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Research Article

Classification of diabetic retinopathy grades using CNN feature extraction to segment the lesions

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Abstract:

Diabetes's microvascular aftereffect, diabetic retinopathy (DR), is the primary cause of eyesight loss in the globe. In order to prevent vision impairment and to intervene promptly, early detection and precise classification of DR severity are essential. Using standard methods for diagnosing DR requires ophthalmologists to grade cases by hand, a process that can be laborious, subjective, and subject to observer error. In supervised learning task of classification, data instances are classified into predefined classes based on features. The relation between the traits and the classes can be found from the labelled data. After the training is completed, the classes of the unseen data. The frequent reason found for the loss of vision in diabetic retinopathy (DR) is found to be diabetes. Visual damage can be prevented by identifying the degree of DR at right time. For the grading of the DR, deep learning techniques are found to be very effective with maximum possible accuracy. The proposed model is useful in accurately classifying the DR images using the feature extraction with lesion segmentation, by implementing the patterns in the DR images. ReLU activation function is used in the proposed model. CNN feature extraction is used for the important feature extraction by applying the Convolution layers, and edges, textures, and forms are identified. As the model proceeds layer by layer, complicated patterns in the photos can be learned by the model, and can be analysed better. The features of the photos were extracted and found useful in segmentation and classification. ReLU is helpful in improving the convergence and also found useful in learning the patterns. Among the other activation functions, ReLU has higher computational efficiency and therefore is used in the model, which suits well for the DR application. A strong framework is proposed for the classification of the DR grade, for the lesion segmentation and CNN feature extraction. DR categorization using the proposed model is evaluated by data visualization of the important calculated metrics and found to be very effective.

1. Introduction

Abnormally high blood glucose levels are a hallmark of the metabolic disease known as diabetes mellitus (DM). Multiple forms of diabetes mellitus (DM) exist, including type 1, type 2, gestational diabetes, neonatal diabetes, maturity-onset diabetes of the young (MODY), and secondary causes resulting from the use of steroids, endocrinopathies, and other factors. Lesion: A damaged organ or tissue resulting from illness or injury. The retinal condition known as retinopathy. It can happen to a diabetic for a number of reasons. Some of these causes include extrusions, microaneurysms, and bleeding. Fluid buildup in the macula, the area in the middle of the retina, is known as macular edoema. Vision becomes blurry and distorted as a result of the macula swelling. Retinopathy is the cause of this fluid buildup; while blood bleeds, other fluids and lipids also spill out. The symptoms of the condition include partial or complete vision loss, floaters, distorted vision, and impaired vision as it advances. The first obvious sign of diabetic retinopathy is typically a microaneurysm. They show up in the retina posterior as little red dots that are dispersed. It is possible for them to be surrounded by a ring of firm, yellow fatty exudates. Although vascular leakage is the cause of exudates, the exact leaky microaneurysm may not always be visible during an ophthalmoscopic examination. The latest information supplied by Globally, 463 million individuals would have diabetes mellitus (DM) in 2019 and 700 million cases in 2045, according to projections made by the International Diabetes Federation (IDF). In working-age people, diabetic retinopathy—the main cause of preventable blindness in this population—is a common side effect of diabetes mellitus. Proliferative diabetic retinopathy, severe no proliferative diabetic retinopathy, and moderate neuropathy are the four stages of diabetic retinopathy that might present. Neurovascular problems can cause diabetic retinopathy and/or diabetic macular edoema (DME) in people with diabetes, whether of type 1 or type 2. After being diagnosed with diabetes, 25% of people developed no proliferative diabetic retinopathy (NPDR) five years later, 60% ten years later, and 80% fifteen years later, according to studies. These investigations showed that the incidence of proliferative diabetic retinopathy (PDR) ranged from 2.5% in individuals with diabetes for less than five years to 15.5% in those with the disease for fifteen years or longer. The study was conducted using a range of diabetic retinopathy levels and distinct retinal pictures. Mild DR is the term used to describe the disease's initial mild blood vessel changes in the eyes. In this situation, the patient might be able to fully recover and beat the illness. If the state of this disease is not controlled, moderate DR will develop. Blood vessel leaking may start at a moderate level of DR. In the second case, if the condition gets worse, it can become severe and proliferative DR, which could result in total blindness. Figure 1 depicts the four levels of DR's classification. In figure 2, the DME classification is displayed. Photographs of the back of the eye are called fundus images, sometimes referred to as retinal fundus photographs or fundus photos. Comprising the retina, optic disc, macula

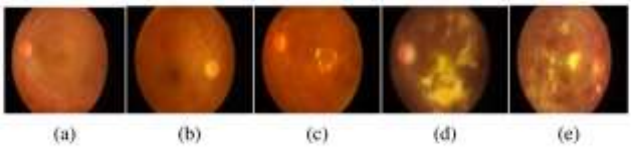

Figure 1. *Fundus picture classification DR-0, DR-1, DR-2, DR-3, and DR-4 are the available options*

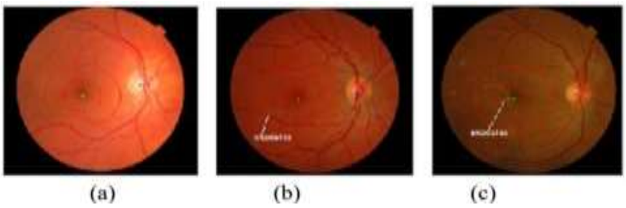

Figure 2 *Diabetic Macular Edema classifications: DME-0, DME-1, and DME-2*

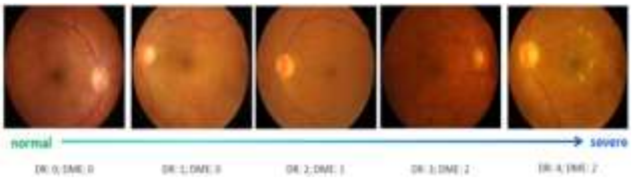

Figure 3. *Fundus pictures with varied pathological severity of joint DR and DME*

and blood vessels, the fundus of the eye is the internal surface of the eye located in opposition to the lens. Specialised cameras known as fundus cameras or retinal cameras are used to take fundus images. Glaucoma, age-related macular degeneration, diabetic retinopathy, and hypertension-related retinopathy are just a few of the disorders and diseases for which these images offer important diagnostic information. As a vital diagnostic and monitoring tool for eye problems, fundus imaging is used in ophthalmology. At an eye clinic in Nanded, Maharashtra, India, retina specialists take the fundus photographs. In figure 3, these pictures are displayed. Table1 shows the retinopathy severity levels based on the complication stage. The thin, light-sensitive membrane covering the retina is the rear of the eye, and blood vessels have an impact on it in diabetic retinopathy, a typical consequence after diabetes.

Table 1. *Retinopathy complication levels*

DR stage	Medical Observation	Complication	Level of Severity
Type0	Normal Retina	No Complication	No DR
Type1	The retina's tiny blood vessels have little bulges.	Microaneurysms	Non-proliferative mild DR
Type2	Blood vessels start to smell and deform.	spots, dots, haemorrhages, and micro-aneurysms	Mildly non-proliferative diabetes
Type 4	Development of atypical and delicate new blood vessels	Development of new blood vessels in the disc haemorrhage of the vitreous	Proliferant The DR

The retina's inadequate oxygenation is the cause of it. Blindness could result from it if untreated. Generally, blindness is avoidable if detected early and treated appropriately. Proliferative and non-proliferative retinal diseases are the two types of retinal diseases. In non-proliferative retinopathy, which is the less severe kind, the retina may have haemorrhages or bleeding, and there may be blood or serum leaks that result in a "wet retina." The result could be a reduction in vision. Proliferative retinopathy is the name for an extreme variation of diabetic retinopathy. An approach, as illustrated in figure 4, has been adopted by the proposed model to classify the various stages of the disease. New, aberrant, fragile vessels may develop from their surface on the retina and grow into the centre of the eye, as figure 5 illustrates.

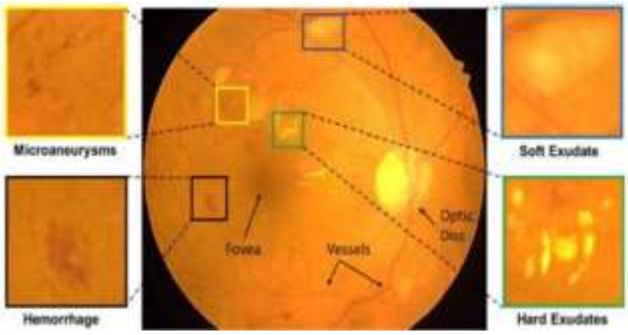

Figure 4. *DR and DME joint fundus images with varying pathogenic severity Representative and atypical retinal pictures*

2. Literature survey

Zhou et al.'s publication [1] provides a standard for the segmentation, grading, and transferability of research on diabetic retinopathy. This benchmark offers a thorough framework for assessing and improving methods in three crucial areas of analysis for diabetic retinopathy. Shaukat et al.'s study [2] suggests a three-dimensional semantic segmentation method for lesions associated with diabetic retinopathy. Their novel strategy, which incorporates a deep learning framework and makes use of transfer learning, has enormous potential for ophthalmic customized treatment. It focuses on precisely classifying and evaluating lesions associated with diabetic retinopathy. A novel ML-CAD (Machine Learning for Computer-Aided Diagnosis) approach for identifying various diabetic retinopathy grades was presented by researchers in a recent study. Numerous datasets have seen the successful application of this method. Furthermore, Sau and Bansal [3] suggested a novel approach that uses a modified deep neural network to assess diabetic retinopathy. To improve the precision and efficacy of diagnosis, their method segments blood vessels and retinal abnormalities. In the meantime, the UNIConv convolutional model from InceptionV3 was created especially for diabetic retinopathy management by using semantic segmentation in retinal fundus pictures. In 2022, Hualin Wang et al. have published a research paper that presented a new method for anomaly segmentation in retinal images. The methodology has used Poisson-blending data augmentation techniques for improving the model's ability to detect and classify the anomalies in the images [4-6]. Amin, Anjum, and Malik have suggested an unique methos for the classification of NPDR lesion using transfer learning model, DeepLabv3+and the equilibrium optimizer. By using the process of semantic segmentation, a very good feature selection process, the precision can be improved in terms of DR diagnosis and classification [7]. global transformer block (GTB)was observed to be more accurate in maintaining the information, proposed by the authors and found lesion patterns capturing algorithm [8]. Yunlong He et al have found a novel way of learning lesion segmentation with accuracy and disease diagnosis with better accuracy [9]. Spatial spectral matrix representation was proposed by the authors. Tao Li et al have proposed a novel technique for the diabetic retinopathy screening [10]. In-depth analysis of performance of different algorithms in their potential utility in the diagnosis was discussed in the research paper [11] by developing a global and local residual U-Net. Updated patches were used for the segmentation map collection for the improved weighted U-Net cascade structure. Segmenting arterioles and venules were derived from the retinal pictures were accomplished from the CNN methods [12]. DRIVE and STARE datasets were analysed using the U-Net and patch learning models A dense segmentation was used by the authors [13]. Instead of U-Net, D-net was used by the authors for the segmentation [14]. Multiscale information and the fusion model were developed, for different layers of classification. U-Net architecture with forwent max pooling for the convolution operation was proposed by the authors [15]. Max pooling-based U-Net was used to segment retinal arteries. The dual residual stream-based vessel segmentation network proposed by the authors have reduced the number of layers and the training parameters. Framework augmentation was proposed by the authors and suggested a two-stage novel relational mathematical graph technique for the pattern identification [16,17]. STARE, DRIVE, and HRF fundus images were used for the better classification by the users [18]. Gaussian match filter is used along with morphology-based global thresholding [19]. Morphy based approach is suggested by the authors for the filtering and conjunction with U-Net. Relative entropy thresholding with matched filter is used by the authors [20]. Heuristic image analysis, shape analysis and the edge detection were used by the authors for automatic blood vessel segmentation [21]. DCNN model was used by the authors for the DR classification [22].

Data collection and annotation techniques are first used to prepare the dataset. A median filter was also utilised as part of the preprocessing step of the data. Additionally, during the DR diagnosis process, the DCNN is used to classify the Normal, Moderate, Heavy, and Severe classes. Additionally, hospitals that offer web services to their patients employ this strategy. An innovative deep learning hybrid was proposed by the authors of [23] as a solution for the challenge of automatically identifying diabetic retinopathy. An Inception-ResNet-v2 that has already been trained is given a transfer learning application, and a custom block of CNN layers is layered on top to create the hybrid model. A unique automatic deep learning-based severity detection technique was presented by the authors in [24] using a single Colour Fundus image (CFP). A visual embedding is provided by the proposed method, which makes use of DenseNet169 encoder. Adding Convolutional Block Attention Module (CBAM) to the encoder's top layer enhances its discriminating ability even more. Authors of [25] introduced Deep Convolutional Neural Network (DCNN) architecture with 2 stages which can successfully divide DR into controls, moderate DR, and severe DR. Furthermore, severe DR was classified using a refined ResNet-50, while mild DR was classified using a refined ResNet-18. The proposal for DR grading in [26] called for a new fundus photo collection. First, how does this scale differ from the current ones, which primarily use pathological alterations in the retina to assign grades to fundus photos? Furthermore, the fundus image in accordance with its anomalies and the required treatment plan. In the end, the dataset served as the training set for several DCNN models designed to diagnose DR. For the five investigative levels of DR, the authors of [27] suggested a multitasking technique. Moreover, the future extracted by these two models and is framed as a multilayer perceptron network enabling the categorization of the five stages of distance learning. The authors of [28] proposed the Radon Transform and Supervised Learning for Automated Microaneurysms Detection in Retinal Images. The fundus picture input is initially pre-processed and categorised. Upon completion of the ONH and vessel segmentation procedures independently, two outputs are generated: the final ONH mask and the vessel segmentation. In the MA detection procedure, the final steps are Partitioning-Radon, SVM, Candidates, and Final MAs Detection. The authors of [29] suggested multifractal geometry for early identification of DR. The first step in the analysis of macular optical coherence tomography angiography (OCTA) images. Another is to automate the diagnosis process and hence increase accuracy by using a supervised machine learning technique like the Support Vector Machine (SVM) algorithm. At last, the accuracy of the categorization system has reached 98.5%. The authors in [30] reported a DR classification method based on a convolutional neural network (CNN). The retina picture dataset was provided by the Asia-Pacific Tele-Ophthalmology Society (APTOS), and CNN was first trained under three different circumstances. Additionally, imbalances caused by consecutive sampling are balanced out by under- and oversampling. In the end, the classification strategy of the suggested study needs to be applied clinically. The DR and DME were found by the authors in [31] using a network of specified convolutional filters with class-balanced cross-entropy loss. The IDRiD dataset was pre-processed using the Gabor filter in this approach as well. In [32], a neural symbolic learning concept combined with retinal eye fundus image segmentation is used to develop an Explain DR classification technique. However, the accuracy obtained with the IDRiD dataset was only approximately 61.9%. Using CNN-based recursively conditional gaussian for ordinal unsupervised domain adaptation, the authors of [33] carried out the joint DR-DME classification. Nevertheless, this approach had a larger computational complexity. The authors in [34] introduced an ensemble CNN (ECNN) model for distinguished DE and DME disorders classification. The max-voting method is also applied to ascertain the ultimate grade of abnormality in the retinal eye fundus images. In [35], breast cancer is categorized using the BACH-2018 dataset, whereas DME and DR are graded using the IDRiD dataset. Additionally introduced are pre-processed datasets and the enhanced DenseNet model. The joint DR-DME classification ISBI sub-challenge 2 was participated in by the AVSASVA model. However, this technique's incredibly low accuracy performance only allowed it to place fourth, with only 47.57% accuracy.

In order to propose a multi-CNN classification technique for DME risk categorization and DR grading, the authors in [36] used three different CNN models. A fusion technique is also applicable to unify the collected information and arrive at the final classification result. The authors of [37] created an ensemble-based system for assessing DME and DR using AlexNet plus a few hand-crafted (i.e., traditionally used analytical) characteristics. The accuracy performance obtained from the IDRiD dataset is compared with the ledger board placements from the ISBI challenge. The cross-disease attention network (CANet) model is utilised in [38,39] for combined DR-DME classification, using ResNet-50 architecture as a basis for feature extraction and CNN-based disease-dependent and disease-specific modules for deep feature extraction. For DME classification and DR grading, this approach makes use of feature blending and extraction blocks. Unfortunately, only 61.16% of the total accuracy of DR-DME was achieved by the classification accuracy. In order to classify individual DME, DR, and combination DR-DME from retinal eye fundus photos, [40] presents the DLCNN model with disease-specific and disease-dependent modules. Moreover, the modified grey-wolf optimizer with variable weights (MGWO-VW) is a perfect feature selection technique utilised to improve classification performance. The combined DR-DME was classified by the authors of [41] using a traditional image processing method called the two-dimensional Fourier-Bessel series expansion-based flexible analytic wavelet transform (2D-FBSE-FAWT). However, it hasn't been able to identify the subtle differences between certain DME and DR conditions. The authors of [42] established a structural relationship between the instances in a bag using multi-instance learning (MIL). The CenterNet model is presented in [43], which employs CNN for classification and DesnseNet-100 for feature extraction. CNN feature extraction model is also presented in [44-47]. Unfortunately, the lack of a feature selection procedure in this method results in a high computational complexity. In the work presented, first and foremost, preparation and data collection are crucial. To improve model performance, a dataset of retinal pictures labelled with varying DR grades must be gathered. By using the concepts of resizing, normalizing and augmentation the images were pre-processed. Pre-trained CNN model (ResNet or VGG) is used for the feature extraction from the retinal pictures for the effective classification. Efficient training and assessment classification model is implemented by splitting the data into training, validation and testing datasets. Data splitting is carried out using dropout regularization for the collected features. After the effective training is completed, assessment on the validation dataset can be carried out. Optimization and fine-tuning methods were implemented by using the concepts of increased learning rate and regularization methods. Classification of DR grading for the generalization of the assessment of the training model. The DR classification is performed more precisely by the proposed model and is proved to be effective in the early detection and grading.

3. Methodology for dr classification

Algorithm of the proposed model for CNN Feature Extraction to Classify Diabetic Retinopathy Grades:

Step1- Data Acquisition and Pre-processing:

Compile a dataset with retinal pictures that have been assigned varying degrees of DR. To improve model generality, preprocess the photos by resizing, normalizing, and enhancing them.

Step2- CNN Model Selection:

To extract features, use a CNN model that has already been trained. A few well-liked options are Inception, ResNet, and VGG. Just the feature extraction portion of the CNN should remain once the fully connected layers (top layers) are removed.

Step 3: Feature Extraction:

Utilize the chosen CNN model on the pre-processed images to extract features. To obtain meaningful representations, extract features from the final convolutional layer or any intermediate layer.

Step 4: Data Splitting:

To evaluate and train the classification model, separate the dataset into test, validation, and training sets. Training, validation, and testing should be conducted in the following order: 70-15-15.

Step 5: Classification Model Building:

Use the features that were extracted to create a classification model. When classifying, incorporate a few fully linked, dropout regularised layers. It is suggested for multi-class classification to use softmax activation in the output layer and ReLU activation in hidden layers.

Step 6: Model Training:

Make use of the training set to educate the categorization model. Adjust the model's parameters with methods such as Adam optimization or stochastic gradient descent (SGD). Track performance on the validation set and make any necessary hyperparameter adjustments.

Step 7: Model Evaluation:

Utilising the test set, assess how well the trained model performed. Calculate assessment parameters like F1-score, recall, accuracy, and precision. To comprehend the model's performance across various DR grades, examine the confusion matrix.

Step 8: Fine-tuning and Optimization:

Based on the findings of the evaluation, adjust the model's architecture and hyperparameters. Try varying CNN designs, learning rates, and regularization strategies to enhance performance.

Ordinal regression is often used in DR grading because it takes into account the ordered character of the DR grades. By calculating the cumulative likelihood that the true result falls into each category, ordinal regression models forecast the ordinal variables, such as the severity levels of DR. Tasks where the goal variable has a natural ordering, like the evolution of DR from moderate to severe stages, are appropriate for this methodology. Depending on the particular requirements of the work and the characteristics of the data, other regression approaches, such as logistic or linear regression, can also be modified for DR grading tasks. In the model implementation, Python code was used with several libraries. With capabilities for opening, modifying, and storing a variety of image formats, PIL (Python Imaging package) is a robust package for image processing tasks. For work involving numerical computing, Numpy is necessary since it offers effective mathematical functions and array operations. With features for object recognition, feature detection, and image and video processing, OpenCV (cv2) is a feature-rich computer vision library. By facilitating communication with the operating system, the of module makes file manipulation and directory operations possible. Deep learning model building is made easier using Keras' high-level neural network API. TensorFlow is a well-liked machine learning framework for effectively creating and optimizing neural networks. To improve code readability, hide warnings suppresses unneeded warning messages. Prior to the introduction of convolution in 1998 as a concept for digit classification, support vector machines, logistic regression, KNN, and other techniques were employed for picture classification. Pixel values were taken into consideration as characteristics in those algorithms. After the convolution layer uses information from nearby pixels to down-sample the image into features, prediction layers are utilized to estimate the target values.

A dot product is computed by applying multiple convolution filters, also known as kernels, over the image. The features that each filter takes from the image vary. Stride refers to a single pixel-wise kernel sliding. Various stride values can be used by the kernel to extract different types of characteristics. The convolutional layer computes a dot product between the filter weights and the input at each point by sliding a series of learnable filters, also called kernels, over the input image. This process aids in identifying regional patterns and characteristics. The max pooling layer reduces over-fitting and the spatial size of the features by providing an abstracted representation of the convolved features. This method of discretization relies on samples. It functions similarly to the convolution layer, with the exception that we compute the maximum of the input region that the kernel overlapped rather than the dot product between the input and the kernel. Following the convolution process, a rectified linear unit (ReLU) activation function is applied element-by-element to the convolutional output. By substituting zero for any negative value, ReLU adds non-linearity to the model.

The ReLU activation ($f(x) = \max(0, x)$) improves the model's mathematical capacity to understand intricate correlations and helps better capture detailed aspects in the data. The network can learn hierarchical features in a data-driven way thanks to the combination of ReLU activation and convolutional operations. The network is able to recognize and extract ever-more-abstract elements automatically as it moves through different levels. Through the use of activation functions to introduce non-linearity, the model is able to learn complex functional mappings between the response variables and inputs. Evaluate the performance of the trained model using the test set.

Compute evaluation metrics such as F1-score, recall, precision, and accuracy. Look at the confusion matrix to understand how the model performs for different DR grades. The spatial dimensions of the feature maps are often down sampled using the max pooling layer, which follows after the convolutional layer. The process of pooling entails choosing the maximum value among a range of nearby values. A 2x2 max pooling operation, for example, keeps the maximum value from a 2x2 grid and discards the remaining values. Memory management and the data processing by reducing the spatial dimensions of the data was found very effective with the max pooling.

Translation invariance that can increase the network resistance to any change in the object placement in an image is achieved by the pooling methods. Better learning by the CNN model using the convolution layers and ReLU activation functions can effectively retrieve the features of the hybrid model proposed. This causes a learning process to extract the very important features of the images. Image classification and the detection of object in an image is found to be very effective with the proposed model.

A) Convolution Method:

1. **Essential Building Elements:**

Residual blocks are the fundamental building components that make up ResNet. Each residual block typically contains two convolutional layers with Batch Normalization and ReLU activation functions. Shortcut connections (skip connections) are added to skip one or more layers, connecting the input directly to the output of the residual block.

2. **Identity Mapping:**

Recognizing the difference between a block's input and output—known as the residual mapping—is the central concept of ResNet. ResNet works by learning to fit the residual mapping, which is easier to optimize than fitting the intended underlying mapping directly.

3. **Residual Connections:**

There are residual connections introduced when one or more levels are skipped and a skip connection is created. Because of these connections, the vanishing gradient problem can be solved and very deep networks can be trained. Gradients can spread throughout the network.

4. **Architectures at Bottlenecks:**

In residual blocks, bottleneck topologies are frequently used by ResNet to lower computing complexity. With bottleneck designs, the number of input channels is first decreased via 1x1 convolutions, then increased via 3x3 convolutions, and finally the number of channels is restored through the use of 1x1 convolutions once more.

5. **Network Depth:**

With hundreds of layers in the most advanced versions, ResNet designs can be quite deep. Remaining links enable the training of deeper networks without experiencing vanishing gradients, hence enabling the deep network depth.

The numbers indicate the total number of layers in each architecture, and ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152 are some of the depths of ResNet architectures. Deeper variations often outperform more complex variants on demanding tasks, even though they require more RAM to train. Among the many computer vision applications where ResNet topologies have proven remarkably effective are segmentation, object recognition, and image categorization. They have generated innovative results and won several competitions on industry standard datasets such as ImageNet.

B) ReLu Method:

Step 1: Input Calculation

Start with the weighted sum of a neuron's inputs and weights:

$$z = w_1x_1 + w_2x_2 + \cdots w_nx_n + +b \qquad \text{--1}$$

where the number of inputs (n), the bias term (b), and the weights (w_i) of the inputs (xi).

Step 2: Apply ReLU Activation

The weighted total is subjected element-by-element to the ReLU activation function:

$$f(z) = \max(0, z) \qquad \text{--2}$$

f(z)= max(0,z) ; if z is positive, the output is z.
if z is negative, the output is 0.

Step 3: Output

The ReLU activation results in the neuron's output. This updated result is sent to the next layer of the neural network.

Step 4: Non-Linearity Introduction

Non-linearity is added to the model by the ReLU function. For the network to be able to recognize intricate patterns and correlations in the data, this is essential. In order to enable the network to simulate more complex properties and relationships in the data, rectification, setting negative values to zero is performed.

Benefits of ReLU:

ReLU is proved to be simple and effective especially in the image processing research and is becoming very popular compared to other activation functions. The simplicity of ReLU also has the advantage of faster training convergence. Deep neural networks frequently use ReLU in their hidden layers. Deep learning architectures are made possible by the computational efficiency and non-saturating nature of these patterns, which enable networks to learn and represent ever-more-complex patterns.

C) Stochastic gradient descent:

ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152 are the several depths of the ResNet designs, each indicated by a number that represents the total number of layers in the design. Though their training costs rise with system complexity, deeper variations often outperform on hard tasks. In several computer vision applications, ResNet topologies have shown impressive efficacy in segmentation, object recognition, and picture categorization. On the important and popular datasets, ResNet topologies were more effective comparatively. They perform iteration over the entire dataset for the preset number of epochs until the criteria set for the convolution gets satisfied. An effective optimizer, named Stochastic gradient descent is used for the update of the weights based on the retrieved gradients calculated on the mini batch training data. It is effectively used in neural networks and other optimization largescale data.

D) Output Layer:

The neural network proposed has an output layer for deciding the performance of the proposed model in terms of the categorization and grading of the DR images, for the early detection and estimation of the severity of the disease. It is generally found the number of DR classes and the number of neurons would match in the number. Every neuron in the output layer may adopt different activation function for obtaining the diversified DR grading, that depends on the task performed while the process of categorization.

4. Results and discussions

The dataset under consideration has 34247 pictures of different DR classes and severity. The testing dataset has 10274 randomly chosen photos. 10274 images were considered for the validation. The overall performance of the model is verified on the testing dataset while the overfit problem is specifically tested on the validation dataset. Every dataset used by a model is very important to do its task effectively. The ResNet CNN technique is used for the development and validation of the model. Robust performance is ensured by its capacity to successfully train deep networks, detect intricate patterns in retinal images, and reduce overfitting. ResNet's superior transfer learning and cutting-edge performance further improve its applicability for DR classification. By utilizing pre-trained ResNet models, generic image recognition tasks' expertise may be efficiently utilized, increasing the accuracy of DR grade diagnosis. ResNet is an effective method for accurate and dependable diabetic retinopathy (DR) classification, helping in early identification and treatment of the condition. Its strengths lie in feature extraction and classification. Every image was resized to a 50×50 pixel size and 250 filters were applied on each image. In the architecture of the proposed model, 3 hidden layers were implemented, with variable weights. ReLU activation algorithm is applied before the output layer. Figure 5 shows the comparisons between training accuracy and the validation dataset accuracy. The validation dataset id compared with respect to the testing dataset. To see the convergence and evaluate overfitting, the plot the training and validation loss curves over epochs is shown in figure 5. The training and validation accuracy curves should be plotted over epochs to track the model's capacity to learn and generalize, as shown in figure 5. To see how well the model performs in identifying various DR classes, create a confusion matrix. Consider factors like as memory, precision, and F1-score for each DR grade. Figure 6 displays the evaluation metrics. To evaluate the model's cross-class discrimination capability, plot the Receiver Operating Characteristic (ROC) Curve, as seen in figure 7. Calculating the area under the ROC curve (AUC) yielded an overall performance score of 0.6 for the classification.

During the classification procedure, the photos with the highest risk of stage-4 disease are found. The performance of these photos is assessed by comparing them with the truth table in the common separated file format. A small number of photos classified as high-risk diseases and stage 4 images are displayed in figure 8. In the process of classifying and grading, the images of the left and right eyes are separated.

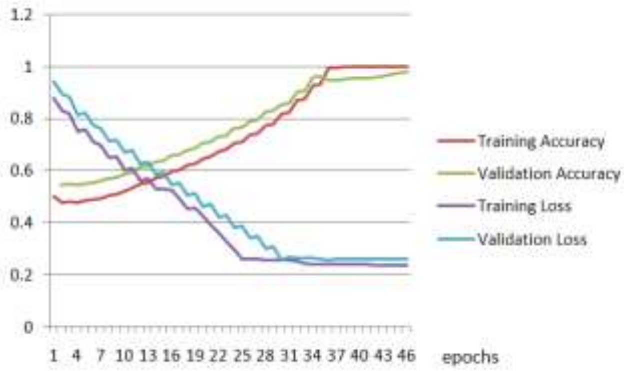

Figure 5. *Validation check for ResNet CNN technique implemented*

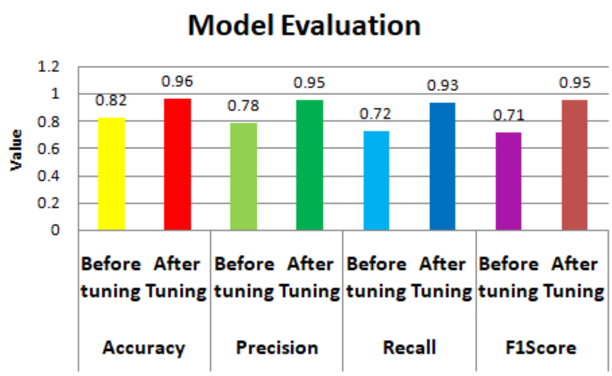

Figure 6. *Model evaluation metrics*

The images with highest risk and stage-4 disease are identified in the process of classification. These images are compared with the truth table in the common separated file format and the performance is evaluated. Figure 8 shows few images identified as high-risk disease and stage 4 images. While classification and grading, the left eye and the right eye images are separated to perform the classification. Identified common trends or issues the model faced by analysing the samples that were incorrectly or misclassified. Areas for more data collection or improvement are highlighted. Interesting trends in accuracy and loss metrics were observed during the training and validation phases of the diabetic retinopathy (DR) classification model. It was evident that the model could learn new skills from the training set as its training accuracy grew gradually over time. The model's

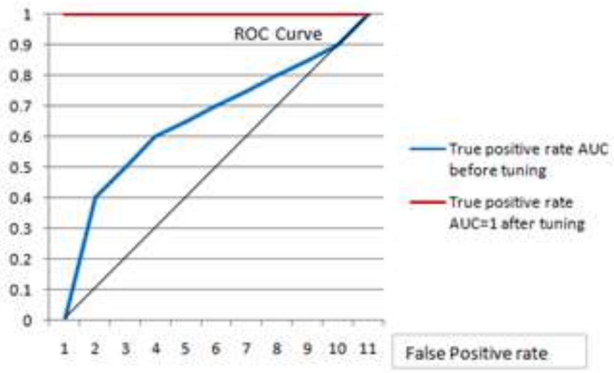

Figure 7. *The model's adjusted ROC curve*

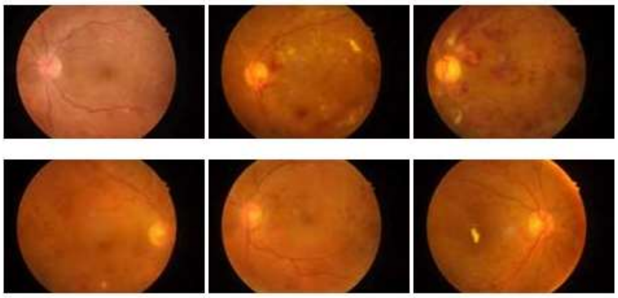

Figure 8 *Sample images with highest risk of Macular Edema*

performance on unseen data stagnated, however, and although the validation accuracy initially rose, it eventually plateaued, indicating possible overfitting. As a result of the model's increased capacity to reduce mistakes on the training set, training loss, on the other hand, continuously dropped over the course of the epochs. On an independent validation dataset, the strategies of regularization were implemented to address he problem of overfitting and underfitting. Much betterment to the proposed model can be obtained, by using the regularization and evaluation methods, using the hyper parameters, and generalization with the help large number of samples of DR clinical images. Assessment of the model is done using accuracy, precision, recall, and F1 score. High accuracy rate is observed and model is proved to effective in the DR classification and early detection. The classification of the DR images to very accurate and is shown in the result plots. The reduction of false positives is depicted by the precision and the actual positives were identified by the parameter known as recall. F1 score balances the recall and precision parameters and the DR grading diagnosis of the model is useful in the model. The diabetic retinopathy symptoms were found very effective in grading the DR images.

The ROC curve illustrates the discriminative power of the model; a higher AUC indicates better performance in the classification of diabetic retinopathy. Each image in the validation dataset is

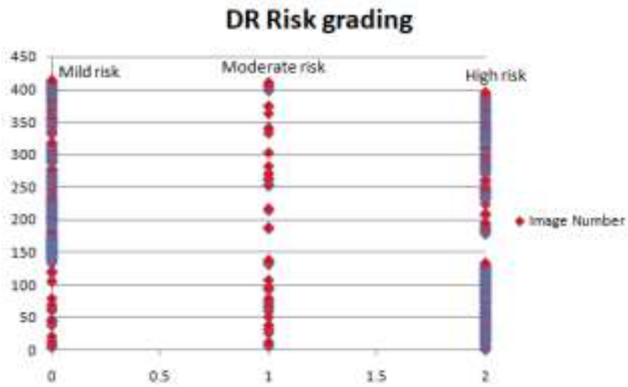

Figure 9. *DR risk grading for different severity of the disease*

tested for the severity of the disease being representing mild risk, 1 representing moderate risk and 2 representing high risk. After the classification, the validation dataset is tested with the labelled test dataset to check if the classification was correct or not. Figure 9 represents the graph plot for the expected grade of severity from the validation set and testing set, which exhibit the correlation. A critical first step in improving early identification and therapeutic options for this illness that can cause blindness is the creation of diabetic retinopathy (DR) classification models. Advances in deep learning and ordinal regression, two of the most advanced machine learning approaches, have made significant progress in accurately categorising DR severity levels and facilitating timely clinical interventions. Because of the remarkable improvements in model performance enabled by the integration of many datasets and sophisticated model architectures, robust predictions may be achieved even in the presence of complex retinal disorders. Ongoing research efforts and collaboration across interdisciplinary teams are nevertheless required due to persistent obstacles such dataset imbalance, model interpretability, and generalizability across varied populations. Furthermore, there is potential to expand the application of DR classification models to underprivileged groups and remote locations by the incorporation of innovative imaging modalities, real-time monitoring technologies, and telemedicine platforms. We can further support healthcare practitioners in their attempts to stop vision loss and enhance patient outcomes for people with diabetes mellitus by developing and improving DR categorization algorithms.

5. Conclusion

The risk of the macular edema of the Retinopathy grading is effective by the proposed model. The severity of the disease is found based on the trained proposed model. The accuracy of the model, loss, difference in the loss during the training process and validation performance are displayed in this section. ReLU is found very effective. Recurrent procedures were run to test the sample images to find the category of the images. The grading of the disease is done based on the classification done. Retinal pictures were examining to get the features of the images by obtaining the anomalies, problematic images, are used for the model classification patterns. The regions of the patterns were identified and the concentration was put on the efforts to put the images in correct classification for the better classification process. The quality and diversity of the training dataset, fine tuning, hyperparameter adjustment are done using the latest methods. We can increase the applicability of diabetic retinopathy (DR) classification models by integrating state-of-the-art imaging modalities, real-time monitoring tools, and telemedicine platforms. More broad use is made possible by this integration, even in rural and neglected communities. Preventing blindness and improving the quality of life for those with diabetes mellitus are the ultimate objectives. A key component of accomplishing this objective is creating precise DR classification algorithms. Dataset imbalance is one significant problem that impacts model performance at various DR severity levels. Despite their immense capacity, deep learning models frequently act like mysterious black boxes. They base their conclusions on intricate patterns discovered through a great deal of data, but it can be difficult to understand how they do it. To avoid these problems, the model evaluation curation of the dataset and the interpretability must be handled properly by the researchers. The DR classification can be improved with this process for the reliability and practicality. DR images with the clinical settings must use the latest technical tools for the correct detection and grading of the disease. DR categorization with advanced imaging techniques and ResNet CNN techniques is found to be very effective, and can be observed from the result plots. For the future scope, and to construct a complete diagnostic system, joining the CNN features with other imaging modalities (such angiography or OCT images) could be effective. Accuracy could be increased by the fusion approaches. A telemedicine platform that enables remote monitoring of the progression of retinopathy could be developed. Timely interventions may be facilitated by real-time lesion segmentation and grading.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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