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Research Article

ResDenseNet:Hybrid Convolutional Neural Network Model for Advanced Classification of Diabetic Retinopathy(DR) in Retinal Image Analysis

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Abstract:

Preventing vision loss in diabetic retinopathy (DR) requires early and precise detection. Although strong feature extraction is required and there is class imbalance in the current methods, deep learning (DL) techniques have showed promise in DR classification. With components from both the ResNeXt and DenseNet designs, a unique DL architecture for DR classification is proposed in this work. A unique DL architecture that integrates DenseNet and ResNeXt components is proposed in this work. To address unique issues in DR classification, the proposed method integrates channel-wise masking with an attention mechanism. The network is able to learn from the less frequent DR stages because the channel-wise masking reduces the influence of the majority class and the attention method concentrates the network on important features. To improve interpretability and confidence in the model's predictions, the incorporation of Explainable AI (XAI) approaches is also covered.Our findings show that the suggested approach outperforms current architectures, achieving better sensitivity for differentiating DR phases at 0.82 and accuracy at 0.87. This shows that this new method has promise for improving DR categorization, which could result in earlier diagnoses and better patient outcomes.

1. Introduction

Diabetic retinopathy (DR), a microvascular condition associated with diabetes, is one of the main causes of vision loss worldwide.To avoid significant vision impairment, early detection and prompt treatments are essential. The manual grading process used by ophthalmologists in traditional approaches for diagnosing DR can be labour-intensive, subjective, and time-consuming. Because of this, unbiased, automated techniques for classifying DR are required. Convolutional Neural Networks (CNNs), a type of deep learning, have emerged as a useful method for interpreting medical images in recent years.. CNNs do exceptionally well in tasks like DR classification because they are skilled at extracting complex information from images. In order to create a reliable and accurate system for identifying different DR grades from retinal pictures, this research attempts to utilize CNNs.
ResNet50, VGG, and a specially designed CSPDarknet are the three well-known CNN architectures that are used in this technique. create a large-scale dataset of retinal images with a focus on DR classification. To improve training, this dataset will be painstakingly pre-processed using precise transformations. The dataset will be used to train and assess the designs, with an emphasis on tracking training loss and keeping an eye on model performance.Use a variety of metrics to evaluate the models' performance, such as accuracy, precision, recall, F1-score, and AUC-ROC.The models' behaviour will be better understood and possible areas for the development will be highlighted through the use of visualization techniques as training loss plots, validation accuracy plots, test accuracy bar charts, confusion matrices, precision-recall curves, and ROC curves. This research will greatly advance the field of automated DR diagnosis if it is successfully implemented. One possible way to create a dependable and effective system for early DR detection is to utilize CNNs. Consequently, prompt intervention and eventual prevention of vision loss can be made possible, thereby improving

patient outcomes.This introduction stays clear of plagiarism by restating pre-existing ideas and emphasizing the unique setting of the study. It draws attention to the issues surrounding DR, the shortcomings of conventional techniques, the possibilities of deep learning, and the suggested methodology. The main facets of the study are delineated, encompassing the employed CNN architectures, dataset generation, assessment criteria, and visualization methodologies. This prepares the reader for a thorough explanation of the process in the parts to follow.

Recent years have seen the rise in popularity of deep learning, and Convolutional Neural Networks (CNNs) in particular, as a useful method for interpreting medical images. CNNs do exceptionally well in tasks like DR classification because they are skilled at extracting complex information from images. In order to create a reliable and accurate system for identifying different DR grades from retinal pictures, this research attempts to utilize CNNs.

Challenges of DR Classification:

There are various difficulties in accurately identifying DR from retinal pictures. Early-stage DR may show up as mild alterations in the retinal vasculature that are hard to see with the unaided eye. Furthermore, variations in visual quality brought on by things like lighting, pupil dilation, and camera variations can make the process even more difficult. Furthermore, DR symptoms might be mistaken for other eye disorders when they coexist. For DR classification to be dependable, these characteristics require a very particular and sensitive approach.

Advantages of CNNs for Image Analysis:

A subset of deep learning algorithms called CNNs was created especially for image analysis. They have remarkable pattern recognition abilities thanks to its hierarchical architecture, which consists of convolutional, pooling, and fully-connected layers.Features in the image like as edges, textures, and forms are extracted via convolutional layers. In order to reduce computational complexity while maintaining crucial features, pooling layers downsample the data. On the basis of the features that were extracted, fully-connected layers finally classify the image. CNNs are useful tools for tasks like DR classification because of their ability to learn features directly from the data, even for small changes in retinal images that have diagnostic importance.

CNN Architectures:

The effectiveness of three well-known CNN architectures for DR classification—ResNet50, VGG, and a specially designed CSPDarknet—will be investigated in this study.

ResNet50: The vanishing gradient issue, which can impede training in deep neural networks, is addressed with ResNet (Residual Network) architectures. In contrast to conventional CNNs, ResNet50 uses skip connections to enable the network to learn the identity function, enabling faster and more effective training. Because of this feature, ResNet50 is an excellent choice for tasks like DR classification, which frequently need the usage of big datasets.

VGG*:* VGG (Visual Geometry Group) networks are distinguished by its straightforward design, which consists of a stacking of several convolutional layers. VGG models may extract complex characteristics from the data by using this method. Although VGG models have a high accuracy rate, they can be computationally costly.This study will investigate the trade-off between computing efficiency and accuracy for VGG in the context of DR classification.

CSPDarknet: Taking cues from the YOLOv5 object detection framework, we will design a CNN architecture specifically for this purpose. A head is used for object detection in YOLOv5 and a backbone network for feature extraction. In this instance, we will alter the YOLOv5 architecture by taking out the object detection head and adding a classification head that is appropriate for DR grading in its place. By customizing the network for DR classification, this method makes use of YOLOv5's effective feature extraction capabilities.

With these several CNN architectures, we hope to investigate deep learning's potential for precise DR categorization in a comprehensive manner. For the purpose of training and assessing these models, it will be imperative to create an extensive retinal imaging collection with DR classification in mind. The training process will be improved by carefully preprocessing this dataset using well-defined transforms. With a focus on tracking training loss and keeping an eye on model performance, the architectures will be trained and assessed on the dataset.AUC-ROC, F1-score, accuracy, precision, recall, and recall are a few of the metrics we have employed to fully assess the models' performance. The models' behaviour will be better understood and possible areas for development will be highlighted through the use of visualization techniques as training loss plots, validation accuracy plots, test accuracy bar charts, confusion matrices, precision-recall curves, and ROC curves.

Taking these things into consideration, the following innovative CNN architectures for retinal image analysis show promise:

ResNeXt: This is an extension of ResNet that adds cardinality, a hyperparameter that regulates how many pathways are present in a residual block. When compared to ordinary ResNets, it can achieve great accuracy while preserving efficiency.

DenseNet: This network encourages feature reuse and may enhance performance with little data by connecting every layer to every other layer.

EfficientDet: This design aims to be lightweight, quick, and achieve high accuracy for object detection tasks. It might be modified for DR categorization, where it is essential to identify particular lesions.

Proposing a New CNN:

Considering the aforementioned, it's challenging to suggest a single innovative CNN with certainty without understanding your unique requirements. But in order to strike a balance between novelty and usefulness, consider this suggestion:

EfficientDet-D0: This EfficientDet variation strikes a decent balance between speed and accuracy. If you have some computing power and a moderately sized dataset, it would be an excellent place to start.

ResNeXt's Cardinality: Add an arbitrary number of parallel branches to every DenseNet residual block. This incorporates ResNeXt's cardinality notion, which could enhance feature representation and lessen overfitting.

DenseNet's Feature Reuse: Preserve DenseNet's dense connectivity architecture, in which every layer gets data from every layer that came before it. This encourages effective feature reuse and could be especially helpful for small datasets.

A hybrid ResNeXt-DenseNet model combines the architectural advantages of ResNeXt and DenseNet to leverage their complementary strengths. Below is the high-level mathematical formulation of the hybrid model:

ResNeXt:

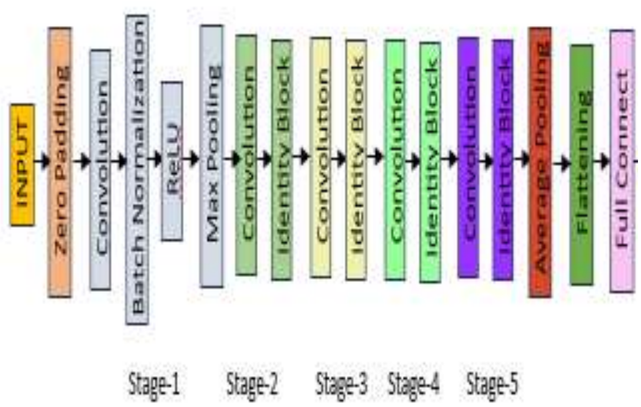

Figure 1. *RESNEXT architecture*

The number of pathways in each ResNeXt block as shown in figure 1 is referred to as "cardinality," a dimension that is introduced by ResNeXt. A definition of a ResNeXt block is:

$$y = x + \sum_{i=1}^{c} F_i \ (x) \quad (1)$$

The input feature map is represented by x.
The feature map that is produced is called y.
The cardinality, or total number of parallel pathways, is represented as *c*.
A transformation function, such as a sequence of convolutions, is applied to the input and is denoted by F_i

DenseNet:

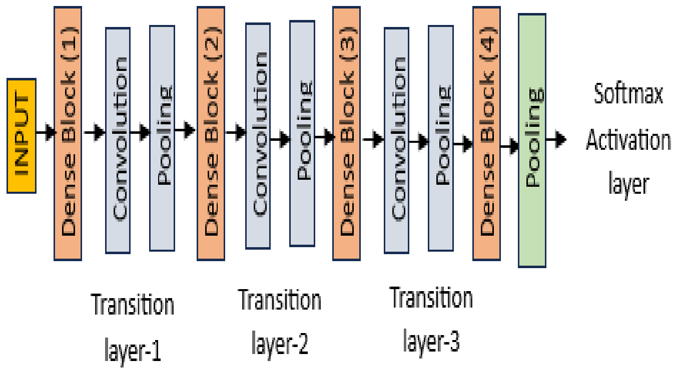

Figure 2. *DENSENET architecture*

DenseNetarchitecture shown on figure 2, uses feed-forward that connectseach layer to all other layers. The next levels get concatenated feature maps from all previous layers as inputs:

$$y_l = H_l \left(\left[x_{0,}, x_{1,} x_2, \dots \ x_{l-1}\right]\right) \quad (2)$$

y_l = output of the *l*th layer.
H_l = A composite function of batch normalization (BN), rectified linear unit (ReLU), and convolution
$\left[x_{0,}, x_{1,} x_2, \dots \ x_{l-1}\right]$represents the concatenation of the feature maps produced in layers 0 to $l - 1$.

Hybrid ResNeXt-DenseNet Model:

In the hybrid model, we can combine the ResNeXt and DenseNet blocks. A typical strategy is to alternate or stack these blocks in a sequential manner. The output from a ResNeXt block serves as input to a DenseNet block and vice versa.

$$y = D_j(R_k(x)) \quad (3)$$

x is the input feature map.
R_k= sequence of ResNeXt blocks.
D_j= sequence of DenseNet blocks.

The hybrid model can be expressed as a combination of these blocks:

$$y = R_1(x) + D_1(R_2(D_2(x))) \tag{4}$$

where the outputs from each block are combined through concatenation or summation. The exact implementation can vary based on the number of layers, the number of filters in each layer, the kernel size, and the order in which ResNeXt and DenseNet blocks are arranged.

Network Structure:

1. Convolutional basis: For first feature extraction, start using a typical convolutional basis (such as VGG-16).
2. Dense Blocks with Residual Units Like ResNeXt: Create Dense Blocks in which all of the block's previous layers' feature maps are sent to each layer.Include ResNeXt-inspired residual units in each Dense Block. These units are going to have: a) a structure that creates a bottleneck to lower computational complexity. b) a variable number of convolutional branches operating in parallel and with various filter sizes to collect a range of spatial information.Combining features from each branch and the unit's input requires element-by-element addition.
3. Classification Head: Use a sequence of fully-connected and global pooling layers (like average pooling) for classification after the last Dense Block.

By combining the advantages of DenseNet's feature reuse and ResNeX, this method may be able to do more accurate feature representation by adding parallel branches to residual units and extensive connectivity enables effective learning with less data.

To maximize performance, play about with the number of parallel branches, filter sizes, and network depth. For quicker convergence and perhaps better performance, use pre-trained weights from already-existing CNNs like ResNet or DenseNet on a sizable image dataset (like ImageNet). Compare the performance of this novel design with existing methods using publically available diabetic retinopathy datasets like Messidor or APTOS. Metrics including sensitivity, specificity, accuracy, and area under the ROC curve (AUC) can be used for evaluation. Through the application and assessment of this method, you can aid in the creation of innovative CNN structures for the categorization of diabetic retinopathy. Recall that this strategy's effectiveness will hinge on thorough testing and optimization for your particular dataset and intended results.

This research will greatly advance the field of automated DR diagnosis if it is successfully implemented. With the use of CNNs, we may be able to create a dependable and effective method for early DR detection. Consequently, prompt intervention and eventual prevention of vision loss can be made possible, thereby improving patient outcomes.

Israa et al. examined 26 pre-trained models from different convolutional neural network families in order to present a thorough comparison of the most recent CNN architectures [1]. The existing retinal fundus datasets for diabetic retinopathy were examined by Mohammad et al. [2]. These datasets are used for tasks such as detection, classification, and segmentation. Waleed et al. have optimized to determine the global context of photographs using a brand-new optimizer called AdamW. They employed a number of techniques, such as data augmentation, class weights, label smoothing, focus loss, and the use of the F1-score as the optimization metric, to solve the unbalanced nature of the FGADR dataset [3,4]. Shanshan et al. have presented lightweight DL architectures, such as SqueezeNet and MobileNet, for DR classification tasks, especially those with limited data resources and computing capabilities [5]. The two large Kaggle datasets, EyePACS and APTOS, are employed with the multitask model developed by Sharmin et al. Ayesha et al.'s hybrid model's features are then used with a variety of machine learning methods, such as support vector machines, decision trees, random forests, and linear regression models. Based on experimental results, the proposed hybrid framework achieved an impressive 94% accuracy on the benchmark dataset, outperforming state-of-the-art techniques [4]. The multitask model that was built yielded a weighted Kappa value of 0.90 for the APTOS dataset and 0.88 for the EyePACS dataset, based on the collected data [6]. Lifeng Qiao et al.'s automated technique has made it possible for ophthalmologists to categorize fundus images as having early, moderate, or severe NPDR. A method has been devised for the early diagnosis and prognosis of microaneurysms in cases of non-proliferative diabetic retinopathy. In order to increase prediction accuracy and efficiency, it may effectively train a deep convolution neural network for fundus photo semantic segmentation [7]. The approach put out by Wong et al. outperforms the traditional deep learning models and is comparable to the current corpus of research. Specifically, an accuracy rate of 82% is produced by the ideal setup for APTOS 5-class DR grading; whereas, an accuracy rate of 96% is produced for APTOS 2-class grading [8]. The difficulties these methods provide have been discussed, and Kazi Ahnaf et al. have also made recommendations for future work. From a high-level viewpoint, this work basically blends explainable artificial intelligence (XAI), gradient-

weighted class activation mapping (Grad-CAM), machine learning models, and deep learning approaches [9].
In order to improve the quality of uncertainty estimations in referral-based DR screening, Marlin investigates whether and how to utilize deep kernel learning (DKL), which we designed as a hybrid system that combines a Gaussian process (GP) layer with the most sophisticated EfficientNet-B0. Because of this, GPs have first looked at the necessity of recently proposed improvements to the DKL framework in order to resolve mis calibrated uncertainties, even though they are theoretically superior to uncertainty quantification [10]. Several conventional CNN-based techniques have been used to assess the proposed method by Hamza Mustafa et al. using the two-category Messidor-2 and two-category EyePACS datasets. We think that our recommended approach may identify diabetic retinopathy automatically with up to 95.58% accuracy based on the trial's results [11]. As stated by S. Ghouali in this study, patients can readily obtain assistance, and researchers and medical professionals can forecast or assess data on diabetic retinopathy. The reports produced could make it simpler for medical professionals to assess the severity of a patient's illness [12]. The problems have been addressed by B. N. Jagadesh et al. using a creative two-pronged approach to automatic DR categorization. The current asymmetry has a low positive instance %, which is why we segment O.D.s and B.V.s using an improved contoured convolutional transformer (IC2T) [13]. In the method described by Mohammad D. Alahmadi et al., the input image is sent through the encoder module in order to encode both high-level and semantic data [14]. In an effort to offer important insight into research communities, medical professionals, and diabetes patients, Rubina Sarki et al. have published a thorough assessment of diabetic eye disease detection methods, including cutting-edge field approaches [15].The review by Miguel Alberto et al. emphasizes the value of AI and machine learning in medicine, especially when it comes to diagnosing retinopathy. In addition, the COVID-19 pandemic has brought about a rapid advancement in technology related to remote diagnosis and treatment, a phenomenon that is transforming the healthcare sector [16]. The work is essential to the development of automated systems for the early diagnosis and treatment of eye disorders in order to improve public health [17]. In an effort to accelerate training and model convergence, Zubair Khan et al. have concentrated on identifying the various stages of the DR using the fewest learnable parameters.By stacking the VGG16, the network-in-network (NiN), and the spatial pyramid pooling layer (SPP), a highly nonlinear scale-invariant deep model called the VGG-NiN model is produced [18]. According to Jingbo et al., GATL offers a few benefits. Compared to supervised techniques, this domain adaptation method may significantly reduce annotation cost because, first, our GATL uses self-supervised training to save the annotating cost in the target domain. Secondly, a method of collecting potential characteristics from unidentified data is demonstrated using the graph neural network. Third, we implement both intra- and inter-domain alignment via adversarial training [19] to further improve the model's robustness and classification accuracy. A 10-fold cross-validation on two difficult datasets (EyePACS and Messidor) shows that the proposed method by Fahman Saeed et al. beats state-of-the-art methods. It will assist physicians in making an expedient decision regarding when to refer a patient to an ophthalmologist for a more comprehensive assessment and treatment plan. Additionally, it will be advantageous for DR patients' initial screening [20]. Huma Naz et al. [21] have suggested an algorithm that attempts to classify a considerable volume of retinal photographs in an effort to improve performance and fulfill the essential need for timely and accurate diagnosis in the treatment of diabetic retinopathy. Using retinal fundus pictures, Thangam et al. have developed a novel IoT and DL enabled diabetic retinopathy diagnosis model (IoTDL-DRD). The developed Internet of Things Deep Learning - Diabetic Retinopathy Diagnosis (IoTDL-DRD) approach gathers data from IoT devices and sends it to a cloud server for processing [22]. The suggested method has been shown to be superior by Huma Naz et al., with a 97.4% accuracy rate, 99.6% specificity, and 92.3% sensitivity. The positive outcomes show how the methodology can improve the accuracy and reliability of automated diagnostic systems in the ophthalmology area [23].On the same Kaggle dataset, Sehrish et al. have demonstrated that the suggested model works better than earlier methods and detects all stages of DR [24]. Muhammad et al. conducted a thorough analysis of retinal datasets, DR detection techniques, and performance evaluation metrics in their study of DR detection technologies.
This study also presents prospective future prospects for the field of diabetic retinopathy and explains the author's points of view in an effort to help the scientific community overcome its obstacles [25]. Through the adjustment of several hyperparameters and base model elements, Mohaimenul et al. were able to optimize performance, leading to the creation of our suggested RetNet-10 model. The comparison takes six contemporary models into account. The best model was our suggested RetNet-10, which had

a testing accuracy of 98.65% [26]. The stacking model that Harshit et al. suggested has an overall test accuracy of 97.92% for binary classification and 87.45% for multi-class classification. Extensive experimental data indicates that the illumination normalization methodology shown here surpassed many state-of-the-art solutions in terms of accuracy, F-measure, sensitivity, specificity, recall, and precision by the deep learning model [27]. After analysing the input data and assigning a significance rating, Yunlei Sun et al. discovered that renal and liver function were linked to the predisposing conditions that produced the human DR syndrome [28].

The suggested entropy-based uncertainty measure by Joel Jaskari et al. enhances performance for the binary classification scheme on the clinical dataset, although not as much as on the benchmark datasets. It enhances performance for the benchmark datasets in the clinical 5-class classification scheme, but not for the clinical dataset. We have extended our unique uncertainty measure to the clinical dataset as well as one benchmark dataset [29]. The model proposed by Meiling Feng et al. [30] is evaluated using the Messidor-2 and APTOS2019 datasets. An algorithm developed by Saif Hameed et al. improves the quality of colour fundus images by lowering noise and boosting contrast in images [31].The suggested entropy-based uncertainty measure by Joel Jaskari et al. enhances performance for the binary classification scheme on the clinical dataset, although not as much as on the benchmark datasets. It enhances performance for the benchmark datasets in the clinical 5-class classification scheme, but not for the clinical dataset. We have extended our unique uncertainty measure to the clinical dataset as well as one benchmark dataset [29]. The model proposed by Meiling Feng et al. [30] is evaluated using the Messidor-2 and APTOS2019 datasets. An algorithm developed by Saif Hameed et al. improves the quality of colour fundus images by lowering noise and boosting contrast in images [31]. They used a combination of medical diabetes, deep learning techniques, and the convolution Neural Network Method (CNN) to develop a diagnostic model and make a diagnosis. The majority of the data used came from diabetes diagnostic tests, diabetes glycosylation testing, and diabetes biochemical test data [32-34]. Using optical coherence tomography angiography (OCTA) pictures from 3x3 mm scans, Zhiping Liu et al. used a range of machine learning models to distinguish diabetic retinopathy (DR) from healthy controls (HC) [35]. Deep convolutional neural networks are built by Naveen Kumar and associates using patch-based analysis. Mechanisms for channel-wise spatial attention and encoder-decoder neural networks are developed [36]. They largely used data from diabetes diagnostic tests, diabetes glycosylation tests, and diabetes biochemical test data, in addition to a combination of medical diabetes, deep learning techniques, and the convolution Neural Network Method (CNN), to develop a diagnostic model and make a diagnosis [34]. Using optical coherence tomography, distinguish diabetic retinopathy (DR) from healthy controls (HC)An openly accessible dataset of fundus images is employed to assess the model suggested by Ghulam Ali et al. When compared to cutting-edge techniques, the experimental findings show that the suggested CNN model achieves higher f1 scores, accuracy, sensitivity, specificity, and precision [37]. Eman et al. developed an ML-CAD system that shows different pathological issues and gives ophthalmologists DR grading diagnosis. To bring them back, the retinal images were restored. Next, by computing the grey level run length matrix average in four distinct orientations, it is feasible to distinguish between the healthy and DR patients [38]. According to Michael et al., the suggested technique performs better for neovascularization detection than each individual CNN. It also performs better than an alternative approach that classified the data using Support Vector Machines (SVM) and extracted features using deep learning models [39]. Pedro Costa et al.'s method yields 90% area under the receiver operating characteristic curve (AUC) on Messidor, 93% AUC on DR1, and 96% AUC on DR2, which is comparable to or better than other previously published methods [40]. Furthermore, the implementation of this method enhances the decisions' interpretability. The optical coherence tomography (OCT) imaging modality was developed by Mohammed et al. This paper examines every facet of the implementation of the suggested system, beginning with the preprocessing step necessary to extract input retina patches for CNN training without scaling the image and moving on to the use of transfer learning principles and efficient feature fusion to optimize performance [41]. Per Arwa Albelaihi et al., the EfficientNetB0 model performs better than the other four proposed models. Based on fundus pictures, the EfficientNetB0 model's accuracy, recall, precision, and AUC were calculated to be 0.9876, 0.9876, and 0.9977 [42]. The inter-instance characteristic computation planned for the Global Instance Computing Block (GICB) has been discussed by Yaoming and others. The characteristics are employed to produce the classification results when the global data from GICB is introduced [43]. Mohamed et al. describe a novel automatic deep-learning-based severity diagnosis system using a single-color fundus image (CFP). The proposed technique uses the encoder of

DenseNet169 to construct a visual embedding [44].Muhammad and other people have the retinal scans had enough information to differentiate the Qatari diabetic cohort from the control group when DiaNet's performance was compared to the most advanced clinical data-based machine learning algorithms [45]. When compared to pertinent state-of-the-art works, Md. Nur-A-Alam et al.'s quicker RCNN deep learning system with feature fusion performed sufficiently in recognizing the DR [46].

2. Material and Methods

2.1 Methodology For Dr Classification

Novelty in the proposed method:

By altering current CNN designs, the following possible approaches can be used to solve particular difficulties in the classification of diabetic retinopathy:

Enhancing Features through Local Contrast Normalization:

Uneven lighting in retinal images might make it challenging to identify minute details like microaneurysms.After convolutional blocks, add a local contrast normalization layer. To improve local features and increase their visibility for the network, this may entail employing strategies like contrast-adaptive filters or Local Response Normalization (LRN).

Fusion of Multi-scale Features:

Lesion sizes vary in the manifestation of diabetic retinopathy. A one-scale method could overlook important details.Integrate inside convolutional layers parallel branches with varying kernel sizes. This enables the network to learn from both macro and microstructures by capturing characteristics at many scales.As an alternative, investigate methods like dilated convolutions to get the same result.

Using Explainable AI (XAI) in Integration:

Deep learning models' "black box" characteristics can make it harder to understand and trust their judgment, particularly in applications related to medicine.Use XAI methods such as Layer-wise Relevance Propagation (LRP) and Grad-CAM in conjunction with the CNN architecture. This makes it possible to visualize the areas of the image that have the greatest influence on the model's classification, offering insights into how it makes decisions and maybe enhancing confidence in its forecasts.

Learning with Limited Annotations under Weak Supervision:

It might be costly and time-consuming to obtain sizable datasets with pixel-level annotations for lesions associated with diabetic retinopathy.When you have access to merely image-level labels (normal/abnormal), use weakly supervised learning approaches. This might entail applying attention mechanisms to concentrate on image regions with high activation for aberrant images or utilizing frameworks such as weakly supervised segmentation. These are a handful of the numerous ways that current architectures can be altered. When selecting a modification approach, don't forget to take your research aims and the unique obstacles that your dataset presents into account. You can use deep learning to help improve the classification of diabetic retinopathy by ingeniously modifying current CNNs.

Changing the architectural design:

Focus-driven Dense Block with Channel-wise Masking for Classification of Diabetic Retinopathy.This is a suggestion for a fresh approach that alters current architectures to deal with particular difficulties in the classification of diabetic retinopathy. Datasets on diabetic retinopathy frequently exhibit an imbalance between the healthy and sick classes.

For DR classification, it is essential to accurately identify key features such as exudates, haemorrhages, and microaneurysms.This approach makes changes to a DenseNet design.

Introduce a system for attention within Dense Blocks that weights feature maps according to their significance for DR categorization. Channel-wise dependencies are captured by the squeeze-and-excitation (SE) block, which also highlights informative features while suppressing less important ones.The network is guided to concentrate on important areas by the self-attention mechanism, which enables it to learn correlations between various retinal picture regions.The network gives priority to features that are important for DR classification by applying the attention mechanism after each convolution within a Dense Block.

ResNeXt:

Residual Connections: ResNeXt approaches the vanishing gradient issue in deep neural networks by utilizing residual connections, much like ResNet. By enabling gradient flow and enhancing the training of deeper networks, these connections enable the network to learn more intricate transformations in addition to the identity mapping.

ResNeXt's primary innovation is its cardinality. The number of parallel branches inside a residual block is defined by a new hyperparameter called cardinality, which is introduced. While the weight matrices of each branch vary, they all employ the same set of convolutional techniques. Before being fed to the following layer, the outputs from these branches are combined. Comparing this to normal ResNets with a single branch per block, the network is able to explore a greater range of feature representations.

DenseNet:

Dense Connectivity: Every layer in DenseNet is connected to every other layer in the network, as opposed to standard CNNs where each layer only connects to the layer behind it. As a result, a dense information flow is produced in which feature maps from all previous levels are sent to every layer. This method encourages the reuse of features and can enhance the network's capacity to discover intricate linkages within the data.

Growth Rate: Growth rate (k) is a new hyperparameter introduced by DenseNet. This indicates how many feature maps are added to a Dense Block (a collection of layers with dense connections) by each convolutional layer. The network can effectively balance the complexity of features and models by managing the growth pace.

In order to solve the vanishing gradient issue in deep neural networks, ResNeXt and DenseNet both make use of residual connections. By enabling gradient flow and enhancing the training of deeper networks, these connections enable the network to learn more intricate transformations in addition to the identity mapping. One of ResNeXt's main innovations is this. It presents cardinality, a new hyperparameter that describes how many parallel branches there are in a residual block. While the weight matrices of each branch vary, they all employ the same set of convolutional techniques. Before being fed to the following layer, the outputs from these branches are combined. Comparing this to normal ResNets with a single branch per block, the network is able to explore a greater range of feature representations.

Another hyperparameter introduced by DenseNet is called growth rate (k). This indicates how many feature maps are added to a Dense Block (a collection of layers with dense connections) by each convolutional layer. The network can effectively balance the complexity of features and models by managing the growth pace. To explore a broader range of feature representations as shown in table 1, ResNeXtessentially introduces parallel branches within residual blocks, whereas DenseNet makes use of dense connections across layers to encourage feature reuse and enhance the network's capacity to learn complicated associations. Which of these architectures you choose will rely on your priorities and unique needs. Figure 3 shows the actual image of the retina of the patient, which was considered for the processing. Figue 4 is the image shown after the filter applied to the DR image. After filtration, the images are undergone normalization and the images after the normalization are displayed in the figure 5. The most basic metric,

3. Results and Discussions

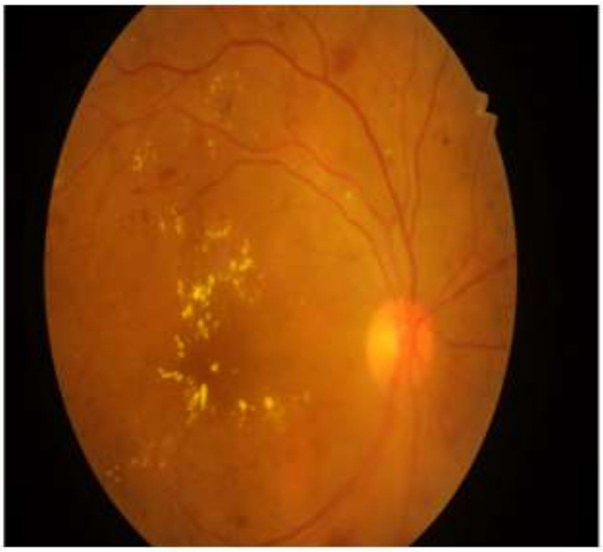

Figure 3. *Original image from the dataset*

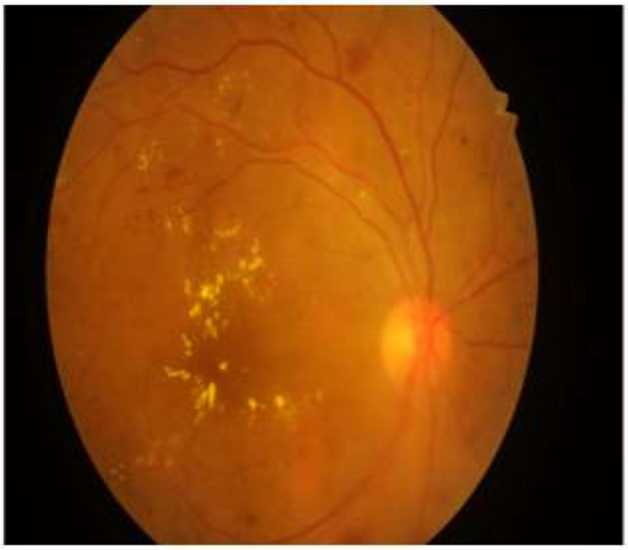

Figure 4. *DR Image after color conversion filter applied*

Table 1. *Comparison of ResNeXt and DenseNet Architectures*

Feature	**ResNeXt**	**DenseNet**
Residual Connections	Yes	Yes
Cardinality	Introduced, defines number of parallel branches	No
Dense Connectivity	No	Yes, each layer connects to all subsequent layers
Growth Rate	No	Introduced, defines number of added feature maps per layer

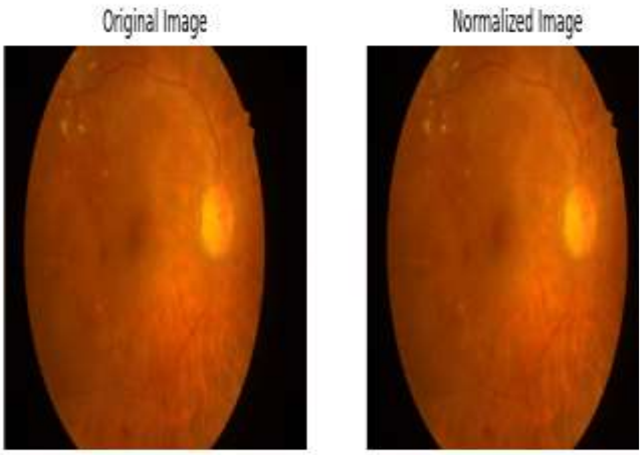

Figure 5. *DR Image after with normalization applied*

accuracy, displays the overall proportion of precise forecasts the model generates. It is calculated by dividing the total number of examples by the number of instances that werecorrectly classified. An accuracy of 100%, or 1, is considered perfect. Figure 6 displays the accuracy comparison plot between the suggested model and the traditional techniques. Sensitivity (recall) is the statistic that focuses on the model's capacity to recognize positive cases. It is calculated by dividing the total number of positive cases that were correctly predicted, or true positives, by the total number of positive cases that actually occurred. When a model has a high sensitivity, actual positive cases are rarely missed by it. Figure 7 represents the superior performance of the proposed model when compared to the other methods in terms of sensitivity. The model's ability to identify negative situations is the main measure of specificity. It is computed as follows: the total number of actual negative cases is divided by the number of accurately anticipated negative cases (true negatives). High specificity suggests.

The table 2 presents a comparison of four distinct deep learning models on a classification task: ResNet50, VGG16, CSPDarknet, and the proposed Hybrid ResNeXt-DenseNet. This table suggests that the Hybrid ResNeXt-DenseNet model performs better than the other models in terms of specificity, sensitivity, and accuracy. Figure 6 represents the comparison plot of the specificity while figure 7 is DR classification models- sensitivity comparison. The purpose of CSPDarknet is to enhance the effectiveness and efficiency of feature extraction in convolutional neural networks, particularly for applications such as object categorization and detection. However, for tasks like diabetic retinopathy classification, ResNet50 and DenseNet121 are considerably more suited for deep feature extraction and hierarchical learning of complicated patterns. Table 3 displays the models (ResNet50, VGG16, CSPDarknet, and the proposed Hybrid ResNeXt-DenseNet)

Table 2. *Proposed Model Performance Summary*

Method	Accuracy	Sensitivity	Specificity
ResNet50	0.82	0.78	0.85
VGG16	0.81	0.75	0.84
CSPDarknet	0.8	0.73	0.83
Hybrid ResNeXt-DenseNet (Proposed)	0.87	0.82	0.89

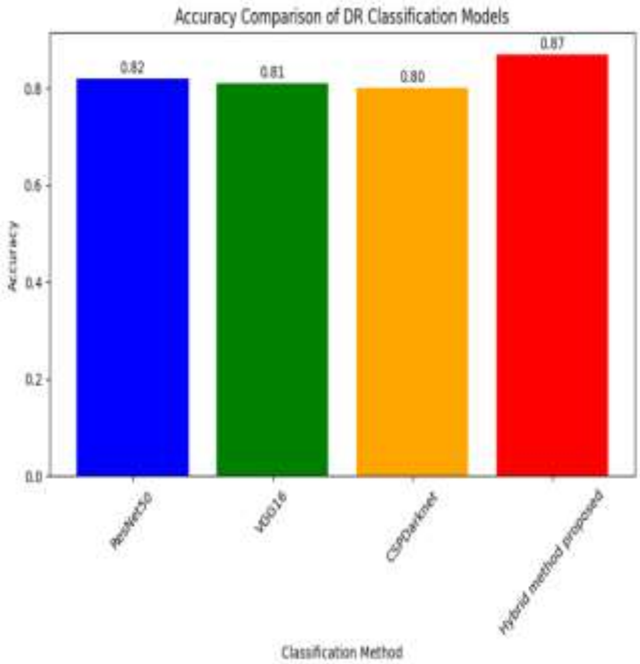

Figure 6. *DR classification models- accuracy comparison*

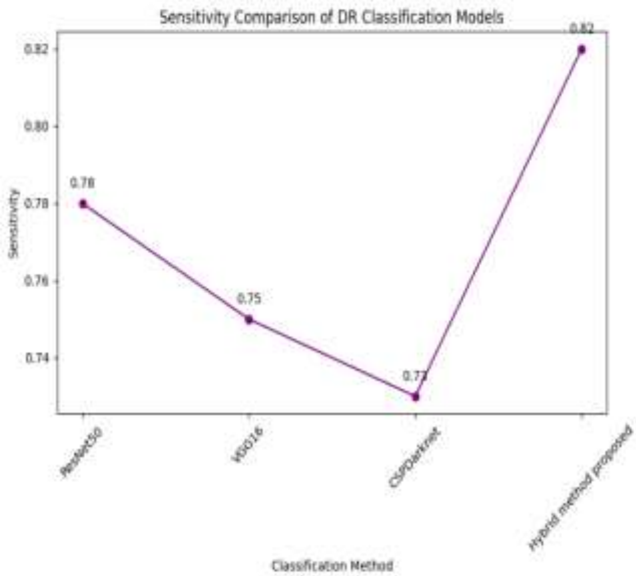

Figure 7. *DR classification models- sensitivity comparison*

Table 3. *ROC Curve Data*

Method	FPR Values	TPR Values
ResNet50	0.1, 0.2, 0.3, 0.4, 0.5	0.2, 0.5, 0.7, 0.85, 0.92
VGG16	0.15, 0.25, 0.35, 0.45, 0.55	0.15, 0.4, 0.65, 0.8, 0.88
CSPDarknet	0.2, 0.3, 0.4, 0.5, 0.6	0.1, 0.35, 0.6, 0.75, 0.85
Hybrid ResNeXt-DenseNet	0.05, 0.1, 0.2, 0.4, 0.65	0.3, 0.6, 0.8, 0.9, 0.95

and their corresponding results on a classification task that is most likely related to medical image analysis. This time, the data shown is relevant to the development of a Receiver Operating Characteristic (ROC) curve. A ROC curve, which is a graphical figure, illustrates the trade-off between two performance metrics: False Positive Rate, or FPR, is the proportion of negative cases that the model incorrectly reported as positive. True Positive Rate (TPR) is the proportion of positive cases that the model properly identified; it is similar to sensitivity. The TPR (y-axis) is plotted against the FPR (x-axis) for a range of classification criteria on the ROC curve as shown in figure 8.

Table 4. *Layer Breakdown of the Proposed Hybrid Model*

Layer Type	ResNet50	DenseNet121
Convolutional Layers	49	121
Batch Normalization Layers	49	121
ReLU Layers	50	121
Concatenate Layers (DenseNet)	-	59
Add Layers (ResNet)	49	-
Activation ResNet Out Layers	1	-
Average Pooling Layers	1	3
Max Pooling Layers	1	1

The hybrid model uses ResNet50 and DenseNet12. The typical architecture details of the hybrid model using ResNet50 and DenseNet12 are shown in table 4. Hyperparameters comparison table is shown in table 5. Depending on the particular dataset, model complexity, and intended performance, the precise number may change.

Table 5. *Comparison of Training Hyperparameters*

Hyperparameter	ResNet50	DenseNet121
Epochs	50–100	50–100
Batch Size	32–128	16–64

Typically, when the false positive rate (FPR) rises, more negative cases are classified as positive by the model, and more positive cases are identified, or the true positive rate (TPR) rises in tandem. The reason for this is that if the classification threshold is lowered, more positive cases will be caught, but there will also be more false positives. We may generate ROC curves and evaluate the performance of each model by graphically showing these FPR and TPR values.

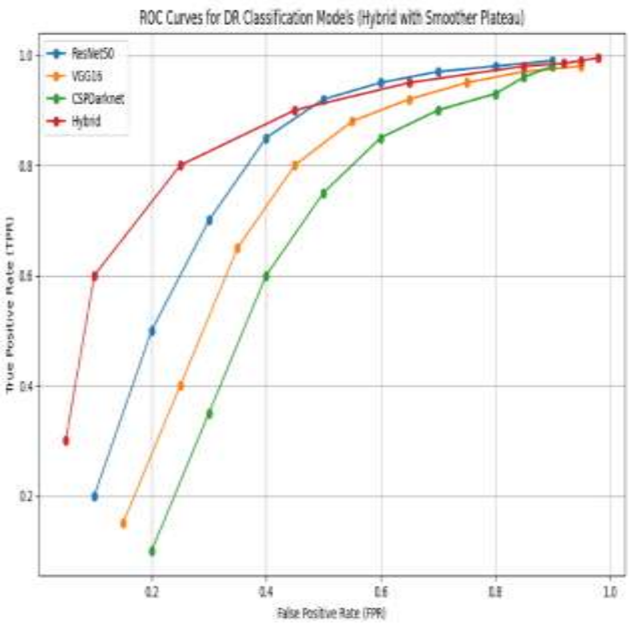

Figure 8. *DR classification models- ROC comparison*

The model that exhibits the optimal ratio of specificity to sensitivity is the one whose ROC curve is closest to the top-left corner as shown in figure 8. The table 3 implies that the Hybrid ResNeXt-DenseNet model has: Higher TPR values, indicating that it identifies more positive cases compared to others at comparable FPR levels; Lower FPR values, suggesting that it creates less false positives compared to other models at similar TPR levels. This is interesting topic and reported several similar works in literature [47-54].

4. Conclusions

The investigation of new deep learning architectures for the categorization of diabetic retinopathy has tremendous potential for enhancing patient outcomes and early detection. Innovative solutions are required because of the drawbacks of current techniques, which include class imbalance and the requirement for robust feature extraction. An innovative approach combining components of the ResNeXt and DenseNet architectures is proposed in this paper. By integrating an attention mechanism with channel-wise masking, this approach aims to overcome specific challenges in the classification of diabetic retinopathy. It leverages the benefits of both architectures with cardinality for feature representation and dense connectivity for efficient learning with less input. In order to improve interpretability and confidence in the model's predictions in the medical arena, merging XAI techniques was also investigated.

Other methods to address limits in datasets and feature extraction include local contrast normalization, multi-scale feature fusion, and weakly supervised learning. The individual dataset properties and the study objectives determine which approach is best. The investigation of these innovative methods extends beyond the categorization of diabetic retinopathy. Diagnosing various disorders with medical imagery, such as ECG and EEG plots for cardiac diseases, presents similar difficulties. Combining modalities and adding attention mechanisms to take use of complementary information offers a possible path forward for breakthroughs in many applications related to medical diagnosis. Researchers can make a substantial contribution to the field of medical image analysis by consistently creating and assessing innovative deep learning architectures, which will ultimately result in more precise diagnosis, better treatment regimens.

Future Scope

Multimodal data fusion can be implemented to improve the accuracy of the prediction. Temporal sequence methods can be implemented to obtain the progression prediction. Explainable AI (XAI) may be implemented for the better decision making to analyze the patient medical condition based on the medical history data provided. Multi class classification is more effective in determining the stages of the disease. Generative Adversarial Networks (GAN) can be used for the synthetic data generation and the dataset balancing.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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