 and 85.72) with 10-cross fold validation method. It is also revealed that ANN and SVM techniques obtain similar F1-score rates using 10-cross fold validation method. Hence, it stated that proposed diabetic retinopathy detection system is provide more accurate results in terms of accuracy and F1-score rate for detection of diabetes retinopathy. It is also seen that proposed detection model achieves more than 94% F1-score rate using 10-cross fold validation method for diabetic retinopathy. Further, 10-cross fold validation method significantly enhances the accuracy and F1-score

Table 4.2: Results of proposed model and other techniques for diabetic retinopathy using sensitivity and specificity parameters.

Technique	Training/Testing (70%-30%)		Training/Testing (80%-20%)		5- Cross Fold Validation		10-Cross Fold Validation	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
KNN	71.42	71.04	74.28	77.92	82.61	83.29	85.04	86.37
ANN	71.04	73.12	78.34	80.21	84.73	85.03	86.12	87.99
SVM	75.34	78.23	78.73	81.37	85.34	86.12	87.13	88.71
VGG16	76.81	77.56	80.03	82.23	87.24	88.38	88.75	90.52
VGG19	77.43	80.07	82.64	83.46	88.41	90.74	90.35	92.28
Inception V3	80.21	83.41	86.02	87.04	89.83	90.45	91.47	91.13
Proposed System	86.73	88.24	88.13	90.11	92.04	92.96	93.46	94.84

results more than 6% and 7% in comparison to training/testing (70%-30%) method. Sensitivity and specificity parameters are also considered for evaluating the performance of the proposed diabetic retinopathy detection system. These parameters are evaluated the performance of the model in term of true positive rate i.e. actual presence of the diabetic retinopathy with respect to false positive and false negative. The experimental results of proposed diabetic retinopathy detection system and other techniques based on sensitivity and specificity are reported into Table 4.2.

It is observed that proposed diabetic retinopathy detection system achieves higher sensitivity and specificity rate such as (86.73 and 88.24) with training/testing (70%-30%) method, (88.13 and 90.11) with training/testing (80%-20%) method, (92.04 and 92.96) with 5-cross fold validation method, and (93.46 and 94.84) with 10-cross fold validation method. Similar, KNN technique obtains less accurate results in terms of sensitivity and specificity for diabetic retinopathy using training/testing and cross validation methods. It is seen that the sensitivity and specificity rates of KNN technique with Training/Testing (70%-30%), Training/Testing (80%-20%), 5-CrossFold Validation, and 10-CrossFold Validation are (71.42 and 71.04), (74.28 and 77.92), (82.61 and 83.29), and (85.04 and 86.37) respectively. It is also seen that ANN technique provides minimum sensitivity rate (71.04) with training/testing (70%-30%) method as compared to other techniques. It is also stated that 10-cross fold validation is more significant method as compared to other methods like Training/Testing (70%-30%), Training/Testing (80%-20%),and 5-CrossFold Validation methods as this method improve the sensitivity and specificity rates up to more than 6% and 7% in comparison to training/testing (70%-30%) method. The accuracy, F1-score, sensitivity and specificity rates based on training/testing and validation methods using all techniques are presented into Fig 4.2-4.5. The accuracy results of proposed diabetic retinopathy detection system and other techniques are showed into Fig 4.2.

It is revealed that proposed detection system obtains higher accuracy results using all training/ testing and validation methods in comparison to other techniques.It is also analyzed that among all training/testing and validation methods, the training/testing (70%-30%) method with all techniques including proposed diabetic retinopathy detection system provides less accurate results than 10-cross fold validation method. It is also stated that 10-cross validation method significantly improves the experimental results of all techniques.

Fig 4.3 presents the F1-score results of proposed diabetic retinopathy detection system and other techniques using all methods. Similarly, 10-cross validation method having better F1-score rate than other all techniques. The experimental results of sensitivity and specificity parameter using training/testing and validation methods are demonstrated into Fig 4.4-4.5. It is revealed that 10-cross fold validation method significantly improves the simulation results of all technique as compared training/testing (70%-30%), training/testing (80%-20%), and 5-cross fold validation methods. It is also found that all techniques exhibit less accurate results with training/testing (70%-30%) method. Hence, it is concluded that 10-cross validation method is an effective method for assessing the simulation results of techniques for diabetic retinopathy. Furthermore, it is found that proposed diabetic retinopathy detection system obtains better results for diabetic retinopathy with all training/testing and validation method as compared to other techniques.

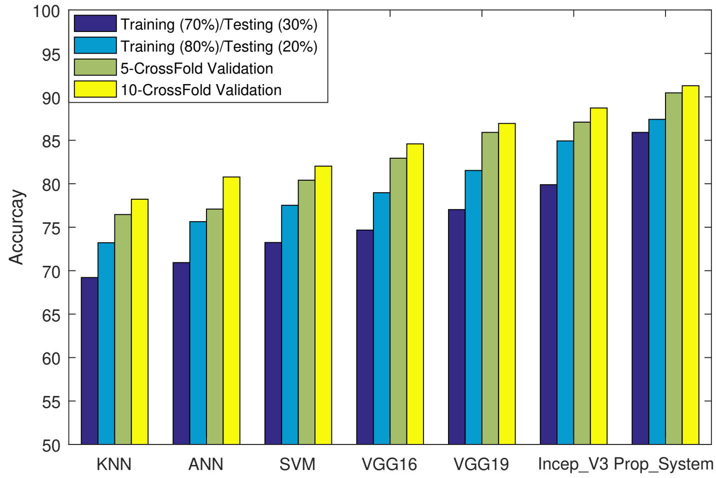

Fig. 4.2: Illustrates the accuracy results of proposed diabetic retinopathy detection system and other techniques using training /testing and validation methods.

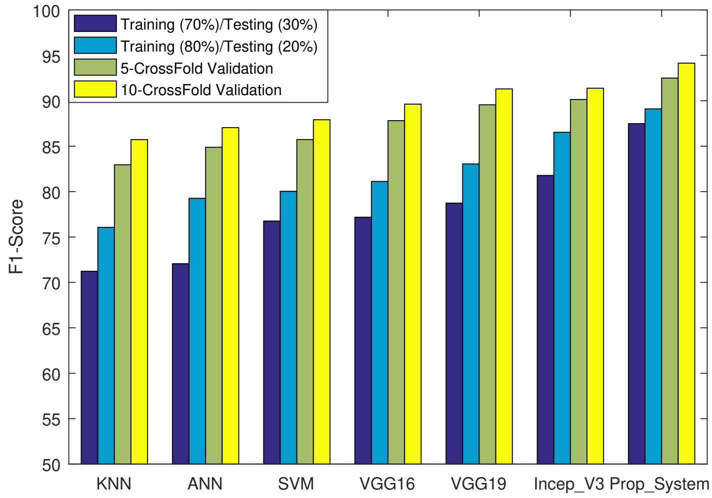

Fig. 4.3: Illustrates the F1-score results of proposed diabetic retinopathy detection system and other techniques using training /testing and validation methods.

Further, the experimental results of AUC parameter for proposed diabetic retinopathy detection system and other technique are presented into Fig 4.6. The AUC result of proposed diabetic retinopathy detection system is compared with KNN, SVM, ANN, VGG16, VGG19 and InceptionV3 techniques. The AUC parameter is defined in terms of true positive rate (TPR) and false positive rate (FPR). The TPR and FPR are used to plot the AUC result which is shown in Fig 4.6. It is stated that proposed model achieves higher AUC rate than other techniques. Hence, this parameter showed the effectiveness of the proposed diabetic retinopathy detection system for detecting the diabetic retinopathy. Finally, it is stated that proposed diabetic retinopathy detection system achieves more accurate results in terms of accuracy, sensitivity, specificity, F1-score and AUC parameters than other techniques.

5. Conclusion. This paper presents a diabetic retinopathy detection system for accurate diagnosis of diabetes retinopathy through retinal fundus images. The efficacy of the proposed diabetic retinopathy detection

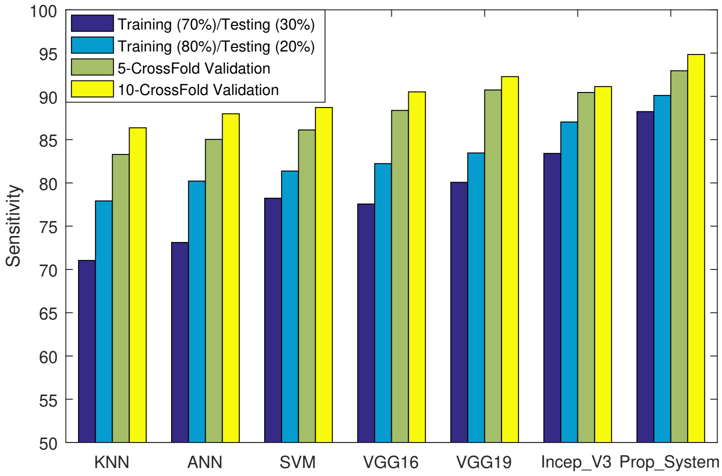

Fig. 4.4: Illustrates the sensitivity results of proposed diabetic retinopathy detection system and other techniques using training /testing and validation methods.

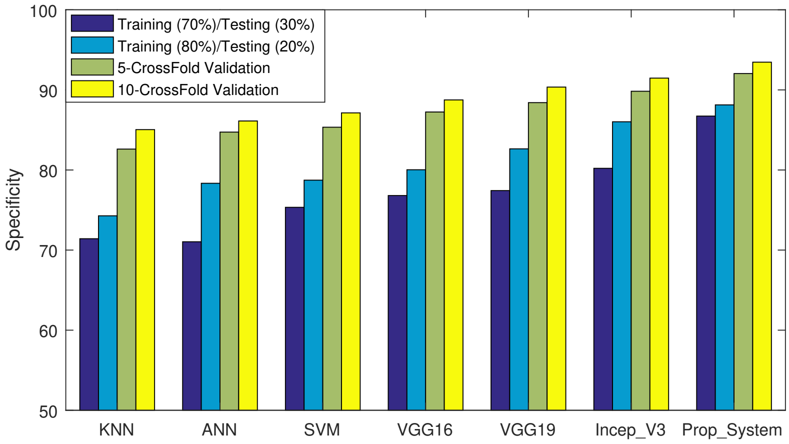

Fig. 4.5: Illustrates the specificity results of proposed diabetic retinopathy detection system and other techniques using training /testing and validation methods.

system is evaluated on three thousand two hundred retinal fundus images in which twenty four images are affected with diabetic retinopathy and rest of images are without diabetes retinopathy. Several preprocessing techniques are employed on image dataset in terms of threshold and luminosity, grayscale, edge detection, histogram and k-means based segmentation technique. In turn, processed dataset is constructed for detecting the diabetes retinopathy. In this work, deep belief nets are adopted for accurate diagnosis of diabetes retinopathy. Prior to implement the deep belief nets, an adaptive learning strategy is integrated into deep belief nets for computing the optimal learning rate in each iteration. The experimental results are evaluated using accuracy, sensitivity, specificity, F1-score and AUC parameters and also compared with state of art existing techniques like ANN, KNN, SVM, VGG16, VGG19, InceptionV3. Moreover, the experimental results of proposed are also assessed using Training/Testing (70%-30%), Training/Testing (80%-20%), 5-CrossFold Validation, and 10-CrossFold Validation methods. It is found that proposed diabetic retinopathy detection system achieves more accurate results than other techniques in terms of accuracy, sensitivity, specificity, F1-score and AUC parameter. It is also notice that proposed system obtains 94.14% F1-score rate using 10-cross fold validation method. On the

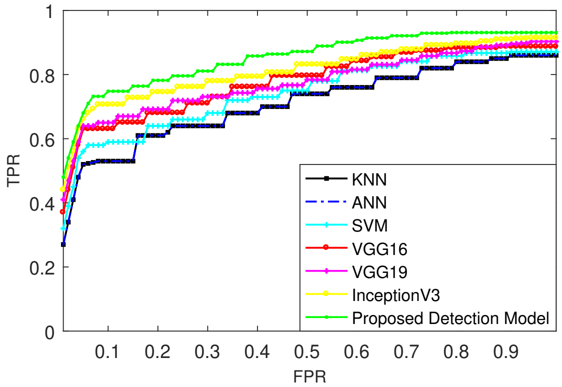

Fig. 4.6: Illustrates the area under curve (AUC) results of proposed diabetic retinopathy detection system and other techniques.

analysis of different training/testing and validation methods, it is found that 10-cross fold validation method achieve better accurate results than other methods, while training/testing (70%-30%) method having less accurate results for detection of diabetic retinopathy. Finally, it is concluded that proposed diabetic retinopathy detection system provides better results than other techniques using all training/testing and validation methods. Hence, it is stated that proposed diabetic retinopathy detection system is an effective and efficient technique for detecting diabetes retinopathy.In future, meta-heuristic algorithm-based segmentation techniques will be explored to determine the region of interest. This work considers the statistical and spatial features to design the diabetic retinopathy dataset. In future work, the features from fundus images will be extracted using first-order and second-order derivatives. Recently developed meta-heuristic algorithms can utilize to detect diabetic retinopathy more accurately and effectively.

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