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DIABETES RETINOPATHY SEVERITY GRADING USING MULTI-SCALE IMAGE PYRAMID TECHNIQUES

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ABSTRACT

Diabetic Retinopathy (DR) is a frequent diabetic complication that affects blood vessels in the retina, which is a light-sensitive tissue. It is one of the most prevalent causes of vision loss in diabetic individuals, and in older adults. DR severity level diagnosis is important since early therapy can significantly reduce or perhaps prevent vision loss. The majority of today's DR detection and classification algorithms focus on single fixed scale picture properties for prediction, ignoring the multi-scale nature of images. Although items in medical pictures typically exist in diverse forms and sizes, the constant input scale will limit the efficacy of spatial feature integration and will fail to collect scale-dependent details. These problems can be overcome by merging scale-dependent information from the DR image with features from multiple scales. As a result, this study presents a multi-scale feature descriptor technique for DR classification that addresses the disadvantages of a single-scale approach while also improving classification performance. The proposed multi-scale features were created utilising a gaussian pyramid to create a mixture of three different scales. The Local Binary Pattern (LBP) extractor was used to extract the features of the three created scales. The collected features were fed into Decision Tree (DT) and Error-Correcting Output Codes (ECOC) classifiers for training and prediction. The IDRiD dataset was utilized to test the proposed Multi-Scale Feature Descriptor (MSFD) approach. In comparison to the performance of single-scale features, the suggested MSFD technique produced an accuracy of 66.35%, which was higher than the accuracy of 54.80% achieved by the single-scale feature for DT prediction. The new technique also outperformed earlier studies using the IDRiD dataset. The values of the accuracy, precision, recall and f-score obtained imply that the suggested approach can detect and assess DR severity levels.

Keywords: Diabetic Retinopathy, Image Pyramid, Multi-scale Features, Severity Grading

1. Introduction

Diabetes is a serious disease in humans, and it is responsible for a wide range of problems around the world (Mangrulkar, 2018). Diabetes is a metabolic illness. The body gets its energy from glucose, which is formed because of food digestion. Insulin is produced by the pancreas, an organ situated close to the stomach, and assists digested food travel through the bloodstream. When you eat, the pancreas produces just the right quantity of insulin to allow glucose to be absorbed from the blood into the cells (Amin *et al.*, 2016). The pancreas generates very little or no insulin in people with diabetes (Selby & Taal, 2020). This results in a buildup of glucose in the blood, which then spills into the urine and is eradicated. As a result, the body loses its primary source of energy, even if the blood contains a lot of glucose (Ahmad *et al.*, 2014; Inuwa *et al.*, 2021).

The kidneys, eyes, nerves, and heart are all affected by diabetes (Tarr *et al.*, 2013). Diabetic retinopathy (DR) is a vision-related complication of diabetes. It's a diabetic eye disorder in which the blood vessels in the retina swell and leak fluid, resulting in vision impairment (Rajalakshmi *et al.*, 2018). DR may cause no symptoms or just minor vision abnormalities initially. However, in diabetics, DR is a degenerative illness that is among the leading causes of vision loss and blindness (Li *et al.*, 2019).

Early detection and regular eye exams can help avoid vision loss and impairment, and they are essential for DR treatment (Ganesan *et al.*, 2014; Inuwa *et al.*, 2021). Knowledgeable optometrists use retinal fundus photos obtained with a mydriatic or nonmydriatic camera to perform retinal screening as a conventional and effective alternative for the early identification of DR (Rahimy, 2018; Sandhu *et al.*, 2018). However, even among experienced ophthalmologists, this traditional and manual DR screening is difficult to execute and is subject to high inter-and intra-observer variance, which can lead to incorrect interpretation, a delay which could lead to inappropriate diagnosis, and a load on healthcare systems (Arcadu *et al.*, 2019; Sandhu *et al.*, 2018; Sarki *et al.*, 2020).

There has been a lot of research done on DR diagnosis. However, most of these researches focused on early-stage DR diagnosis rather than the stage of DR proliferation. Detecting DR at early stage is important as it helps control the spread of the disease. However, a system focused on just identification of DR at early-stage would no be effective at detecting DR at advanced stages. Hence, the stages of DR proliferation are explored in this study.

The majority of the filters and feature descriptors used to recognize and analyze DR are applied at a constant scale to the fundus image, while image features are available at varying scales. Single feature scale methods were adapted in previous works because of its simpilicity. Nonetheless, as medicine directly involves human life, accuracy is regarded as one very important metric for machine model evaluation. Current deep neural network and shallow learning work on DR detection has remained focused on extracting DR features at a fixed scale, ignoring the multi-scale nature of images (Arcadu *et al.*, 2019; Gulshan *et al.*, 2016; Li *et al.*, 2020). A fixed input size will restrict the effectiveness of spatial feature integration and will fail to grasp scale-dependent data because medical pictures commonly contain things of varied shapes and sizes (Cui *et al.*, 2016). The Multi-Scale Feature Descriptor (MSFD) based method is presented to accept objects of various scales and effectively utilize spatial contexture. The following are the research's main contributions:

1. Identification of challenges of existing diabetic retinopathy identification techniques
2. Development of a multi-scale technique for diabetic retinopathy identification.

The remainder of the paper is organized as follows: The second section summarizes recent studies on diabetic retinopathy classification. Section 3 explains the proposed strategy. The results and findings from the experiment, as well as the conclusions drawn, are discussed in Section 4. Finally, part 5 wraps things up and looks ahead to future endeavors.

2. Related Works

Bilal *et al.* (2021) presented an innovative hybrid technique for earlier DR detection and classification. Different models were merged based on the majority vote technique to make DR identification robust. The proposed study employs preprocessing, extraction of features, and classification techniques. The preprocessing step enhances irregularity identification and separation; the retrieval step only extracts essential features; and the classification step uses classifiers such as Support Vector Machines (SVM), and K-nearest neighbor (KNN). The study achieved a 98.06% accuracy, 83.67% sensitivity, and 100% specificity by using multiple severities of ailment categorization databases. However, the proposed technique's complexities is a disadvantage. The model is complex because it is more expensive to develop, train, and deploy.

A reformed capsule network was constructed by Kalyani *et al.* (2021) to recognize and categorize DR. The convolution and principal capsule layers are utilised to retrieve characteristics from fundus photos, while the class capsule layer and softmax layer are used to assess the probability that the picture belongs to a specific class. The suggested reformed capsule network efficiency is tested against four performance indicators using the Messidor dataset. The developed capsule network achieved 97.98%, 97.65%, and 98.64%, accuracy respectively on healthy retina, stage 1, stage 2, and stage 3 fundus images. However, the suggested capsule networks are more difficult to build than Convolutional Neural Networks (CNNs), making the suggested framework sluggish, owing to the dynamic routing algorithm's inner loop.

Tymchenko *et al.* (2020) proposed utilising multi-stage transfer learning to diagnose DR using fundus photos. Three different CNN architectures were merged in the study. The CNN was employed as a feature representation and classifier. Imagenet-pretrained CNNs were utilized as the encoder's seed. The proposed methodology was employed as a screening method for early identification of DR, with a sensitivity and specificity of 0.99. The Shapley Addictive exPlanations (SHAP) were utilised to characterise elements that were useful in determining illness stage. Using SHAP guarantees that the algorithm learns meaningful features throughout training and validation and employs the proper features. This method's main advantage is that it employs a network ensemble that has been trained on a large data and fine-tuned on the targeted dataset to increase generalization and reduce uncertainty. This method can be improved by computing SHAP for the entire ensemble instead of just a single network, resulting in a more exact hyper-parameter optimisation.

Li *et al.* (2019) demonstrated a novel CNN approach. The author utilised a fractional max-pooling layer instead of the traditional CNN max-pooling layers. Two CNNs with various numbers of layers were built for categorisation to achieve additional discriminatory properties. After combining attributes from picture metadata and CNNs, the Support Vector Machine (SVM) classifier was trained to discover each category's underlying constraints of distributions. The suggested DR method classifies diabetes retinopathy phases into five categories, each of which is assigned a number between 0 and 4. According to the test findings, the proposed method can achieve an identification rate of up to 86.17%. The proposed technique was limited by the lack of images of lesions 3 and 4 in the training data set used in this investigation.

In conclusionexisting DR detection techniques based on deep neural networks and shallow learning have remained focused on extracting DR characteristics at a fixed scale, ignoring the multi-scale nature of images. The effectiveness of spatial feature integration will be limited by a fixed input scale, which will fail to grasp scale-dependent data because medical pictures commonly contain things of varied shapes and sizes. The Multi-Scale Feature Descriptor (MSFD) based technique is proposed in this study to handle objects of various scales and effectively utilize spatial contexture.

3. METHODOLOGY

This section explains the methods that will be employed to attain the study's goal. Figure 1 presents the proposed techniques.

Each of the steps and techniques shown in Figure 1 is explained in detail in the subsections 3.1, 3.2, 3.3 and 3.4.

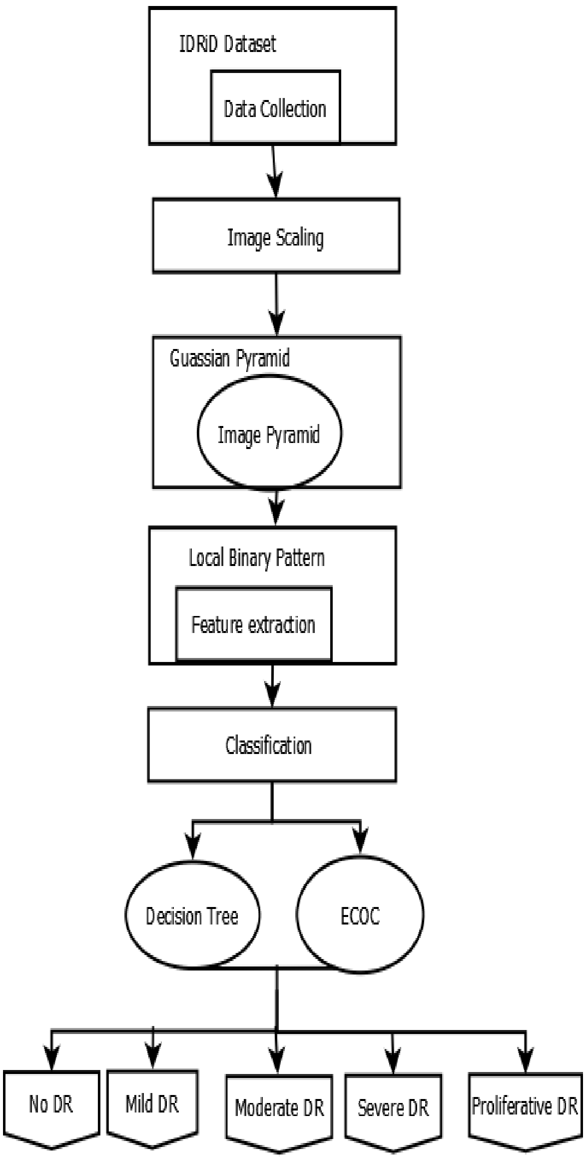

Figure 1: Proposed System

3.1 Data Collection

A total of 516 DR fundus picture data were used in this study. These photographs were taken from the IDRiD database (Porwal *et al.*, 2018). The IDRiD data is a free collection of 516 retinal fundus images classified into two categories: DR and/or Diabetic Macular Edema (DME) retinal images, and normal retinal images (without DR and/or DME) retinal images. (Porwal *et al.*, 2018).

The medical experts graded all 516 photographs, which depicted a variety of DR and DME clinical scenarios. By keeping a good blend of disease categorization, the dataset is divided into a training and testing set, each comprising 413 (80%) and 103 (20%) images, respectively. The IDRiD dataset contains information on the degree of DR, which runs from 0 (no apparent DR) to 4 (severe DR), as well as the severity level of DME, which varies from 0 (no DME) to 2 (severe DME) for each image (severe DME). As a result, it's suitable for developing and testing image processing algorithms for detecting diabetic retinopathy (Porwal *et al.*, 2018).

3.2 Image scaling

Most filters are applied at a set scale to an image, although image features exist at different scales. Image Pyramid generates several image resolutions. By configuring multiple sizes of filtering windows, the image Pyramid filtering technique was utilised to achieve multi-scale feature extraction of the DR image, retaining more edge details. To build a multi-scale feature detection, the results of filtering all layers of the image pyramid were combined.

Multi-scaling of photos captures the local geometry of neighborhoods described by a sequence of distances between points or groups of closest neighbors, since most machine learning models employ Euclidean distance distance between two data points in their operations. That is, very small features are captured in a narrow space within the image at high scale, whereas larger features are captured at lower scale. These various sizes result in better feature representation. Given that multi-scaling is a type of data augmentation, it also dramatically reduces the sample size required to attain high accuracy. These are the grounds why multi-scaling produce better accuracy than utilizing the original image scale alone.

3.2.1 Image Pyramid.

A multi-scale depiction of an image is known as a "image pyramid." The use of an image pyramid allows us to locate items in photographs at various scales. In its original size, the original image is at the bottom of the pyramid (in terms of width and height). The image is shrunk (subsampled) and optionally smoothed at each subsequent layer (usually via Gaussian blurring). The image is gradually subsampled until a stopping condition is reached, which is usually a minimal size at which no more subsampling is required (Suarez *et al.*, 2017).

In this investigation, the Gaussian pyramid was used. A Gaussian average is used to scale and score subsequent pictures in a Gaussian pyramid (Serwa, 2020). Each pixel bearing a local average correlates to a neighbouring pixel on a lower level of the pyramid. This form of accurate mathematical blurring is commonly utilised as a preprocessing step in computer vision. When the edges of objects in a digital shot are blurred in this way, for example, they are easier to detect, allowing a computer to recognise them automatically (Choudhary *et al.*, 2012).

The DR photos were rescaled into three different scales using the image pyramid. The DR fundus image was initially scaled to 1440 by 960 pixels, then half that size, to 720 by 480 pixels. Finally, the final resolution is 360 by 240 pixels. The multi-scale features can be used to improve the DR classification results since they comprise discriminative properties from both the spectral dimension and their respective spatial scales.

3.3 Feature **Extraction**

Features are components or shapes of an object in an image that help us to identify the object. Features include properties like corners, colors, edges, gradient, areas of interest points, texture, and ridges. Many methods are used to obtain these useful features from images. In this study, the Local Binary Pattern (LBP) was utilised to retrieve the texture features from the DR images. For each of the images at different scales the LBP features were extracted. The extracted LBP features of one single image at the three different scales were concantenated to give the final feature sets.

3.3.1 Local Binary Pattern (LBP)

The LBP descriptor was used to extract single-scale and multi-scale features. LBP was utilised for extracting features because it has shown to extract extremely high-grade features, resulting in improved prediction performance (Huang *et al.*, 2011). LBP is a form of gray-level texture measure that uses an image's local contrast measure(Heikkilä *et al.*, 2009). LBP is an image texture descriptor that creates a cutoff for neighbouring pixels based on the value of the current pixel (George & Zwiggelaar, 2019). On a circle with a radius of R, there are C sampling sites in the neighbourhood. And if given a pixel at (x_p, y_p). LBP can be expressed as shown in equation 1:

$$LBP_{C,R(x_p,y_p)} = \sum_{C=0}^{C-1} s(i_C - i_P)2^C \quad (1)$$

where i_c and i_p are, respectively, grey-level score of the central pixel and The surrounding pixels in a circle with a radius R are denoted by P, and the function S(x) is defined by equation 2 as:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (2)$$

The LBP texture descriptor was utilised in this study because previous research Humeau-Heurtier (2019) has shown that it is easy to implement, and the cost of computatng is low. LBP is also invariant to monotonic illumination changes and LBP methodology combines architectural and statistical approaches, resulting in improved texture analysis performance (George & Zwiggelaar, 2019).

For each images scale 59 LBP features were extracted, Given that each single image has three different scales, the LBP features of each single image scale was concantenated to give a total of 177 feature vectors for a single DR image.

3.4 Image Classification

The capacity of machine learning to generalize is defined by its ability to accurately identify unidentified data founded on models generated using the training dataset. In this study, ECOC and Decision Tree (DT) were utilized as machine learning different classifiers for training and classification purpose.

3.4.1 Decision Tree (DT)

Data is regularly segregated depending on a specified parameter in DT, which is a type of supervised learning (Sharma & Kumar, 2016). The DT moves from observations of an item (expressed by the branches) to conclusions about the item's goal value using a tree-like structure (denoted by the leaves) (Alsagheer *et al.*, 2017; Rokach & Maimon, 2005). The DT algorithm can be used to tackle regression and classification problems. DT is simple to comprehend and view. Therefore, does not necessitate data standardisation or preparation, and it necessitates less labor. The decision to execute strategic splits has a big impact on the precision of a tree (Alsagheer *et al.*, 2017). Entropy is one of the approaches used to choose which characteristic to ascribe to the location at the tree's root or different levels.

The entropy of a data is a degree of its randomness(Li & Song, 2007). Entropy for a single point is stated in equation 3.

$$E(S) = \sum_{i=1}^{n} -p_i log_2\, p_i \tag{3}$$

Where S represents the current state, $p_i$is the probability of an event i of state S.

3.4.2 Error-Correcting Output Codes (ECOC)

The ECOC technique decomposes a multiclass categorization problem into a series of binary task, allowing native binary classifier to be employed directly (Armano *et al.*, 2013). The ECOC provides for the embedding of an immeasurable sequence of binary categorization tasks for each category (Dietterich & Bakiri, 1995). ECOC has error-modifying capabilities and has proved that the learning process' bias and variation could be reduced (Escalera *et al.*, 2010).

3.5 Performance Metrics

1. **Accuracy:** Accuracy is measured by the percentage of correctly classified instances. Accuracy is simply t he number of correct estimates divided by total number of forecasts. In equation 4, the precise formulation is given:

$$\text{Accuracy} = \frac{\text{TP+ TN}}{\text{TP+ TN + FP + FN}} \tag{4}$$

2. **Recall:** It is also recognized as sensitivity, and it is a measure that counts the number of correct positive predictions made out of all possible positive predictions. The formula in equation 5 is used to calculate recall.

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

3. **Precision:** is a measurement that counts the number of correct positive forecasts made. It is calculated by dividing the total number of true positives and false positives by the number of true positive elements. It is calculated using the formula in equation 6.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

Where TP is True Positives, TN is True Negatives, FN is False Negatives and Fp is False Positives.

4.0 Results and Discussion

In this paper, two types of experiments were conducted. Firstly, the image features were extracted on fixed scale. This single fixed scale image features were fed to the ECOC and DT classifier for the DR grading. Secondly, the DR images were scaled into three scales using the image pyramid method. The first scale was 1440 by 960, this scale was reduced by half to get the second image. Then, the third scale was obtained by reducing the second image by half. The features of these three images of different scales were extracted using the LBP extractor. After extraction these features were concatenated horizontally to form the multi-scale features. The multi-scale features were then supplied to the DT and SVM classification models for DR severity grading. The results of the different experimentations are shown in Table 1.

Table 1 *DR Severity Grading Result*

Method	Accuracy	Precision	Recall	F1-Score
Single scale +ECOC	52.88	45.06	52.88	48.16
Multiscale +ECOC	65.05	48.31	64.66	55.10
Single scale + DT	54.80	56.68	54.80	50.62
Multiscale + DT	66.35	50.01	66.35	55.40

From Table 1, it can be inferred that all the extracted features produced a good accuracy value. The multi-scale characteristics, on the other hand, generated the best classification accuracy, with a score of 65.05% as compared to the single-scale features with a classification accuracy of 52.88% for ECOC model classification. Based on the precision metric for ECOC, the multi-scale features produced a slightly higher precision value of 48.31% than the single-scale features with 45.06% precision.

Looking at the obtained recall values for ECOC, the multi-scale features have a high recall value of 64.66%, This shows that the total number of accurate predictions made is better than the single-scale positive forecast, which has a recall of 52.88%.

Evaluating from the F1-score perspective for ECOC, the multi-scale features also produced the best F1-Score of 55.10%.
Comparing the single and multi-scale features based on the results obtained by the DT classification model, the single scale had lower accuracy, recall and f1-score of 54.80%, 54.80% and 50.40%, respectively, than multi-scale features with an accuracy of 66.35%, recall of 66.35% and f1-score of 55.40%. However, the quality of a positive prediction made by the DT model using single scale features was higher with a precision of 56.68 than when multi-scale features were used with a precision of 50.01%
From the accuracy, recall, precision, and f1-Score obtained, it can be concluded that the multi-scale features are more appropriate for a DR severity grading than the single-scale features. Figure 2 represents the DR severity grading result presented in Table 1.

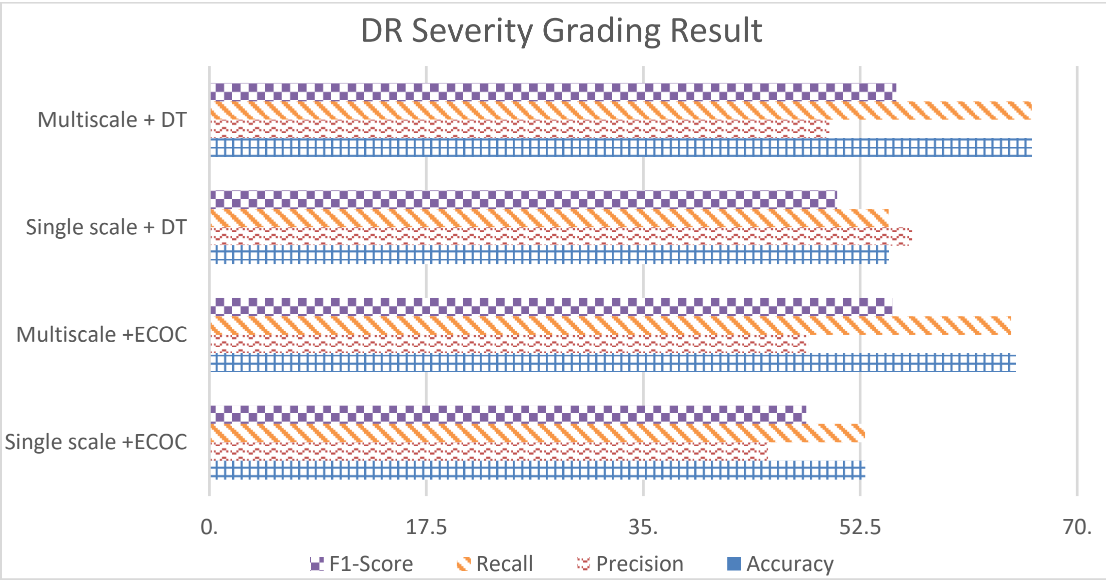

Figure 2 Classification Result for ECOC and DT

Table 2 Comparison with the reported results on the IDRiD leaderboard.

METHOD	ACCURACY (%)
LzyUNCC (Porwal *et al.*, 2020)	74.76
Proposed Multiscale features	66.35
VRT [40]	59.22
Mammoth (Porwal *et al.*, 2020)	54.37
HarangiM1 (Porwal *et al.*, 2020)	55.34
AVSASVA (Porwal *et al.*, 2020)	55.34
Harangi M2 (Porwal *et al.*, 2020)	47.57

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On the IDRiD challenge dataset, Table 2 displays the outcomes of the proposed technique and various challenge participation approaches (Porwal *et al.*, 2020). Only the data from Sub-challenge 2 was used to train the suggested model. The accuracy of the MSFD is 66.35%, which is greater than the performance of the five teams in the scoreboard, with a relative improvement of 7% in accuracy. Only the result produced by LzyUNCC (unpublished) on outperformed the suggested system. Finally, the suggested model was trained solely on data from the IDRiD dataset's Sub-challenge 2, however other (unpublished studies) may have included model ensembles or even other guidance from other Sub-challenges.

I. 5.0 Conclusion and Future Works

This study was able to execute DR severity rating more reliably than previous DR detection research. This is owing to the system's capacity to extract DR traits at various scales. From this study, it can be concluded that applying the multi-scale features improves the performance of classification models. The multi-scale feature descriptor had the best performance with an accuracy of 66.35%, precision of 50.01%, recall 66.35%, and f1-score of 55.40. On the other hand, the single scale feature descriptor had the least performance with an accuracy of 54.80%, precision of 56.68%, recall of 54.80% and f1-score of 50.62%. In conclusion, a system was developed to perform the diagnosis of the severity level of DR using multi-scale feature extraction.

This suggested model will be trained using lesion descriptions in the future to improve DR grading performance even more. In addition, this study only considered DR severity without considering the diabetic macular edema grading. Hence for further work, diabetic macular edema grading will be considered and integrated with DR grading.

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