Early Detection of Diabetic Retinopathy Using Dynamic Routing CapsNet with EfficientNet Feature Extraction

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Abstract: Diabetes patients may develop diabetic retinopathy, an eye disorder that may result in blindness and vision loss. It is considered as the major cause of blindness in the world among the working-age people. It can result in blindness if it is not discovered early. Moreover, there is no cure for DR; treatment keeps the eyesight intact. Early diagnosis and treatment of DR can greatly lower the possibility of visual loss. This paper proposes a novel Dynamic Routing-CapsNet (DR-CN) algorithm by integrating Dynamic Routing algorithm and Capsule Networks (CapsNet). The Dynamic Routing algorithm is used to train the network and create relationships between the capsules. Then, the EfficientNet is used for feature extraction because of its high accuracy and scalability. Also, the Capsnet is used for employing the relationship between the features by enhancing the performance of the method to differentiate among the various stages of DR. This method was performed based on the dataset which achieves a result of 98% accuracy by using the Convolutional Neural Networks (CNN) employing classification accuracy. Moreover, CNN is very effective for the classification of the images because they can easily learn about the features from the input images. These findings demonstrate that Dynamic Routing-CapsNet (DR-CN) algorithm provides a solution for DR screening, efficiently helps in early detection, and is useful for the healthcare system by reducing its difficulty in detection. Dense U-Net demonstrated exceptional segmentation performance, achieving accuracy rates of 0.94 (training set variation) and 0.93 (K-Fold cross-validation). Additionally, DR-CN showcased outstanding diabetic retinopathy classification results with 98.6% accuracy, 94.4% sensitivity, 94.3% specificity, and 96.2% F-Measure.

Keywords: Diabetic Retinopathy, Medical Image Classification, EfficientNet, Capsule Networks, Deep Learning

1. Introduction

Diabetes is a devastating disease that is particularly prevalent in Indian society [1]. This is causing diabetes to become overly prevalent, which promotes diseases such as DR [2]. Creating an automated diagnostic model is essential to extending the scope of the patients ocular and condensing morbidity and 422 million people have diabetes [3]. India ranks in the top 3 nations based on the prevalence of diabetes among the population [4]. It grew from 108 million to 422 million half in the last few years. The population resides in Brazil, Indonesia, the USA, China, and India [5]. It is surrounded India, and the United States, which are the most influential three nations according to a Lancet study [6]. Among them in their final day diabetes causes increases [7]. The loss of eyesight associated with Diabetic Retinopathy is the main topic of this research [8]. High blood glucose levels cause diabetic retinopathy (DR) and damage the retina's tiny blood vessels [9]. This causes the macula to thicken and enlarge as an outcome of excess fluid, blood, cholesterol, and other lipids in the retina [10]. Intraretinal Microvascular

Abnormalities, or IrMAs, are aberrant, delicate blood arteries that form in the retina during the process of providing sample blood [11].
The optic nerve may eventually get damaged due to the increased pressure inside the eye due to several issues [12]. Therefore, in simple terms, DR is the result of retinal damaged blood vessels brought on by diabetes problems, which ultimately results in irreversible blindness [13]. One potential method for identifying retinal impairment in its early stages involves retinal screening [14]. Since diabetic retinopathy is asymptotic at first, the majority of individuals are not aware of the disease until it emotionally impairs the way they see [15]. Consequently, early detection and regular screening for diabetic retinopathy are crucial for preventing future complications and managing the disease's development [16]. Exudates, which might appear bagged in the fundus image of the eyes and indicate that the patient is either developing DR or is currently experiencing it, are a major indication of dry eye disease (DR). The early detection of diabetic retinopathy might also be aided by the discovery of lesions in fundus imaging. Ophthalmologists frequently use color fundus images to study diabetic retinopathy (DR). These images include features associated with DR, such as haemorrhages, soft and hard discharge, and microaneurysms (MA), characterized by tiny red dots that resemble mini spaces and are produced by localized distension of the capillary walls.
There are four stages that diabetic retinopathy can pass by means of: (i) Mild non-proliferative retinopathy, considered to be the initial stage and associated with the development of microaneurysms (MA). (ii) Moderate non-proliferative retinopathy, in which one disease-causing blood vessels that supply the retina may enlarge and distort, impairing its ability to carry blood. (iii) Severe non-proliferative retinopathy signals the growth of new blood vessels in the retina by depriving it of blood supply through the obstruction of an increased amount of blood vessels. Many traditional methods such as those based on Deep learning [17], HAR [18], LSTM [19], and Multi-Head Attention Vision Hybrid (MHAVH) [20], however, no appropriate results were obtained. Thus, to enhance outcomes in this study, a novel deep learning technique is put through it.
In this paper, a novel algorithm is developed for the feature extraction and the enhancement of the performance of the method to differentiate among the various stages of DR. The model is trained by the algorithm to create relationships between the capsules. Moreover, CNN is used and is very efficient for the classification of the images because they can easily learn about the features from the input images.
The major contribution is given as follows

- This research integrates the Dynamic Routing algorithm with Capsule Networks (CapsNet) to offer a unique Dynamic Routing-Capsnet (DR-CN) algorithm. The network is trained and linkages between the capsules are established using the Dynamic Routing algorithm.
- It enhances the accuracy of the conventional networks by the combination of EfficientNet and Capsule Networks (CapsNet), which gives a better finding of the various stages of Diabetic Retinopathy.
- This model achieves high efficiency by employing computational time and parameters without affecting the performance.

The following summarizes how the paper is organized: Part 2 identifies the most current literature categories; Part 3 describes the system and problem statement; Part 4 discusses the workflow of the recommended technique; Part 5 offers the findings and discussion; and Part 6 concludes the study report.

2. Related works

Lim, W.X. et al. [21] suggested a hybrid approach to image processing. To get around pixel restrictions, used Simple Linear Iterative Clustering with Gaussian Filter (SLIC-G). Two steps comprised the SLIC-G image processing method: (1) Super-pixel segmentation by simple linear iterative clustering and (2) Gaussian smoothing operation. This created a huge amount of newly processed databases, which were subsequently used to train models. Finally, two performance evaluation criteria that were considered acceptable for unbalanced diabetic retinopathy datasets were employed to assess the usefulness of the proposed SLIC-G. The results reveal that, compared to prior published work results, the proposed SLIC-G displayed an improved performance on image classification of class unbalanced diabetic retinopathy datasets. This study demonstrated the significance of image processing and how it affected the performance.
Sagvekar, V. et al. [22] suggested a novel optimized Hunter-Prey Ladybug Beetle Optimizer Deep Maxout Network (HPLBO_DMN) for DR classification to address the previously mentioned problem.

First, the input image had been pre-processed after it had been obtained from the database. To lower noise in the input image, the Kalman filter and Region of Interest (RoI) extraction were employed during the pre-processing step. After that, the pre-processed image was put through a wavelet transform, used the Meyer wavelet to divide it into subbands for further processing. After that, K-Net, which was trained using HPLBO, was used to segment lesions. By the usage of a wavelet-transformed picture, the Automatic Artery/Vein (A/V) Classification Network (AVNet) simultaneously identified the arteries and veins. Furthermore, the AVNet's output was obtained during the feature extraction phase. In the end, DR classification was completed with the assistance.

Bhulakshmi, D. and Rajput, D.S [23] explored the basic principles of diabetes, as well as the condition's incidence, complications, and artificial intelligence-based treatment approaches, including Federated Learning (FL), Deep Learning (DL), and Machine Learning (ML). Prospective investigations, performance evaluations, biomarkers, screening techniques, and existing datasets were all covered in the study. In-depth analysis was done on a variety of neural network concepts, such as Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), and applications of ML, DL, and FL in the processing of fundus images, like Convolutional Neural Networks (CNNs) and its variants. There was also an outline of possible study techniques, such as the creation of the DL models and combined diverse data sources. Lastly, the difficulties and potential paths for this research were spoken about.

Shamrat, F.J.M., et al. [24] utilized the newly suggested Diabetic Retinopathy Network (DRNet13) model to evaluate the performance of fifteen pre-trained models. By the usage of the fundus images from five different Diabetic Retinopathy (DR) classes, the goal was to identify the most effective model for precise DR staging. The median filter to reduce noise and gamma correction to improve the image quality during the pre-processing stage. Through a variety of augmentation strategies, we increased the size of our dataset from 3662 to 7500 pictures to produce a more general training model. For a thorough comparison of these models' performances, we also assessed several evaluation metrics, such as confusion matrices, accuracy, precision, F1-score, sensitivity, specificity, area under the curve (AUC), mean squared error (MSE), false positive rate (FPR), and false negative rate (FNR).

Shoaib, M.R., et al. [25] provide a novel approach that used the cutting-edge deep learning algorithms to provide better diagnosis precision for DR than conventional methods. The idea of transfer learning lied at the heart of this strategy. This involved the existing, well-proven models—InceptionResNetv2 and Inceptionv3 in particular—to extract features and adjust particular layers in order to meet the particular needs of this particular diagnostic work. Simultaneously, this method introduced a brand-new model called DiaCNN that was specifically designed for the classification of eye conditions. It was used the Ocular Disease Intelligent Recognition (ODIR) dataset, which included the eight distinct types of eye diseases, to demonstrate the effectiveness of the suggested methodology. In the training and testing phases, the InceptionResNetv2 model which incorporated the transfer learning which was registered an astounding 97.5% accuracy.

Bodapati, J.D. and Balaji, B.B., [26] suggested stacking several dual attention-based techniques to create a self-adaptive ensemble method for rating the severity of retinopathy. The dual attention model that had been suggested makes use of two different attention systems. With its first degree of attention, the model might concentrate on areas unique to a lesion, and with its second level of attention, it could discover correlations between different spatial descriptors. The suggested approach used two degrees of attention to accurately predict the degree of retinopathy severity. Additionally, a self-adaptive meta-learner was provided that could efficiently stack several dual attention models. The suggested method beats several current models by obtaining an accuracy of 86.22%, according to experimental research using the benchmark APTOS 2019 dataset.

Li, X., et al. [27] created the machine learning models; for independent external validation, the 169 diabetes patient’s (169 eye) models were utilized. To determine whether DR, referable DR (RDR), and vision-threatening DR (VTDR) were present, techniques such as logistic regression, random forest, Gradient Boosting Machine (GBM), and deep learning were employed. Based on OCTA factors and clinical data, four distinct variable patterns were investigated. Receiver operating characteristic curves (ROC curves) were utilized to analyze the algorithm's efficiency, and the predictive accuracy was measured using the area under the curve (AUC). Higher AUC values for DR, RDR, and VTDR were obtained using the random forest algorithm for OCTA+clinical data-based variables and OCTA+non-laboratory factor-based variables.

Table 1. Existing works

SI.No	Author	Method	Advantage	Disadvantage
1	Lim, W.X. et al. [21]	Simple Linear Iterative Clustering with Gaussian Filter (SLIC-G)	It is beneficial when working with the medical images.	The potential loss might happen
2	Sagvekar, V. et al. [22]	Hunter-Prey Ladybug Beetle Optimizer Deep Maxout Network (HPLBO_DMN)	Efficient and balanced exploration and exploitation	Higher computational complexity
3	Bhulakshmi, D. and Rajput, D.S [23]	Generative Adversarial Networks (GANs)	This method is very effective in generating real-data.	Instability in training
4	Shamrat, F.J.M., et al. [24]	Diabetic Retinopathy Network (DRNet13) model	It achieves high accuracy	Requires a large dataset
5	Shoaib, M.R., et al. [25]	DiaCNN	Faster and accurate detection of accuracy	Requires more computational resources.
6	Bodapati, J.D. and Balaji, B.B., [26]	Dual Attention-based techniques	Better performance	Enhanced computational complexity
7	Li, X., et al. [27]	Gradient Boosting Machine (GBM)	It performs better with several data types.	Training time is large.

3. System model

Diabetic Retinopathy is a major cause of blindness and if it is detected earlier could prevent the vision loss. Two neural networks are combined for enhancing the accuracy and efficiency for the diagnosis of DR in this paper. EfficientNet is used for increasing the ability while maintaining the performance high by using very few parameters. This architecture initially involves the process of extracting the features from the retinal images which optimizes the width, depth, and resolution. The EfficientNet plays a very important role in providing the effective backbone for learning the innate features from the retinal images. This is very useful for finding the symptoms related to the DR at various stages. Capsule networks use the EfficientNet by holding the relation between the features. It efficiently confirms that the changes are accurately detected only at the final stage of classification. While CNN misses some critical information, but the Capsnet retains the important information, which is useful for the DR classification. The algorithm used for training the Capsnet for capturing similar attributes increases the performance, ends up in more classification of DR. This technique holds the automated diagnostic systems, leads to effective and timely treatment of DR patients.

The major problem is to create an efficient, scalable and exact model for the classification of DR to overcome the drawbacks of CNN. By the combination of the algorithm and the Capsnet which provides very effective feature extraction, this approach also enhances the accuracy of the classification. The major difficulty presents in the integration of the two architectures by maximizing their strengths individually, which results in the reliable classification of the DR images. This approach offers a valuable equipment for the early treatment, which results in the reduction of blindness of many diabetic patients around the globe.

4. Proposed methodology

The proposed methodology for DR classification consists of a hybrid deep learning method, EfficientNet for feature extraction, and Capsule Networks with dynamic routing algorithm to train the capsule networks for the increased ability to awareness. Initially, the pre-processing is done where the retinal images are resized, normalized and augmented for enhancing the model strength and stereotype. The EfficientNet is used in the initial stage of the approach for the extraction of the important features from the retinal images to scale with a constant ratio to balance the depth, width and resolution parameters. This can make sure that the images are classified in to subcategories in a larger and repeated way of the retinal images which are captured. This step is very important for finding DR-related abnormalities across various difficulty levels.

The output from the above process is entered in to the CapsNet and the dynamic routing is applied for capturing the arrangement of images in the structured order and the relationships. Sometimes, the CNN may lose the information but the CapsNet stores the relationships and also ensures the small variations of the retinal features are correctly found. Dynamic routing allows the method to prioritize the relevant information by neglecting the irrelevant features. This integration of EfficientNet and CapsNet creates a very robust system for accurately classifying the stages of the DR, addresses the difficulty in retinal images. Finally, the classification was done for the Diabetic Retinopathy, results in the enhanced earlier prediction of DR.

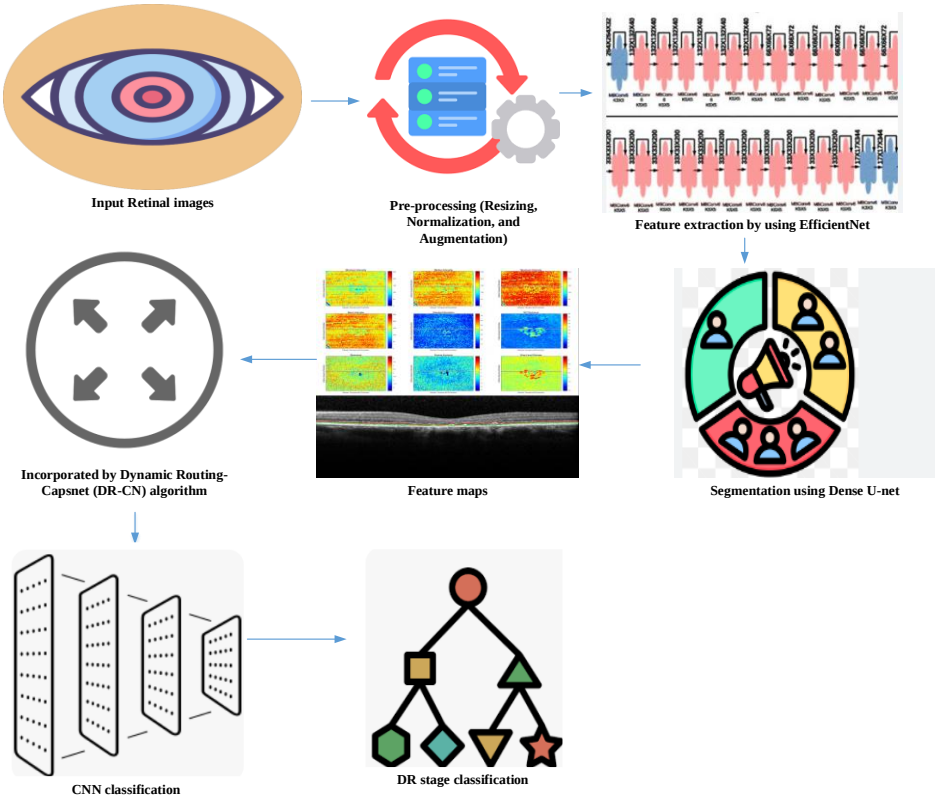


Figure 1. Architecture of the proposed DR-CN for Diabetic Retinopathy Classification Using EfficientNet and Capsule Networks

4.1 Input Retinal images

The input retinal images are of varying resolutions; each retinal image is reduced in size by adding a square mask to the retinal region; the modified retinal image is then split into the three separate channels—red, green, and blue—in RGB color space, and the variance of the blue channel is determined using Equation (1).

$$\rho^2 = \frac{1}{op}\sum_{j=0}^{n-1}\sum_{k=0}^{o-1}[Y(k,l) - \partial^2] \quad (1)$$

Where, $Y(k,l)$, ∂, o, p depicts, in the blue channel, individual pixels, the mean, and the number of rows and columns, respectively. The variance measure is chosen in order to comprehend the variability spread of the data. The table clearly shows that non-red dominant images have a higher blue variance value than red dominant images, with the former having less blue variance. The opponent color model serves as the foundation for both Lab color space and human vision. Since Lab color space is based on human visual perception, Lab color space is chosen in this research. The channel in the Lab space denotes the relation between red and green pixel values in an image, while the channel depicts the yellow-blue

4.2 Pre-processing

Pre-processing is the important step for using the retinal images for the classification purpose. It consists of the following steps

4.2.1 Resizing

The retinal images have different sizes which damages the ability of the method for further processing. Resizing refers to the conversion of the input images to fit for the compatible size required for the EfficientNet model. This is useful for the effective feature extraction without affecting the various image resolutions.

$R_O(y_k) = \sum_{j=1}^{O} \rho_j \, h(x_j . y_k + c_j) = o_k, k = 1, \ldots \ldots N$ (2)

Where, the training set is given as M samples of arbitrary which consists of m attributes and n classes as (y_k, c_j), in which the vector input given as $y_k = y_{k2} \ldots\ldots\ldots y_{kn}$.

4.2.2 Normalization

The values of the retinal images' ranges from 0 to 255. This normalization is useful for making the pixel values in a range between 0 and 1. This makes the method to change faster at the time of training by confirming the input features have the same values, by decreasing due to the higher values and stops the domination of the other features.

$N_O(y_k) = \sum_{j=1}^{O} \rho_j \, h(c_j) = u_k, k = 1, \ldots \ldots N$ (3)

4.2.3 Augmentation

Data augmentation enhances the dataset size by applying the transitions such as rotations, flips, zooming, brightness adjustments, or cropping. This step is required for enhancing the ability by introducing the algorithm to a variety of retinal image abnormalities and perspectives, this crucial phase increases its potential for learning and strengthens its resistance to changes in real-world data.

4.3 Feature extraction using EfficientNet

Google created the highly efficient network model EfficientNet 19 years ago. EfficientNet can extract features from a deeper neural network by using the residual network to extend the neural network's depth. EfficientNet can also alter the number of feature layers for each layer to accomplish additional layers of feature extraction in order to collect additional capabilities. In order to aid enhance accuracy, the computer system can acquire and communicate more information by increasing the resolution of the input image. EfficientNet B7 has an accuracy of 84.4% in detection.

$H_{k+1} = [h_1 \ldots \ldots \ldots h_N]$ (4)

In this equation, H_{k+1} mentions the sensor network depth and layers. Furthermore, using the same failures, EfficientNet increases the detection accuracy by 6% for a variety of residual networks. More focus may be placed on scaling up convolutional neural networks, such as ResNet18 to ResNet200 for residual networks, in order to increase detection accuracy considerably. EfficientNet is achieved by simply scaling every single dimension using ratios, like composite scaling, which maximizes speed and accuracy simultaneously. It strikes a nice compromise between efficiency and precision.

4.4 Segmentation using Dense U-net

A neural network called Dense U-Net was created for the purpose of segmenting images. The network is built on a fully convolutional neural network, whose architecture has been expanded and changed to produce more accurate segmentation while requiring fewer training photos. This network framework's benefit is its ability to precisely segment the intended feature target, process medical pictures efficiently and impartially, and aid in improving the accuracy of medical image-based diagnosis. The segmentation process using the Dense U-Net is shown in the Figure 2.

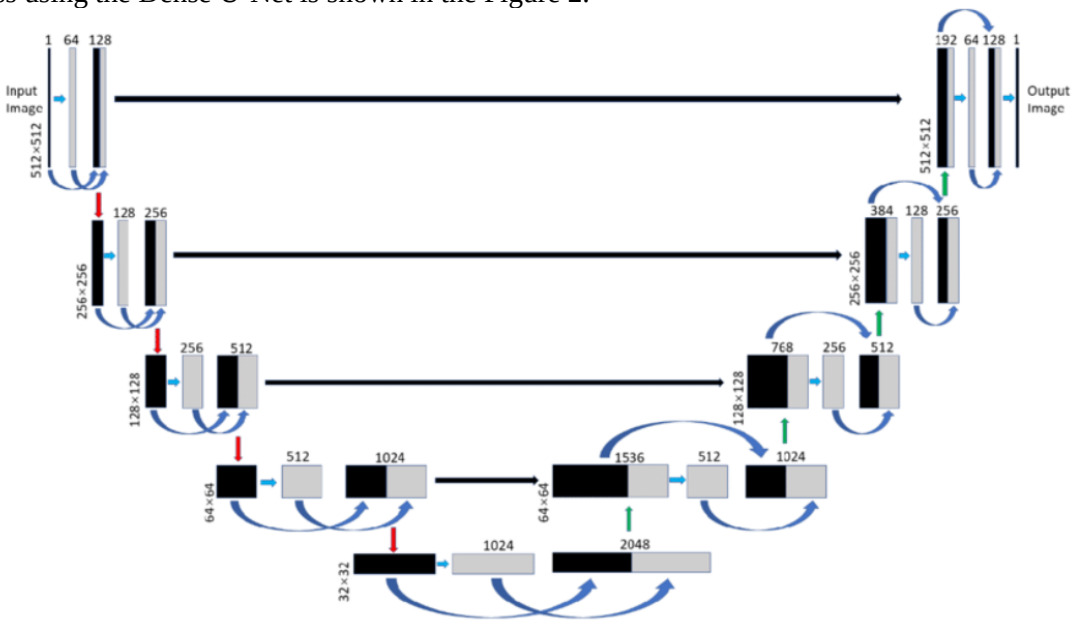


Figure 2. Segmentation using Dense U-Net

4.5 CNN Classification

It has a variety of layers, including output levels with fully linked output layers, pooling layers, convolution layers, and ReLU layers. CNN is able to identify the edges and shapes of a picture. The most common uses for CNNs, a subclass of neural networks, are in voice and picture recognition. Its integrated convolutional layer reduces the large dimensionality of images without losing any information.

4.5.1. Convolutional layer

The first layer in CNN creation is usually a convolutional layer. $P \times Q \times 1$ are acceptable input layers for CNN. The dimensions of a two-dimensional picture with a single layer are $P \times Q$. The outcome is the final image, which is produced by convolving the input image with this curve or shape. The convolution process results in greater values for the shape that closely resembles the input image's curve and is represented by the filter. Convolution may be represented as equation (11),

$$f(e) = (t^{*}u)(e) \quad (5)$$

4.5.2. Pooling layer

Using a pooling layer, the amount of the data is kept to a minimum. The matrix data is divided into segments, and each segment is then changed to a single value. Figure 4 demonstrates how the extreme or average of all values inside the current segment is used to swap the segmented matrices.

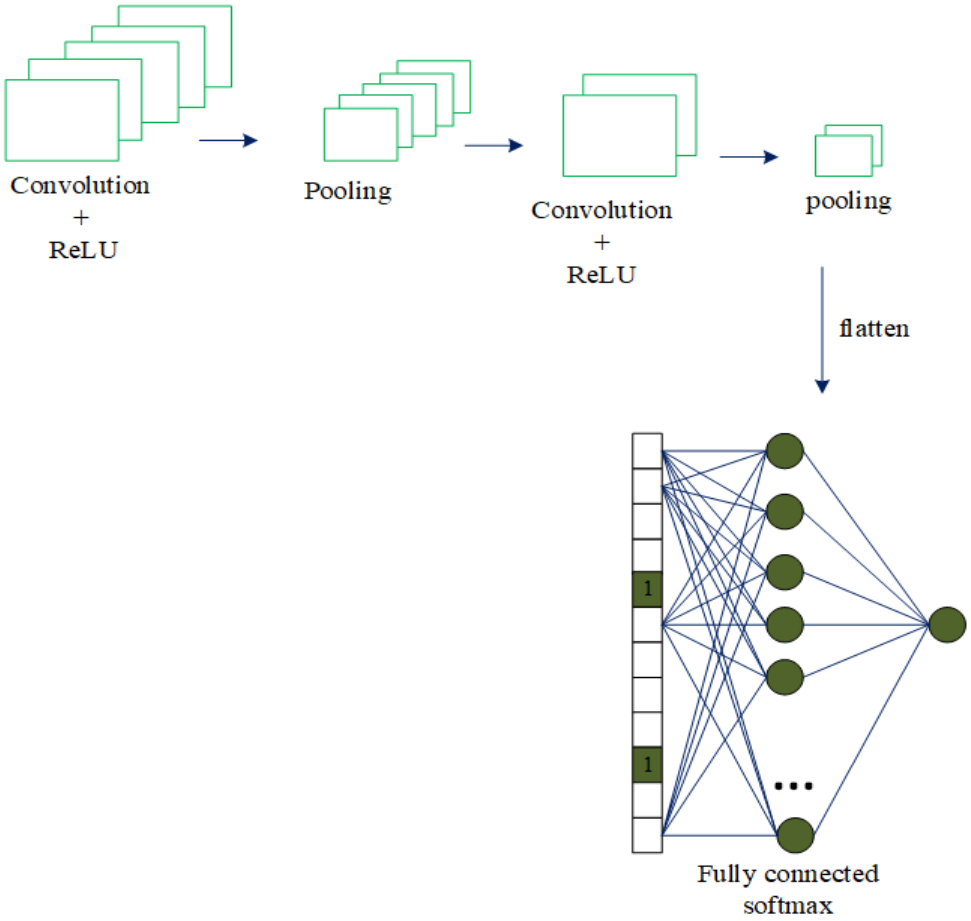


Figure 3. CNN architecture

4.5.3. Fully connected layer

A fully connected layer undergoes dimensional adjustments to fit the network layer design. A totally linked layer has connections between each of its input and output dimensions. As in a conventional ANN, all activations from a previous layer are transmitted on to the subsequent layer. A fully connected layer multiplies the input by a weight matrix before adding a bias vector. One or more fully connected layers come after the convolutional and down-sampling layers. As the name implies, each cell in a level that is fully linked has connections to each and every cell in the level above it.

4.5.4. Softmax layer

When the Softmax function is used, data from earlier layers is converted into a possibility for classes that add up to 1. Because it is the class with the greatest potential for the given data input, this layer, therefore, has a considerable impact on the projected output.

$$g_n(z) = \frac{F^z n}{\sum_r F^z R} \quad (6)$$

Deep neural networks may be used to classify images. Although these networks are already trained to classify various pictures, they may be adjusted using transfer learning by changing crucial parameters to solve our classification challenge. Hyper-parameter training has been kept up for all networks. There was a maximum of 25 epochs utilised to segment the data. Mini-batch size, as its name indicates, is the total number of samples required to update a model's parameters. The size of the training mini-batch was kept at 7, and the initial learning rate was set at 0.0001

4.6 Dynamic Routing algorithm

More than 30 years ago, Anderson and Van Essen (1987) developed the concept of dynamic routing, often known as shifter circuits, as a model for stabilizing the cortical picture representation in the face of retinal drift. Here, the routing dynamics are derived from the principled goal of performing optimal (Bayesian) estimate of a moving spatial pattern using a log-linear Poisson observation model, as opposed to suggesting a routing circuit a priori. Dynamic routing is a technology that determines the optimal way to gather information to take over a network. By using this procedure, a router can send data through multiple routes and arrive at its destination based on the state of communication circuits at that specific instance. Dynamic routers are sufficiently smart to choose the optimal data channel depending on the state of the computer system at that particular moment. The dynamic router uses its algorithm, which gathers and distributes details regarding the current path within itself using routing protocols, for redirecting the prior system across another network in real-time if a segment of the network fails to send data onward.

$$DR_1 = (I_1 I_u)^{-1} I_1^U U_1 \ (7)$$

Where, DR_1 represents the Diabetic Retinopathy features, I_1^U denotes the notable changes in the DR. This algorithm is chosen by using the CapsNet for enhancing the selection of the very difficult retinal features. CapsNet uses the dynamic routing for creating the relationships between the higher- and low-level capsules, and provide the method to find the connections and arrangements between the capsules. This algorithm is very useful for finding the notable changes in the retinal scans such as microaneurysms, haemorrhages, and exudates for the Diabetic Retinopathy. Moreover, the Dynamic routing also makes sure that the suitable features are routed to the proper capsules, results in more accurate diagnosis by better handling the arrangements and differ in the input images.

4.7 Incorporated by proposed DR-CN

In order to improve the selection of the most challenging retinal features, this algorithm is selected with the help of CapsNet. CapsNet provides a way to discover connections and arrangements between the capsules by using dynamic routing to establish links between higher and lower-level capsules. Finding significant alterations in retinal scans, such as microaneurysms, haemorrhages, and exudates for diabetic retinopathy, is made easier with the use of this approach. Furthermore, by handling arrangements and differences in input images better, dynamic routing produces a more accurate diagnosis by ensuring that the right features are routed to the appropriate capsules.

The dynamic routing also note that the network not only knows about the features but also about the scale, relationships and orientation, results in more knowledgeable understanding of the retinal features. The major advantage is the handling of the differences in the data of the patients, like changes in the angle of the camera, and orientation which find difficulty to gather important information. By this process, the method prioritizes the connection and discards the irrelevant data by the dynamic routing between the capsules. This process enhances the accuracy and reduces the false positives. This method enhances the ability for finding the Diabetic Retinopathy at a very early stage, providing more reliable and earlier diagnosis.

4.8 Feature maps

Feature maps are used for the classification and detection in the deep neural networks. Various filters are used to extract the features from the retinal image in the convolutional layer of the network. The feature maps are used for the classification and the values are changed from 0 to 255. These values are

changed from a range of 0 to 255 so that they can be applied to the original image. Then, the pooling layer is used for decreasing the dimensions of the feature map.

4.9 DR stage classification

The two main types of diabetic retinopathy (DR) are proliferative and non-proliferative, which are distinguished by the presence or absence of aberrant new blood vessels emerging from the retina, respectively. The diagrammatic representation of the DR stage is provided in the Figure 4.

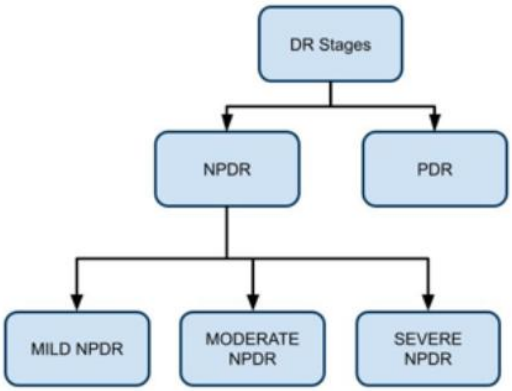


Figure 4. DR classification

4.9.1 Proliferative Diabetic Retinopathy

PDR is mostly treated with pan retinal photocoagulation (PRP), which involves laser photocoagulation of the peripheral retina. A portion of the ischemic peripheral retina is destroyed by the laser in order to reduce VEGF release and cause neovascularization to regress. If effective, vitreous haemorrhage and tractional retinal detachment may be averted. At occasion, the proliferative illness progresses to the point where blood oozing from the eye blocks the laser's path, or scar tissue causes the retina to wrinkle or separate from the eyewall (tractional retinal detachment). Surgery might be required in these circumstances (see vitrectomy for further information).

4.9.2 Non-Proliferative Diabetic Retinopathy

The beginning stages of the illness, known as non-proliferative diabetic retinopathy (NPDR), is characterized by little or non-existent symptoms. The retina's blood vessels become weaker in NPDR. Microaneurysms, which are tiny bulges in the blood arteries, can cause fluid to seep into the retina. The leakage could cause the macula to enlarge.

Table 2. Algorithm for the DR-CN

Algorithm for the DR-CN method
Input: Retinal images $\rho^2 = \frac{1}{op}\sum_{j=0}^{n-1}\sum_{k=0}^{o-1}[Y(k,l) - \partial^2]$ Preprocessing is given in the equation (2) $R_O(y_k) = \sum_{j=1}^{O}\rho_j\, h(x_{j.}y_k + c_j) = o_k, k = 1, \ldots \ldots N$ Normalization is given by $N_O(y_k) = \sum_{j=1}^{O}\rho_j\, h(c_j) = u_k, k = 1, \ldots \ldots N$ #Feature extraction using EfficientNet is provided in the below equation $H_{k+1} = [h_1 \ldots \ldots \ldots . h_N]$ CNN classification is given by $f(e) = (t^* u)(e)$ Softmax layer is represented in the below equation $g_n(z) = \frac{F^z n}{\sum_r F^z R}$ Dynamic routing algorithm is given by $DR_1 = (I_1 I_u)^{-1} I_1^U U_1$ Output: Diabetic Retinopathy Classification

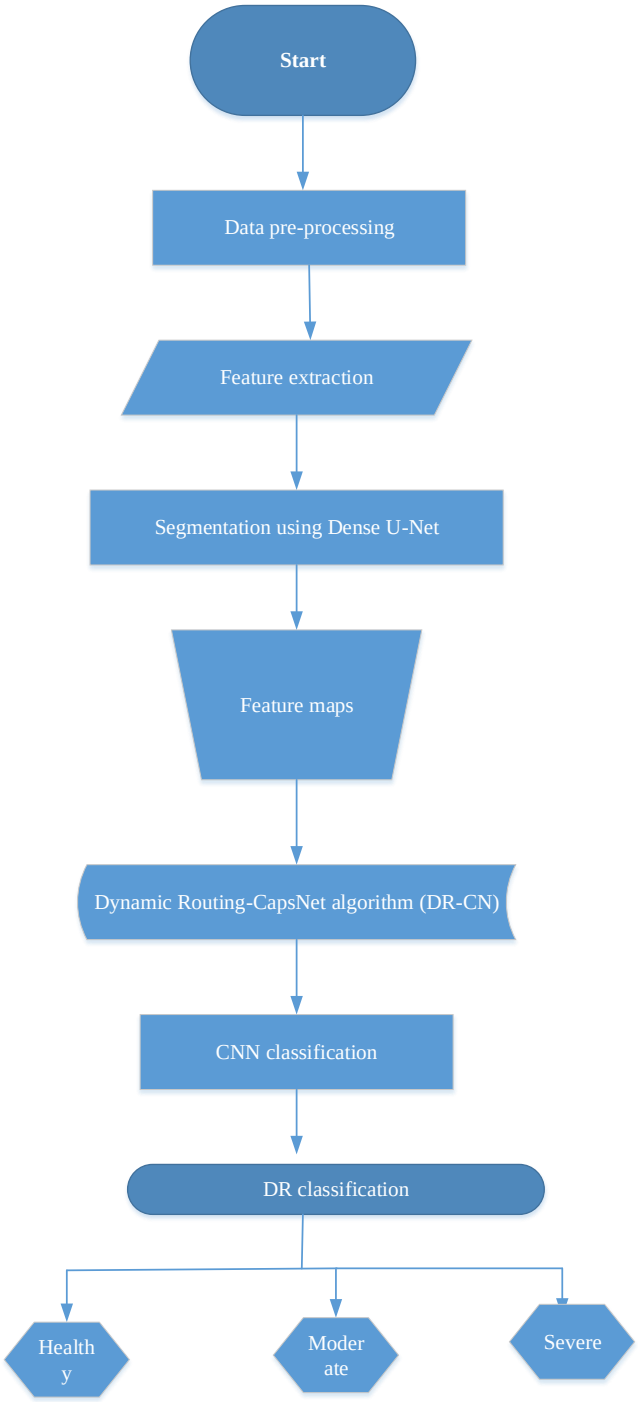


Figure 5. Flowchart Representation

5. Results and discussion

This section presents the results of DR-CN for diabetic retinopathy classification and discusses the implications of our findings.

5.1 Experimental setup

This section describes the computational environment and configuration used to evaluate the performance of DR-CN. Experiments were conducted on a PC with Intel Core i3 processor, 16 GB RAM, and Windows 10 (64-bit) OS. The DR-CN model was implemented in Python.

5.2 Dataset Description

The Indian Diabetic Retinopathy Image Dataset (IDRID) [28] was utilized to evaluate the proposed DR-CN classification method, comprising 516 images (268 diabetic retinopathy and 248 normal) with expert-annotated ground truth labels, resolution 4288 x 2848 pixels, and JPEG format. The dataset

provides a diverse range of retinal images capturing various stages of diabetic retinopathy, making it suitable for training and testing the DR-CN model, and is publicly available for research purposes, allowing for reliable evaluation and comparison of diabetic retinopathy classification methods.

5.3 Performance metrics

To comprehensively evaluate the performance of DR-CN, the following metrics are employed.

Accuracy

Accuracy measures the proportion of correctly classified diabetic retinopathy cases (both positive and negative) out of the total number of cases examined, and the equation is stated as,

$$Acc = \frac{k_{positive} + k_{negative}}{k_{positive} + k_{negative} + m_{positive} + m_{negative}} \quad (8)$$

where, $k_{positive}$ specifies the correctly detected diabetic retinopathy cases, $k_{negative}$ denotes the correctly identified non-diabetic retinopathy cases, $m_{positive}$ denotes the incorrectly detected diabetic retinopathy cases, and $m_{negative}$ denotes the missed diabetic retinopathy cases.

Sensitivity

It measures the proportion of correctly detected diabetic retinopathy cases, which is given by,

$$Sen = \frac{k_{positive}}{k_{positive} + m_{negative}} \quad (9)$$

Specificity

It measures the proportion of correctly identified non-diabetic retinopathy cases, which is stated by,

$$Spec = \frac{k_{negative}}{m_{positive} + k_{negative}} \quad (10)$$

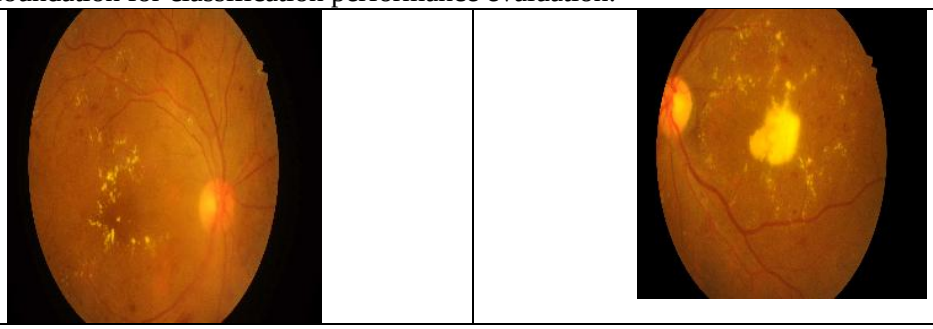
F-Measure

The F-Measure calculates the harmonic mean of precision and recall, providing a balanced measure of a model performance.

$$F1 = 2 \times \left(\frac{\mathrm{Pre} * \mathrm{Rec}}{\mathrm{Pre} + \mathrm{Rec}} \right) \quad (11)$$

5.4 Experimental outcome

The experimental results of DR-CN for diabetic retinopathy classification are presented in Figure 6. (i) Original retinal image from the dataset, (ii) Enhanced image after applying pre-processing techniques, (iii) segmented outcome highlighting regions of interest, and (iv) Extracted features using EfficientNet, showcasing the model ability to capture relevant information. These results demonstrate DR-CN effectiveness in enhancing image quality, accurate segmentation, and informative feature extraction, laying the foundation for classification performance evaluation.



(i)

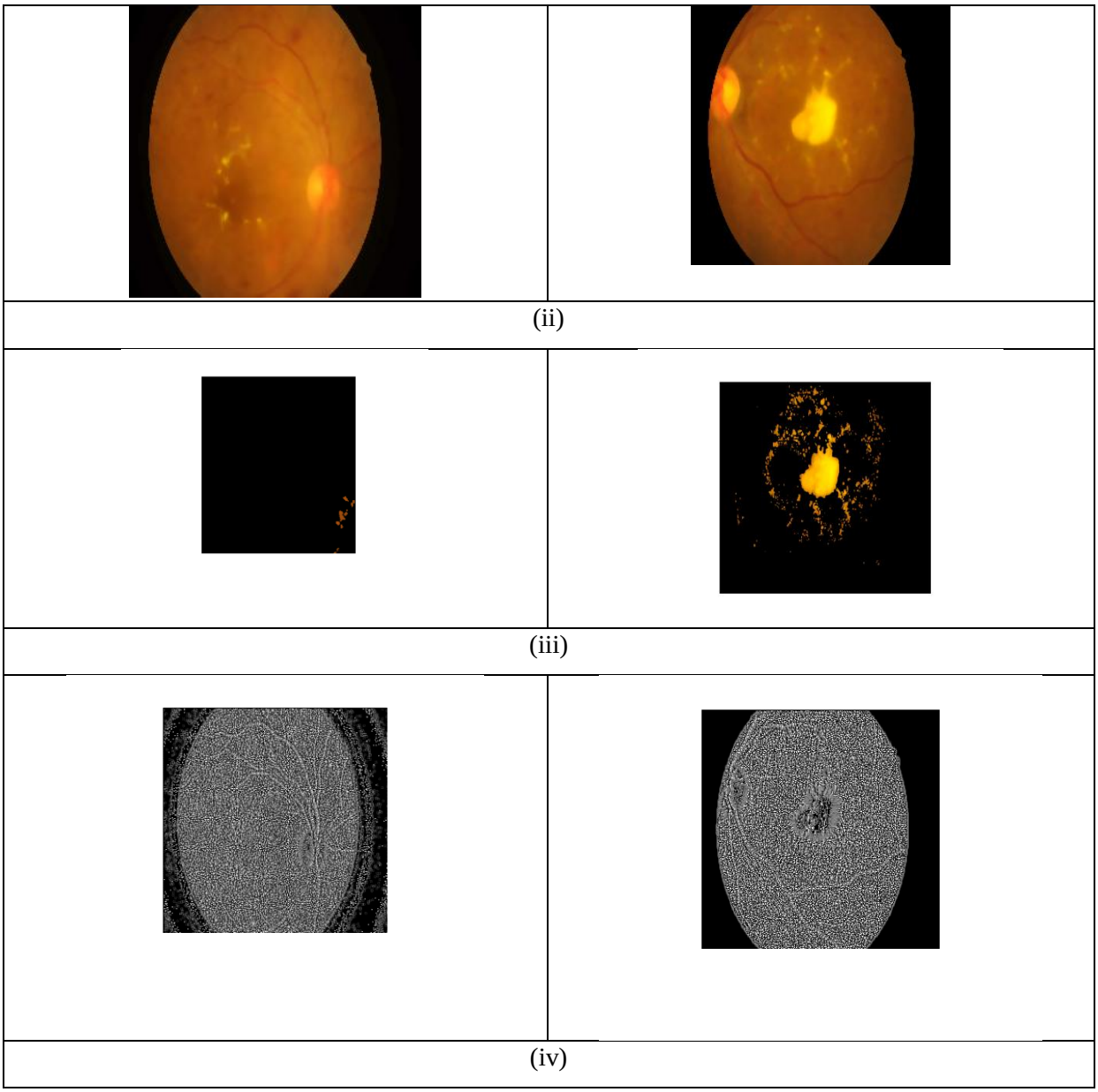


Figure 6. DR-CN experimental outcome: (i) input image, (ii) pre-processed image, (iii) segmented image, and (iv) EfficientNet features

5.5. Comparative Methods

The performance of DR-CN is compared with state-of-the-art techniques, including GAN [3], DRNet13 [4], DiaCNN [5], and HPLBO_DMN [2].

5.6. Comparative examination

A comprehensive evaluation using metrics with varying K-fold and training set is conducted to assess the techniques effectiveness with results presented below to facilitate a thorough comparison.

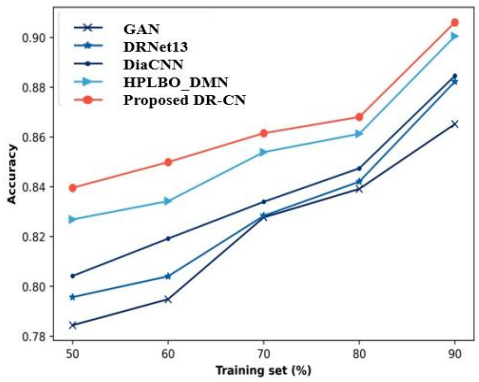
5.6.1. Training set Assessment

Figure 7 evaluates the strategy with a training set, which demonstrates DR-CN superior performance across metrics. Accuracy evaluation is endorsed in figure 7(i). DR-CN achieves an accuracy of 0.845, outperforming GAN (0.790), DRNet13 (0.798), DiaCNN (0.810), and HPLBO_DMN (0.830). Notably, DR-CN exhibits upgrades of 4.524%, 2.650%, 2.318%, and 0.665% over these methods, respectively. This superior performance demonstrates DR-CN enhanced ability to identify subtle retinal abnormalities, reduce false positives and negatives, and improve overall diagnostic reliability, leading to earlier detection, reduced risk of vision loss, and improved patient outcomes. DR-CN accuracy underscores its potential as a reliable tool for clinical decision-making, paving the way for advancements in deep learning-based diabetic retinopathy detection and improved healthcare outcomes. The sensitivity evaluation is endorsed in figure 7(ii). With training set =50%, the sensitivity of DR- GAN, DRNet13,

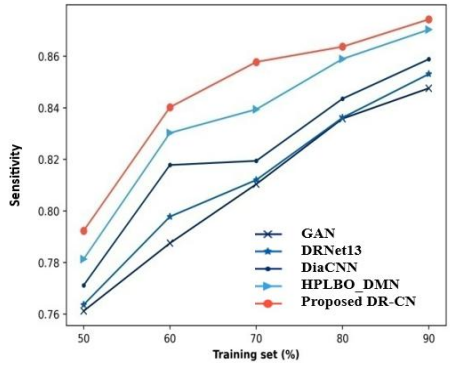
DiaCNN, HPLBO_DMN, and DR-CN are 0.765, 0.770, 0.776, 0.787, and 0.798. The performance upgrading considering existing with respect to DR-CN using sensitivity is 2.977%, 2.406%, 1.719%, 0.460%. This enhanced sensitivity enables DR-CN to identify subtle retinal abnormalities, reducing false negatives and improving overall diagnostic accuracy.

The specificity evaluation is endorsed in figure 7(iii). DR-CN specificity of 0.824 exceeds state-of-the-art methods, ensuring minimal false positives, with upgrades of 4.645% over GAN, 2.495% over DRNet13, 2.268% over DiaCNN, and 1.7% over HPLBO_DMN. This improved specificity allows DR-CN to accurately distinguish between diabetic retinopathy cases and non-cases, reducing unnecessary treatments and enhancing clinical decision-making. The F-Measure evaluation is endorsed in figure 7(iv). DR-CN achieves an F-Measure of 0.849, balancing sensitivity and specificity, with upgrades of 5.595% over GAN, 4.825% over DRNet13, 4.607% over DiaCNN, and 4.387% over HPLBO_DMN. This exceptional F-Measure demonstrates DR-CN overall performance, highlighting its ability to detect diabetic retinopathy cases accurately while minimizing false positives and negatives. The Receiver Operating Characteristic (ROC) curve analysis depicted in Figure 7(v) reveals DR-CN outstanding performance. At an FPR of 20%, DR-CN achieved a TPR of 98%, substantially surpassing other models: DR-GAN (66%), DRNet13 (75%), DiaCNN (85%), and HPLBO_DMN (94%). The ROC curve analysis confirms DR-CN superiority, positioning it as a leading solution for diabetic retinopathy detection.

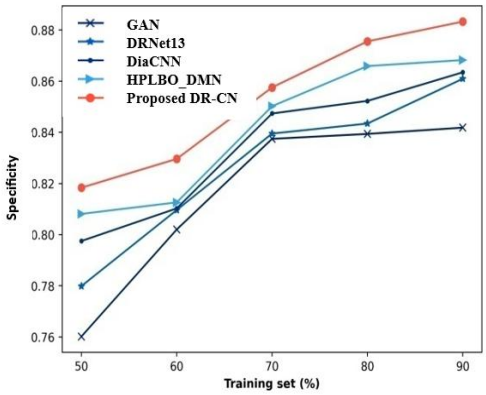
DR-CN exceptional performance enables significant advancements in diabetic retinopathy detection, with its superior accuracy and sensitivity facilitating early detection and treatment, reduced vision loss, and improved patient outcomes. Improved specificity minimizes unnecessary treatments, false positives, and clinical workload, while its balanced F-Measure demonstrates robust detection capabilities and reliability. DR-CN robustness paves the way for further research in deep learning-based detection, integration with existing healthcare systems, and potential applications in related medical domains, ultimately enhancing diagnostic accuracy, patient outcomes, and informing healthcare policy and research directions.



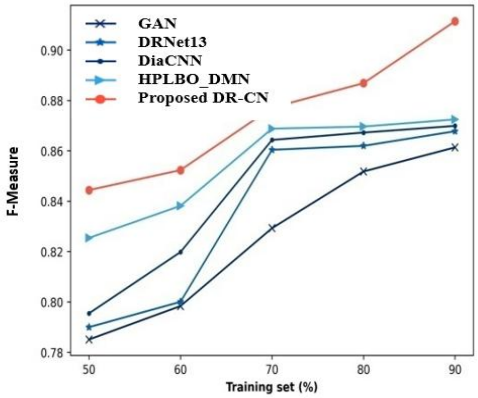
(i)



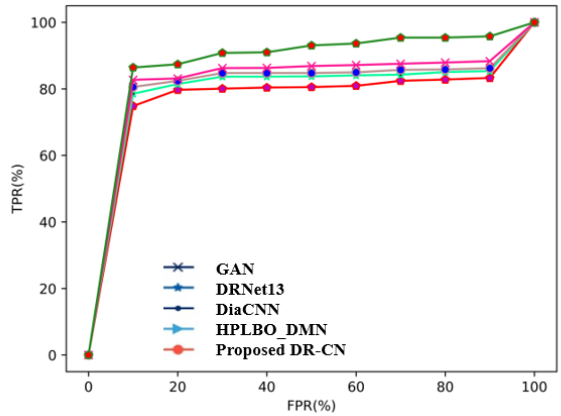
(ii)



(iii)



(iv)



(v)

Figure 7. Strategy comparison by changing training set using (i) Accuracy (ii) Sensitivity (iii) Specificity (iv) F-Measure, and (v) ROC analysis

5.6.2. K-Fold Assessment

Figure 8 provides an explanation of the strategy evaluation by changing the K-fold. In figure 8(i), the accuracy is explained. The accuracy of DR-GAN, DRNet13, DiaCNN, and HPLBO_DMN, is 0.796, 0.780, 0.785, and 0.819, while DR-CN accuracy is 0.836 when K-fold = 5. The accuracy of DR-GAN, DRNet13, DiaCNN, and HPLBO_DMN from K-fold =9 is 0.872, 0.879, 0.887, and 0.900, while DR-CN accuracy is 0.915. The efficiency upgrade taking into account the accuracy of DR-CN is 3.979%, 3.206%, 2.543%, and 0.776%. In figure 8(ii), the sensitivity evaluation is explained. The sensitivity of DR-GAN, DRNet13, DiaCNN, and HPLBO_DMN is 0.767, 0.770, 0.778, and 0.788, while that of DR-CN is 0.797 while taking K-fold = 5. The upgrading of efficiency in relation to DR-CN using sensitivity is 6.430%, 5.397%, and 4.364%. In figure 8(iii), the specificity is analyzed. The specificity of DR-GAN, DRNet13, DiaCNN, HPLBO_DMN are 0.750, 0.775, 0.780, 0.786, while DR-CN specificity is 0.792, when K-fold = 5 is taken into account. The efficiency upgrades that take into account the current state in relation to DR-CN utilizing specificity are 5.349%, 1.280%, 0.815%, and 0.583%. In figure 8(iv), the F-Measure evaluation is shown. When K-fold = 5 is taken into account, the F-Measure of DR-GAN, DRNet13, DiaCNN, HPLBO_DMN are 0.800, 0.808, 0.826, 0.837, while DR-CN F-Measure is 0.849. Using F-Measure, the efficiency upgrade taking into account the current state in relation to DR-CN is 2.784%, 2.676%, 1.673%, and 0.895%. Figure 8(v) ROC curve analysis demonstrates DR-CN exceptional performance with a remarkable TPR of 97% at a FPR of 20%. This surpasses competing models by substantial margins: DR-GAN (68%), DRNet13 (75%), DiaCNN (83%), and HPLBO_DMN (92%), solidifying DR-CN's position as a leading solution for diabetic retinopathy detection.

These results demonstrate DR-CN's superior performance across various evaluation metrics, including accuracy, sensitivity, specificity, and F-Measure with significant upgrades over existing methods. DR-CN enhanced diagnostic capability, improved robustness, balanced sensitivity and specificity, and superior overall performance underscore its potential for real-world clinical applications. Its consistent outperformance across different K-fold values validates its stability, generalizability, and adaptability with implications for clinical practice, research directions, and healthcare policy. Overall, DR-CN establishes itself as a leading solution for automated diabetic retinopathy detection paving the way for improved patient care and outcomes.

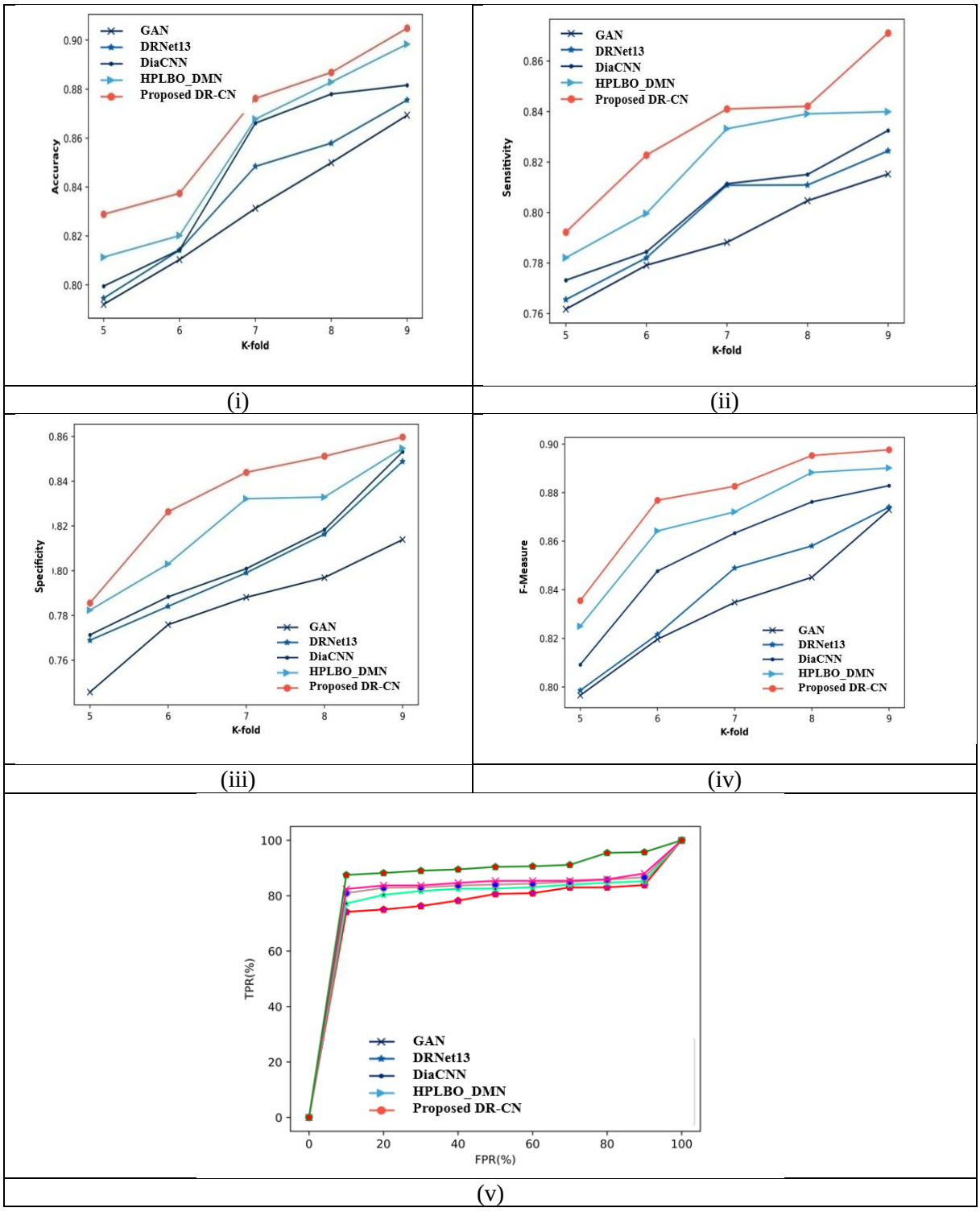


Figure 8. Strategy comparison by changing K-Fold using (i) Accuracy (ii) Sensitivity (iii) Specificity (iv) F1-Measure, (v) ROC analysis

5.7 Segmentation analysis methods

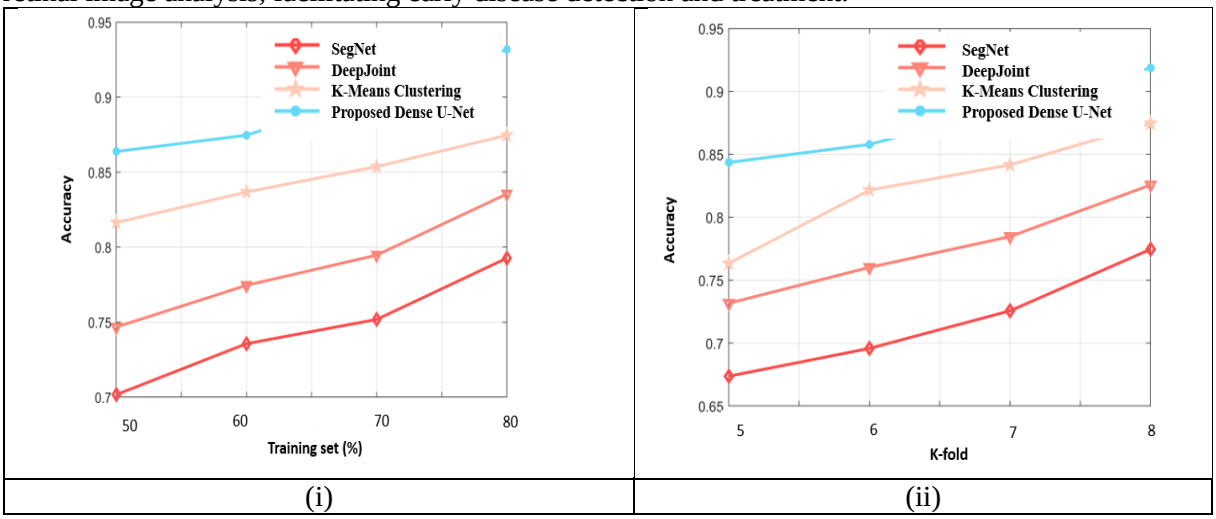
Dense U-Net divides diabetic retinopathy into segments, and this analysis is contrasted with several other techniques, including SegNet [29], DeepJoint [30], and k-means clustering [31].

5.7.1 Segmentation analysis

Figure 9 presents the segmentation analysis, showcasing Dense U-Net superior performance. When varying the training set size to 60, Dense U-Net achieved an accuracy of 0.89, outperforming SegNet (0.77), DeepJoint (0.79), and k-means clustering (0.84). Similarly, under K-Fold cross-validation =7, Dense U-Net maintained its lead with an accuracy of 0.89, surpassing SegNet (0.70), DeepJoint (0.77), and k-means clustering (0.82). This consistent dominance underscores Dense U-Net robustness and

exceptional segmentation capabilities, solidifying its position as a top-performing model for segmentation tasks.

Dense U-Net consistent dominance in diabetic retinopathy segmentation underscores its robustness, exceptional lesion detection capabilities, and cutting-edge architecture, solidifying its position as a premier model for automated retinopathy diagnosis. This sustained superiority confirms its potential to revolutionize retinopathy segmentation tasks, offering unparalleled precision and efficiency in detecting microaneurysms, hemorrhages, and hard exudates. With its unyielding performance lead, Dense U-Net establishes itself as a gold standard for diabetic retinopathy segmentation, redefining expectations for accuracy and robustness. Its remarkable capabilities pave the way for groundbreaking applications in retinal image analysis, facilitating early disease detection and treatment.



(i) (ii)

Figure 9. Segmentation assessment for Accuracy, (i) Varying training set, and (ii) Varying K-Fold

5.7.2 Segmentation assessment discussion

Table 3 presents a comparative analysis of Dense U-Net segmentation performance alongside established methods, including SegNet, DeepJoint, and k-means clustering. Notably, Dense U-Net surpasses its counterparts, achieving maximal accuracy values of 0.94 with varying training sets and 0.93 under K-Fold cross-validation. This consistent dominance underscores Dense U-Net exceptional ability to learn complex features, generalize well, and adapt to diverse retinal image characteristics. The significant performance gap highlights Dense U-Net superiority in addressing diabetic retinopathy segmentation challenges, such as lesion detection, boundary delineation, and noise resilience. By outperforming competing techniques, Dense U-Net demonstrates its potential to enhance automated retinopathy diagnosis, facilitating early disease detection and treatment, and ultimately improving patient outcomes.

Table 3. Comparative discussion of Dense U-Net

Variation	Metrics	SegNet	DeepJoint	k-means clustering	Dense U-Net
Training set	Accuracy	0.81	0.86	0.89	0.94
K-Fold	Accuracy	0.79	0.85	0.88	0.93

5.8. Comparative discussion

Table 4 presents a comprehensive comparative evaluation of DR-CN with existing techniques, assessing performance across various metrics by altering training sets and K-fold cross-validation. By altering training data, DR-CN demonstrates exceptional performance achieving the highest accuracy of 98.6%, highest sensitivity of 94.4.4%, highest specificity of 94.3%, and highest F-Measure of 96.2%. These results underscore DR-CN ability to effectively learn complex patterns and generalize well across diverse training data. By altering K-fold values, DR-CN consistently outperforms existing methods, achieving the highest accuracy of 97.5%, highest sensitivity of 88%, highest specificity of 86%, and highest F-Measure of 88.8%. This highlights DR-CN stability and reliability in handling varying data distributions and fold configurations.

DR-CN innovative architecture, coupled with its optimized training method and robust feature extraction capabilities empowers accurate and reliable detection of diabetic retinopathy. This exceptional performance catapults DR-CN to the forefront of medical solutions, which paves the way

for seamless integration into clinical workflows, multimodal diagnostic approaches, and adaptable transfer learning applications. By enhancing patient outcomes, facilitating timely interventions, optimizing resource allocation, and streamlining clinical decision-making, DR-CN revolutionizes the diagnostic landscape. Its transformative potential solidifies DR-CN position as a pioneering tool in automated diabetic retinopathy detection, poised to improve the lives of millions worldwide. Furthermore, DR-CN impact extends beyond diagnosis, contributing to improved disease management, reduced healthcare disparities, and enhanced patient engagement, underscoring its profound influence on the medical community.

Table 4. Comparative evaluation

Variation	Metrics	GAN	DRNet13	DiaCNN	HPLBO_DMN	Proposed DR-CN
Training set	Accuracy (%)	88.5	90.2	92.5	94	98.6
	Sensitivity (%)	86.8	88.3	90.9	92	94.4
	Specificity (%)	86.2	88.1	90.3	92.8	94.3
	F-Measure (%)	88.1	88.8	90	92.2	96.2
K-fold	Accuracy (%)	88.9	90.6	92.2	95.8	97.5
	Sensitivity (%)	80.5	82.4	84.3	86	88
	Specificity (%)	79.4	81.9	83.3	85.5	86
	F-Measure (%)	83.3	84.4	85.3	86	88.8

6. Conclusion

In this paper, a novel DR-CN algorithm was proposed by integrating Dynamic Routing algorithm and Capsule Networks (CapsNet). The network was trained by using the dynamic algorithm and establish the connections between the capsules. The pre-processing was done at the initial stage, in that the images are resized, normalized and augmented. The EfficientNet was used for the extraction process from the retinal images to scale with the constant ratio. The images were classified in to subcategories in broader and in a large way. Then the process moved into the CapsNet and the dynamic routing was used for the structuring and capturing the relationships. Finally, the classification was done for the Diabetic Retinopathy, results in the enhanced earlier prediction of DR. Dense U-Net achieved remarkable segmentation accuracy, with maximal values of 0.94 using training set variation and 0.93 under K-Fold cross-validation. Meanwhile, DR-CN excels in diabetic retinopathy classification, yielding superior metrics: 98.6% accuracy, 94.4% sensitivity, 94.3% specificity, and 96.2% F-Measure. These outstanding results underscore the effectiveness of Dense U-Net for segmentation and DR-CN for classification, solidifying their potential for accurate and reliable automated diabetic retinopathy diagnosis. In the future, developing tailored treatment plans using AI-driven analysis of patient data will revolutionize diabetic retinopathy management.

References

1. Abushawish, I.Y., Modak, S., Abdel-Raheem, E., Mahmoud, S.A. and Hussain, A.J., 2024. Deep learning in automatic diabetic retinopathy detection and grading systems: A comprehensive survey and comparison of methods. IEEE Access, 12, pp.84785-84802.8
2. Bala, R., Sharma, A. and Goel, N., 2024. Comparative analysis of diabetic retinopathy classification approaches using machine learning and deep learning techniques. Archives of Computational Methods in Engineering, 31(2), pp.919-955.
3. Muthusamy, D. and Palani, P., 2024. Deep learning model using classification for diabetic retinopathy detection: an overview. Artificial Intelligence Review, 57(7), p.185.
4. Moustari, A.M., Brik, Y., Attallah, B. and Bouaouina, R., 2024. Two-stage deep learning classification for diabetic retinopathy using gradient weighted class activation mapping. Automatika, 65(3), pp.1284-1299.
5. İncir, R. and Bozkurt, F., 2024. A study on effective data preprocessing and augmentation method in diabetic retinopathy classification using pre-trained deep learning approaches. Multimedia Tools and Applications, 83(4), pp.12185-12208.
6. Lalithadevi, B. and Krishnaveni, S., 2024. Diabetic retinopathy detection and severity classification using optimized deep learning with explainable AI technique. Multimedia Tools and Applications, pp.1-65.

7. Romero-Oraá, R., Herrero-Tudela, M., López, M.I., Hornero, R. and García, M., 2024. Attention-based deep learning framework for automatic fundus image processing to aid in diabetic retinopathy grading. Computer Methods and Programs in Biomedicine, 249, p.108160.
8. Sivapriya, G., Devi, R.M., Keerthika, P. and Praveen, V., 2024. Automated diagnostic classification of diabetic retinopathy with microvascular structure of fundus images using deep learning method. Biomedical Signal Processing and Control, 88, p.105616.
9. Nigam, A., Sun, J., Subhash, V., Aiello, L.P., Silva, P.S., Huang, Y. and Luo, G., 2024. Deep Learning Approach to Identify Diabetic Retinopathy Severity and Progression Using Ultra-Wide Field Retinal Images. In AI for Health Equity and Fairness: Leveraging AI to Address Social Determinants of Health (pp. 103-116). Cham: Springer Nature Switzerland.
10. Erciyas, A. and Barişçi, N., 2024. A meta-analysis on diabetic retinopathy and deep learning applications. Multimedia Tools and Applications, 83(19), pp.57429-57448.
11. Mukherjee, N. and Sengupta, S., 2024. Application of deep learning approaches for classification of diabetic retinopathy stages from fundus retinal images: a survey. Multimedia Tools and Applications, 83(14), pp.43115-43175.
12. Zhu, S., Xiong, C., Zhong, Q. and Yao, Y., 2024. Diabetic Retinopathy Classification With Deep Learning via Fundus Images: A Short Survey. IEEE Access.
13. Dai, L., Sheng, B., Chen, T., Wu, Q., Liu, R., Cai, C., Wu, L., Yang, D., Hamzah, H., Liu, Y. and Wang, X., 2024. A deep learning system for predicting time to progression of diabetic retinopathy. Nature Medicine, 30(2), pp.584-594.
14. Al-ahmadi, R., Al-ghamdi, H. and Hsairi, L., 2024. Classification of Diabetic Retinopathy by Deep Learning. International Journal of Online & Biomedical Engineering, 20(1).
15. Fu, Y., Wei, Y., Chen, S., Chen, C., Zhou, R., Li, H., Qiu, M., Xie, J. and Huang, D., 2024. UC-stack: a deep learning computer automatic detection system for diabetic retinopathy classification. Physics in Medicine & Biology, 69(4), p.045021.
16. Jabbar, A., Liaqat, H.B., Akram, A., Sana, M.U., Azpíroz, I.D., Diez, I.D.L.T. and Ashraf, I., 2024. A Lesion-Based Diabetic Retinopathy Detection Through Hybrid Deep Learning Model. IEEE Access.
17. Macsik, P., Pavlovicova, J., Kajan, S., Goga, J. and Kurilova, V., 2024. Image preprocessing-based ensemble deep learning classification of diabetic retinopathy. IET Image Processing, 18(3), pp.807-828.
18. Saranya, P. and Umamaheswari, K.M., 2024. Detection of exudates from retinal images for non-proliferative diabetic retinopathy detection using deep learning model. Multimedia Tools and Applications, 83(17), pp.52253-52273.
19. Baba, S.M., Bala, I., Dhiman, G., Sharma, A. and Viriyasitavat, W., 2024. Automated diabetic retinopathy severity grading using novel DR-ResNet+ deep learning model. Multimedia Tools and Applications, pp.1-43.
20. Mishra, R., Satpathy, R., Pati, B., Mohapatra, D., Mishra, P. and Palai, G., 2024. DIABETIC RETINOPATHY IMAGE CLASSIFICATION AND BLIND-NESS DETECTION USING DEEP LEARNING TECHNIQUES. Machine Intelligence Research, 18(1), pp.1056-1077.
21. Lim, W.X. and Chen, Z., 2024. Enhancing deep learning pre-trained networks on diabetic retinopathy fundus photographs with SLIC-G. Medical & Biological Engineering & Computing, pp.1-13.
22. Sagvekar, V., Joshi, M., Ramakrishnan, M. and Dudani, A., 2024. Hybrid hunter-prey ladybug beetle optimization enabled deep learning for diabetic retinopathy classification. Biomedical Signal Processing and Control, 95, p.106346.
23. Bhulakshmi, D. and Rajput, D.S., 2024. A systematic review on diabetic retinopathy detection and classification based on deep learning techniques using fundus images. PeerJ Computer Science, 10, p.e1947.
24. Shamrat, F.J.M., Shakil, R., Akter, B., Ahmed, M.Z., Ahmed, K., Bui, F.M. and Moni, M.A., 2024. An advanced deep neural network for fundus image analysis and enhancing diabetic retinopathy detection. Healthcare Analytics, 5, p.100303.
25. Shoaib, M.R., Emara, H.M., Zhao, J., El-Shafai, W., Soliman, N.F., Mubarak, A.S., Omer, O.A., Abd El-Samie, F.E. and Esmaiel, H., 2024. Deep learning innovations in diagnosing diabetic retinopathy: The potential of transfer learning and the DiaCNN model. Computers in Biology and Medicine, 169, p.107834.
26. Bodapati, J.D. and Balaji, B.B., 2024. Self-adaptive stacking ensemble approach with attention based deep neural network models for diabetic retinopathy severity prediction. Multimedia Tools and Applications, 83(1), pp.1083-1102.
27. Li, X., Wen, X., Shang, X., Liu, J., Zhang, L., Cui, Y., Luo, X., Zhang, G., Xie, J., Huang, T. and Chen, Z., 2024. Identification of diabetic retinopathy classification using machine learning algorithms on clinical data and optical coherence tomography angiography. Eye, pp.1-9.
28. Indian Diabetic Retinopathy Image Dataset (IDRID) available at, "https://ieee-dataport.org/open-access/indian-diabetic-retinopathy-image-dataset-idrid", accessed on September 2024.
29. Badrinarayanan, V., Kendall, A. and Cipolla, R., "Segnet: A deep convolutional encoder-decoder architecture for image segmentation", IEEE transactions on pattern analysis and machine intelligence, vol.39, no.12, pp.2481-2495, 2017.
30. Renjit, A., "DeepJoint segmentation for the classification of severity-levels of glioma tumour using multimodal MRI images", IET Image Processing, vol.14, no.11, pp.2541-2552, 2020.
31. Baghel, J. and Jain, P., "K-means segmentation method for automatic leaf disease detection", Int. J. Eng. Res. Appl, vol.6, no.3, pp.83-86, 2016.