Novel Framework for Enhanced Learning-based Classification of Lesion in Diabetic Retinopathy

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***Abstract*—Diabetic retinopathy is an adverse medical condition resulting from a high level of blood sugar potentially affecting the retina and leading to permanent vision loss in its advanced stage of progression. A literature review is conducted to assess the effectiveness of existing approaches to find that Convolution Neural Network (CNN) has been frequently adopted for analyzing the fundus retinal image for detection and classification. However, existing scientific methods are mainly inclined towards achieving accuracy in their learning techniques without much deeper investigation of possibilities to improve the methodology of type using CNN. Therefore, the proposed scheme introduces a computational framework where a simplified feature enhancement operation is carried out, resulting in artifact-free images with better features. The enhanced image is then subjected to CNN to perform multiclass categorization of potential stages of diabetic retinopathy to see if it outperforms existing schemes.**

***Keywords*—Diabetic retinopathy; convolution neural network; classification; fundus retinal image; multi-class categorization**

I. Introduction

The proposed study presents an analysis of the critical problem of diabetes called diabetic retinopathy (DR) that adversely affect the retina's blood vessels. The primary cause of this medical condition is a high blood sugar level which finally results in the leaking of blood vessels and causes swelling [1]. A person suffering from an advanced stage of diabetic retinopathy could also permanently lose their vision [2]. Hence, it is mandatory to undertake periodic retina assessments for diabetic patients to identify the early stages of diabetic retinopathy. The target of diagnosis and treatment of this condition is mainly to understand the specific state to resist the prominent threat of permanent blindness. This condition also results in lesions which are spots created by leaking fluids and blood in the area of the fundus retina [3]. Conceptually, there are two forms of lesions in diabetic retinopathy, i.e., bright lesion and red lesion, where hard and soft exudates characterize the former.

In contrast, the latter is characterized by hemorrhage and microaneurysm [4]. From the retinal image screening, microaneurysm can be found in red dots of darker origin while haemorrhage can be identified in more prominent spots. Apart from this, the yellow areas in the fundus retinal image represent hard exudates, while soft exudates are represented as fluffy white and yellowish spots. It is not feasible to manually evaluate diabetic retinopathy by an ophthalmologist as there are higher probabilities of outliers in its outcome and could involve significant effort and time. Hence, such form of complications in the diagnosis of diabetic retinopathy is handled by computer-aided diagnosis, which can control effort, time, and cost during the complete diagnosis process [5]-[7]. To understand the stages of progression of diabetic retinopathy, there are five standard stage indicators of the retinal image as follows [8] [9]:

- No DR: Absence of any form of lesions in the retinal image.
- Mild DR: The retinal image is found with microaneurysm only.
- Moderate DR: The overall characteristic of the retinal image is more than the microaneurysm situation and less severe DR.
- Severe DR: There are multiple features of it. When there are significant intraretinal abnormalities within microvascular are in 1+ quadrant. There is the absence of any prominent sign of proliferative DR; this state is equivalent to severe DR. Apart from this if there are particular beading of veins in 2+ quadrant or there are more cases of 20 hemorrhage (intraretinal) in each of 4 quadrants, then this stage also represent severe DR.
- Proliferative DR: If the retinal image is witnessed with pre-retinal hemorrhage or neovascularization, it will represent this stage.

In the medical image-based diagnosis of diabetic retinopathy, there is a significant contribution of deep learning found in existing literature [10] [11]. Deep learning techniques can smartly identify the essential features from the input data subjected to either segmentation or classification tasks [12] [13]. It was also noted that diagnostical approaches using deep learning have majorly performed better in contrast to conventional techniques. One significant advantage of the deep learning technique is the independence from extracting or computing features from the medical image in the form of input. On the other hand, there is a need to carry out training that demands extensive data. It will imply that a higher quantity of trained data will assure better accuracy during the classification process.

On the other hand, there is a dependency on extracting features from the machine learning technique; however, they do not depend on massive trained data like deep learning techniques. In the case of diabetic retinopathy, the machine learning approaches are required to obtain the blood vessel information, primarily followed by extraction of information related to the region of lesions in the form of features. These features will be used for classification. Various forms of operation carried out in the deep learning process are registration and detection of images along with retrieval, classification, and segmentation task. In this perspective, Convolution Neural Network (CNN), being one of the prominent deep learning techniques, is reported to be frequently used for classification as well as analysis of medical images [14]-[17]. Hence, these facts act as a motivation factor for undertaking CNN in the proposed study.

Currently, various research approaches are being carried out to classify diabetic retinopathy, where deep learning has played a significant role [18]-[20]. This diagnosis outcome is meant to assist the ophthalmologist in performing an early diagnosis of diabetic retinopathy concerning its various stages. Unfortunately, most of the existing approaches emphasize identifying the condition of diabetic retinopathy instead of exploring the appropriate stages of this critical medical condition. Another research problem studied from the trends of existing systems is the restricted and standard computational Framework for appropriately localizing the lesion region. Identifying the proper location of the lesion is essential to understanding the severity of diabetic retinopathy. Further, a significant research gap is found in the existing scheme where not enough emphasis is given towards feature enhancement of the fundus retinal images before subjecting it to deep learning techniques. Therefore, the proposed scheme addresses this problem with the following contribution:

- A simplified feature operation is carried out to the fundus retinal image using Gaussian blurring, while preliminary features are extracted using the Sobel Edge operator.
- An adaptive filter is applied using the fuzzy approach to ascertain the specific location in the fundus retinal image, generating different artifact-free and feature-enhanced images.
- The feature-enhanced image is then subjected to deep CNN with multiple convolution layers to analyze the fundus and classify DR stages.

All the above objectives are met to perform multiclass classification of DR with a particular emphasis on feature enhancement and its representation in the learning model. The paper's organization is as follows: Section II discusses various existing techniques for analyzing diabetic retinopathy, and Section III highlights the research gap. In contrast, Section IV introduces the research methodology being adopted followed by an elaborated discussion of algorithm implementation Section V. Section VI discusses the result analysis. In contrast, a discussion of the result is carried out in Section VII. Finally, Section VIII summarizes the proposed study contribution.

II. Related Work

Currently, various approaches are being evolved for classifying diabetic retinopathy stages. From this perspective, it is seen that machine learning has always played a dominant role. This can be seen in the review presented by Atwany et al. [12]. According to this study, deep learning offers a significant advantage in classification, but there is still a broad scope to improve the system's computational efficiency. The recent work of Abdelsalam and Zahran [21] used a Support Vector Machine using multifractal-based geometry system to diagnose and classify. The method has also used lacunarity parameters for accomplishing singular decisions. Another work carried out by Li et al. [22] has used an attention network with a unique grading system to identify the condition of macular edema. This paper aims to learn features based on disease-specific and disease-dependent attributes selectively. The feature maps were constructed using Convolution Neural Network (CNN) with different resolutions.

Study towards quantification in diabetic retinopathy is carried out by Okuwobi et al. [23], where region-of-interest is used, followed by estimation of hyperreflective foci to obtain better segmentation. Adoption of deep learning is also reported in work carried out by Qiao et al. [24] have used CNN for carrying out semantic segmentation for identifying microaneurysms. The technique has also detected lesions using a matching filter response. Further adoption of deep learning was witnessed in the work by Wang et al. [25], which has addressed the non-interpretability issues in its outcome. The model used the Kappa coefficient to assess the features of diabetic retinopathy. The idea is also to determine the severity score and build a relationship between severity scores and their corresponding features. The adoption of the neural network is seen in Zang et al. [26], where a rate dropout is designed to suppress the overfitting problem during classification. The recent work carried out by Zhou et al. [27] has emphasized improving transfer learning function to improve outcomes of classifying segmented lesions. Bilal et al. [28] emphasize detection techniques for classification. This model has presented the extraction of features as preprocessing to address the presence of abnormalities and support an effective segmentation technique.

Further the work implemented by Gayathri et al. [29] has presented a unique multiclass classification with the automated binary system. The study has used multiresolution features and different ranges of classifier e.g. J48, random trees, random forest, support vector machine, etc., over multiple datasets. The idea is to present a unique feature extraction model for assisting binary classification of retinal fundus images. Prakurthi et al. [30] proposed an on-demand preprocessing Framework capable of yielding different forms of high-quality images that could offer better clinical inference.

Hence, it can be seen that there have been various attempts in recent times to use machine learning in diagnosing diabetic retinopathy. Table I highlights the compact discussion of the studied literatures with respect to problems being identified by the researchers, adopted techniques to address the identified research problem, advantages, and limitation being identified from the adopted methodology. However, based on the summarized observation in Table I, it can be seen that irrespective of beneficial features, they are potentially associated with loopholes.

TABLE I. SUMMARY OF RECENT CLASSIFICATION OF DIABETIC RETINOPATHY

Authors	Problems	Technique	Advantage	Limitation
Abdelsalam and Zahran [21]	Early detection	Support Vector Machine, Multifractal Geometry	98.5% of accuracy, extensive classifying performance	Not applicable for higher dataset
Li et al. [22]	Grading of macular edema	CNN, attention network	Enhanced grading performance	Highly iterative process
Okuwobi et al. [23]	Hyperreflective foci	Generation of region-of-interest	Effective segmentation performance	Not benchmarked
Qiao et al. [24]	Microaneurysm	CNN, segmentation	Better classification accuracy	It doesn't emphasize signal quality
Wang et al. [25]	Non-interpretability of deep learning	Kappa coefficient, deep learning	Simplification in image grading	It doesn't consider improving feature quality
Zang et al. [26]	Overfitting during classification	CNN, adaptive rate dropout	95.7% of classification accuracy	Outcomes not benchmarked
Zhou et al. [27]	Overfitting during classification	Transfer learning function	The benchmarked model supports multi-disease identification	It doesn't emphasize preprocessing
Bilal et al. [28]	Early detection	Binary trees, K-nearest neighbor, support vector machine	Accuracy of 98.06%	The highly computational intensive process
Gayathri et al. [29]	Automated classification	Complex wavelets, multi-model classifiers	Accuracy of 99.7%	Demands higher computational resources

Apart from the above-mentioned recent studies, there are also some notable contributions in the same area to prove the effectiveness of deploying machine learning techniques in classifying diabetic retinopathy. An important work carried out by Acharya et al. [31] has used a Support Vector Machine to carry out multiclass classification of various stages of diabetic retinopathy. The model carries out training over 300 stages of disease condition where the study outcome is witnessed with approximately 82% accuracy. The Support Vector Machine has been used to classify various consequential stages of diabetic retinopathy [32]. This study has accomplished a classification accuracy more than that achieved in [31]. Nayak et al. [33] have developed and constructed a framework using CNN where strategies of morphological processing are carried out along with an assessment of texture-based features. The core idea is to find the critical regions of the lesions associated with blood vessels and exudates where the study outcome has reported a more than 90% accuracy score. Another significant modeling is carried out by Pratt et al. [34], where CNN has been deployed for analyzing the data to look for multiple consequences of diabetic retinopathy with a capability to determine various levels of a medical condition. The modeling has been implemented over the Kaggle dataset, which has large fundus images where the outcome shows better accuracy. Adoption of CNN was also reported in Shaban et al. [35], where multiclass classification of diabetic retinopathy is carried out for four different stages.

Further, the modeling implemented by Dekhil et al. [37] has presented a study, especially on the Kaggle dataset [37]. The work presented by Gao et al. [38] has constructed an image dataset consisting of images of the fundus retina. At the same time, the study mainly discusses the informative utilization of such a dataset for identifying multiple severity stages in diabetic retinopathy. Therefore, it is noted that various research is being carried out towards analyzing fundus retinal images to identify different stages of diabetic retinopathy. The majority of them have reportedly used CNN owing to the advantage of its independence from feature engineering. However, after the adoption of CNN, there is still no significant improvement in the accuracy score of the studies [30]-[38], which demands further insights into addressing issues.

The following section briefs about the research gap explored from the existing research models.

III. RESEARCH GAP

The primary research gap identified from the existing techniques is that simplified preprocessing operation has received little emphasis in increasing classification accuracy demands. Without simplifying preprocessing from the perspective of precise feature modeling, the majority of the computational load towards classification accuracy is borne by the classifier algorithm. The secondary research gap identified is that frequent usage of CNN in the classification process of diabetic retinopathy has not addressed the prominent dependency on large data size. Apart from this, CNN doesn't encode the respective position and orientation of an object, which may lead to less accuracy. Therefore, the quality constraints of the fundus image need to be taken care of during system modeling. The ternary research gap of the current study is that the adoption of frequently used machine learning models is relatively slower owing to the inclusion of iterative operation and extensive training process. Although preprocessing can reduce this, such an approach is significantly missing in the existing scheme. The following section outlines the solution to address this research gap.

IV. RESEARCH METHODOLOGY

The primary aim of the proposed system is to design and develop a novel classification framework that could effectively balance accuracy score and computational efficiency. However, for better standardization of an outcome, the proposed model is assessed with a standard dataset consisting of the fundus retinal images in diabetic retinopathy. The core aim of the present implementation model is to address the research gap identified in the prior section by improving upon the methodology of implying frequently adopted machine learning for classifying multiclass stages of diabetic retinopathy with an approach of feature enhancement.

Fig. 1 highlights the adopted methodology of the proposed study, which uses an analytical research methodology scheme. The input of the retinal fundus image is subjected to precise feature modeling and representation using Gaussian blurring, which is then subjected to edge detection using the Sobel operator. The proposed system chooses to use Gaussian blurring as it is one of the simplified technique towards minimizing the noise as well as details present within an image. The prime parameters used for this purpose is the output image, size of Gaussian kernel, and standard deviation of kernel. Further, the scheme makes use of Sobel edge detection technique due to its simplicity in implementation process. One of the unique advantages of it is to offer a gradient magnitude with proper approximation. It is not only capable of identifying edges but also various perspective of orientation involved in it. Further, an integrated method of color compression and enhancement of blood vessels is used, resulting in a feature-enhanced image. This technique adoption significantly obtains an enriched set of distinct features without using many complicated and iterative steps, reducing the operational burden on the adopted CNN technique in machine learning. The classification results in five different DR states no-DR, mild, moderate DR, severe DR, and proliferative. The extensive analysis will be carried out further to justify the proposed methodology's scope that has effectively overcome the research gap. The following section illustrates the algorithm implemented to carry out the proposed classification.

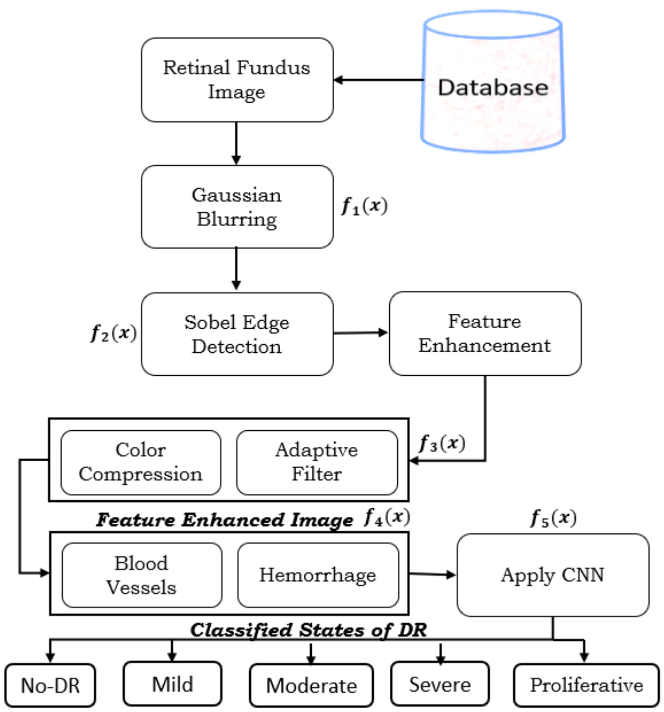


Fig. 1. Adopted Methodology of Classification.

V. System Design

From the prior section, it is now known that the proposed system targets mainly the precise classification and identification of different states of DR for a given image of the retinal fundus. In the present study, the prime emphasis is given to extracting and representing the core features of the CNN model instead of performing any general preprocessing and recognition of the disease. The justification behind this is that there are currently various existing studies (as seen in Section II) that mainly deal with classification using multiple techniques. However, the classification process can be further improved if more appropriate features are extracted in due processing and analysis steps. The proposed scheme has adopted the Kaggle eye dataset [35], which consists of a higher number of fundus retinal images characterized by higher resolution. The presented method of classification makes use of CNN to perform the determination of variable states of diabetic retinopathy. Unlike conventional mechanisms, the proposed scheme chooses to upgrade the methodology of applying CNN. This upgrading scheme involves adopting an appropriate feature enhancement action toward the fundus retinal image. The prime hypothesis behind this adoption scheme is that if the features are improved, it will benefit the classification operation without much computational burden on the CNN module. It should also be noted that the proposed scheme also offers enhancement of contrast and other factors using the prior model [30]. Therefore, the core contribution of the proposed scheme is to introduce a simplified feature enhancement mechanism that cloud further enhances the learning algorithm's performance. The algorithmic steps of the proposed system methodology are as follows:

Algorithm-1 DR States Classification

Input: i(retinal fundus image)

Output: i_{cl} (classified image)

Start

1. Load i ← $data.read\ (file\_path, id\_code)$
2. **for** each $i = 1{:}px$ **do**
3. $i_{gs}=f_1(i)^{\sigma}$ // *gaussian smoothing*
4. $i_{ed}=f_2(i_{gs})$ // *edge detection*
5. $i_{fr}=f_3(i_{ed})$ // *feature representation*
6. **for** each i_{fr} **do**
7. i_c ← apply r2g(i_{fr}) // color compression
8. $i_{fe} = f_4(i_c)$// *feature enhancement*
9. **end for**
10. $i_{cl}=f_5(i_{fe})$ // *DR State Classification*
11. **end for**

End

The discussion of the above algorithmic steps of the proposed scheme is discussed concerning the following operational blocks:

A. Feature Enhancing and Representation

This algorithm's primary step (line-1) is to load all fundus images (i) from the local database. Further, the algorithm considers all the pixels p_x of an input image i (Line-2) to find that there are fair possibilities of the presence of certain features and noise that must be eliminated. For this purpose, the proposed scheme adopts the process of image blurring. The proposed method adopts a Gaussian smoothing scheme to perform feature extraction. The blurring mechanism is carried out using function f_1(x) applied on input image i to obtain a smoothed image i_{gs} as an outcome (Line-3). Here, the function f_1(x) represents one-dimensional Gaussian operation G(x) numerically expressed as follows.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{x^2}{2\sigma^2}} \tag{1}$$

While processing the input image, the mathematical expression in (1) is required to be expanded to form a two-dimension matrix. Therefore, the amended version of expression (1) can be now represented in the form of a two-dimensional matrix G(x, y) as follows:

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

In the above expression (2) for image blurring of f_1(x), the window size is assigned to simplify computation represented by a variable σ. The presented study considers σ =3 while it is noted that this is applied to all the pixels present in an image and is not carried out selectively. The potential amount of noise in the input image is eliminated after using the Gaussian smoothing operation. After the convention of three entities of color (R, G, B), the presented algorithm is further applied to carry out this conversion. After the blurred image is obtained, the next part of the processing of an algorithm consists of getting edge-related feature information. A function f_2(x) is constructed for this purpose which takes the input of smoothed image i_{gs} and applies the Sobel operator to extract edge information of an image, i.e., i_{ed} (Line-4). The next part of the implementation is associated with further performing a feature representation operation using a function f_3(x) considering the input argument of edge information of an image, i.e., i_{ed} (Line-5). The operation carried out by function f_3(x) is multifold. Firstly, the color compression operation is initially carried out to reduce the complexity surface in feature enhancement and model learning. In this process, the recently obtained image (i_{ed}) is compressed to a lower dimension by removing the hue and saturation component of an image while retaining the luminance (Line-7). This process leads to the generation of lower dimension images without losing their clinical attributes and diagnostic properties.

On the other hand, the proposed system constructs an adaptive filter to enhance retinal image features such as hemorrhage and blood vessel, which are very specific to DR identification. The mechanism of the adaptive filter is applied using function f_4(x), which is designed based on the soft computing approach of fuzzy logic. The function f_4(x) takes an input argument of the color-compressed image, i.e., $i_{c.}$ After processing it, the algorithm provides an enhanced image (i_{fe}) in the form of a precise feature representation of blood vessels and hemorrhage. The mechanism of function f_4(x) is discussed in algorithm-2.

Algorithm-2 Adaptive Filter

Input: i_c (color compressed image)

Output: i_{fe} (enhanced feature representation)

Start

1. Initialize threshold T=101
2. $\mathrm{K} = \text{create kernel}\,(\mathrm{T}, 2)$
3. $\text{Init SSIM} = 0$
4. $\text{Set SSIM\_thresh} = 0.8$
5. $\text{While SSIM} < \text{SSIM\_thresh}$
6. $i_{fe} = \text{apply\_filter}(\mathrm{K})$
7. $\mathrm{Ux} = \text{average}(i_c)$
8. $\mathrm{Uy} = \text{average}(i_{fe})$
9. $\mathrm{Sx} = \text{variance}(i_c)$
10. $\mathrm{Sy} = \text{variance}(i_{fe})$
11. $\mathrm{L} = \frac{2.\mathrm{U_x U_y}}{\mathrm{U_x^2 + U_y^2}}$
12. $\mathrm{C} = \frac{2.\mathrm{S_x S_y}}{\mathrm{S_x^2 + S_y^2}}$
13. $\mathrm{SSIM} = \mathrm{L} \times \mathrm{C}$
14. Optimize K with SGD

End

The above-mentioned algorithmic steps describe the procedure of adaptive filter, which adopted design characteristics of the fuzzy soft-computing approach. In the first step, the algorithm initializes an initial threshold value T for transforming each input image pixel according to whether it is inside or outside an acceptable range (Line-1). In the later process, the value of T is set automatically by stochastic gradient descent (SGD) to control the relative image intensity during the filtering operation. In the next step, the algorithm constructs a kernel K using argument T and filter size (2× 2), which returns a binary image after processing the input image (Line-2). Initially, kernel k is assigned with random values, and its operation will be optimized via SGD by computing the structural similarity index (SSIM). Therefore, the algorithm initializes SSIM equal to 0 and sets a threshold equal to 0.8 because the input and out images will carry no SSIM in the initial stage (Line-3&4). The SSIM is calculated in every iteration (Line-5) as well as it is checked if it is below the threshold, the algorithm applies a filtering operation that generates a binarized image, i.e., i_{fe} (Line-6). In the subsequent steps, the algorithm computes a mean or average Ux and Uy of both input images, i.e., i_c and obtained binarized image i_{fe}, respectively (Line-7&8). Similarly, the algorithm then computes variance Sx and Sy, respectively, for both i_c and i_{fe} (Line-9&10). The computation of average and variance values is done to determine the comparison factor such as luminance (L) and contrast (C) tone (Line-11&12) and based on which the SSIM is determined (Line-13). In this way, for each iteration, SSIM is computed, and accordingly, the kernel is optimized with the help of the SGD algorithm. Here, the adaptive filter uses thresholding to convert the image into a binary image. Finally, this is used for comparing with the original image to get SSIM. When the processed and unprocessed images are similar, the while loop ends, and the image is returned.

B. CNN Based DR State Classification

As known, CNN has the potential to resemble the conventional architecture of artificial neural networks. The prime target is learning variable forms of features associated with input images without any involvement of human intervention in the classification process. The proposed scheme implements CNN; the modeling details are highlighted as it can identify essential features without any dependencies from any user-based interaction. At the same time, there are few dependencies on carrying out preprocessing in CNN, making it a simplifier and speedy classification process. However, it cannot be denied that the application of CNN also introduces sophisticated calculations, a higher cost of memory, and uncertainty in performance. So, an improvement is required to revise the performance of CNN owing to the sensitive usage of medical images, where both accuracy and computational efficiency are demanded simultaneously. CNN architecture has various layers, ranging from convolution to polling and completely interconnected layers. A feature map is generated from this outcome of each layer that the other plays as an input argument for its successive layer. The input images associated with the activation map are subjected to a set of linear filters in the convolution layer. The purpose is mainly to obtain a variable number of features corresponding to the clinical state of diabetic retinopathy, e.g., blood vessels, curves, edges, etc. Hence, the proposed system defines its convolution layer $y(l, m, n)$ concerning the 3x3 dimension empirically represented as:

$$y(l,m,n) = \sum_{k=1}^{3} \sum_{i=1}^{3} \sum_{j=1}^{3} H_1 + H_2 \qquad (3)$$

In the above expression (3), the first component H_1 is equivalent to $w(l, i, j, k).x(i+m-1, j+n-1, k)$ while the second component H_2 is equivalent to $b(l)$. Table II highlights the configuration being used towards the development of CNN model.

TABLE II. CONFIGURATION DETAILS OF IMPLEMENTED CNN MODE

Layer	**Shape**	**Param**
Convolution Layer-1 (2D)	(598, 598, 32)	320
Maxpooling (2D)	(299,299,32)	0
Convolution Layer-2 (2D)	(297,297,64)	18496
Maxpooling (2D)	(148,148,64)	0
Convolution Layer-3 (2D)	(146,146,64)	36928
Maxpooling (2D)	(73,73,64)	0
Convolution Layer-4 (2D)	(71,71,64)	36928
Maxpooling (2D)	(35,35,64)	0
Convolution Layer-5 (2D)	(33,33,64)	73856
Maxpooling (2D)	(16,16,64)	0
Convolution Layer-6 (2D)	(14,14,64)	73792
Maxpooling (2D)	(7,7,64)	0
Convolution Layer-7 (2D)	(5,5,64)	36928
Maxpooling (2D)	(2,2,64)	0
Flatten	256	0
Dense 1	64	16448
Dense 2	5	325

The gray level of an input image is represented by the variable x (i, j, k), while the weight of this is represented by w (l, i, j, k). The system also uses biases represented by $b(l)$ associated with the convolution layer. The system still consists of many preferences and weights, increasing the number of parameters. This challenge is mitigated by using a pooling layer where the activation map is subjected to subsampling which significantly enhances the robustness of the features that have been extracted. A set of linear filters can be further deployed to realize the pooling layer in the proposed CNN architecture capable of computing the mean pixel values retained within the masked area of the given feature map. The system can also choose to use a non-linear filter to realize the pooling layer capable of sorting all the values of pixels retained within a specific region of the input feature map, and thereby, max pooling is accomplished.

VI. RESULT ANALYSIS

The results obtained after implementing the proposed algorithm concept discussed in the previous section are discussed in this current section. The proposed system chooses to perform five stages of classification of diabetic retinopathy, i.e., i) normal (no DR) image which doesn't have any trace of disease, ii) mild, iii) moderate, iv) severe, and v) proliferative stage of diabetic retinopathy. The proposed scheme deploys a simplified feature enhancement scheme to represent a specific feature of fundus images to the CNN model to get reliable classified states of DR. The evaluation of the proposed system is carried out on the standard dataset, namely APTOS 2019 blindness detection retrieved from Kaggle website. The dataset consists of 5590 fundus images, including both regular and DR with their ground truth in .csv file format. Among 5590, 3662 images are subjected to training CNN model, and 1928 images are considered for model testing. The experiment is performed on a standard 64-bit Windows environment with NVIDIA GEFORCE GTX graphics card, Intel(R) Core(TM) i5-9300H CPU @ 2.40GHz 2.40 GHz, and 16 GB RAM size. As shown in Fig. 2, the proposed scheme deploys seven convolution layers using the input of feature enhanced fundus image. The performance assessment of the presented system is carried out concerning precision, recall, and F1-score. The study also performs a comparative analysis where the proposed method is compared with the trained CNN, which does not include any feature enhancement module.

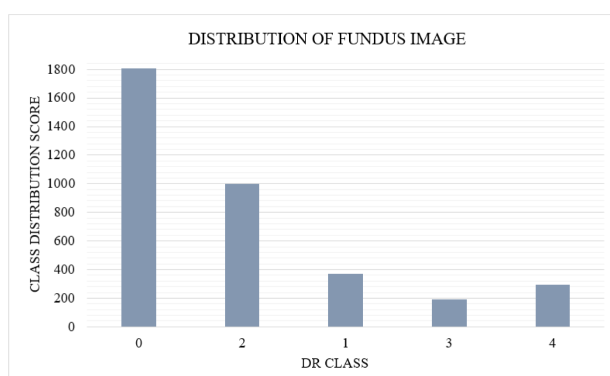


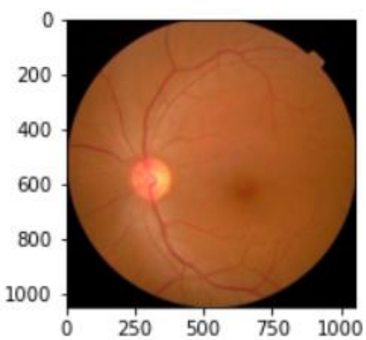
Fig. 2. Class Distribution of Fundus Image in Training Set.

Fig. 2 exhibits the class distribution of the fundus images belonging to the training set. The DR label and its description are given in Table III. There is 1805 fundus image with DR state normal, 999 images with DR state mild, 370 images are subjected moderate DR state, 193 images are related to severe DR state, and the remaining 295 fundus images are subjected to Proliferative DR. Table III highlights the labels being used with respect to the different names of classes towards fundus image.

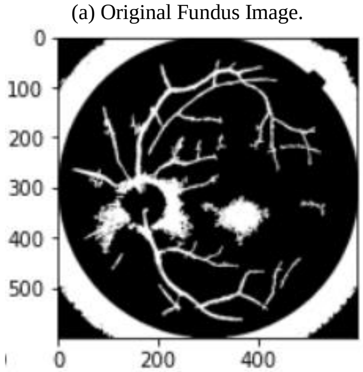
TABLE III. LABELS OF FUNDUS IMAGE

Label	Class Name
0	No DR
1	Mild DR
2	Moderate DR
3	Severe DR
4	Proliferative DR

Fig. 3 highlights the visual outcome of the enhancing operation where Fig. 3(a) showcases the original input image while Fig. 3(b) shows the edge detected enhanced image.



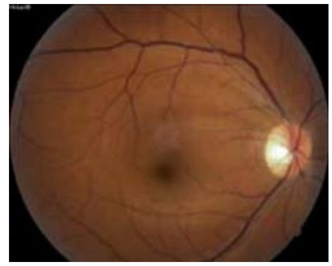
(a) Original Fundus Image.

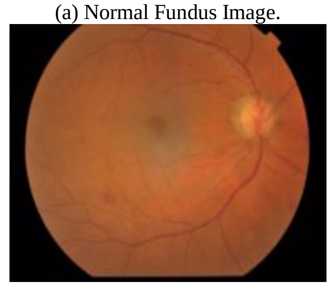


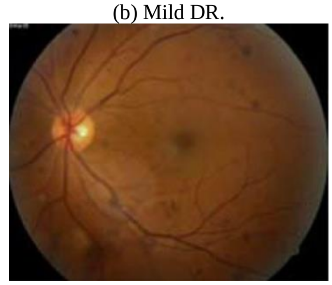
(b) Feature Enhanced Image

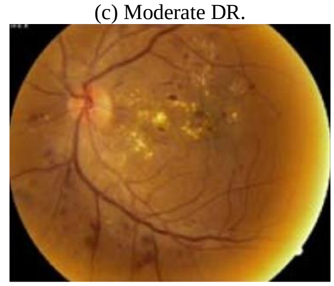
Fig. 3. Visuals of Feature Representation Operation.

From Fig. 3, it can be seen that there is an evident visual outcomes of the enhanced features, while Fig. 4 highlights various stages of processing being carried out towards the sample of normal fundus images. Adopting the proposed scheme towards the involuntary classification method by CNN offers multiple beneficial perspectives. The primary beneficial perspective, as seen from the visual outcome of Fig. 4, is that such a classification system supports any telemedicine-related application for assessing stages of diabetic retinopathy. The secondary beneficial aspect of this scheme is that its accuracy score is highly reliable as preprocessing and feature extraction operation is carried out well before subjecting it to the learning scheme. Hence, the inference of the outcome by any ophthalmologist has become quite a simplified process. The effectiveness of the proposed feature enhancement-based CNN is assessed by comparing it with CNN implemented without any feature enhancement or preprocessing approach. Table IV and Table V highlights the quantified outcomes for proposed system and existing CNN model, respectively towards assessing accuracy as performance parameters.


(a) Normal Fundus Image.


(b) Mild DR.


(c) Moderate DR.


(d) Severe DR.

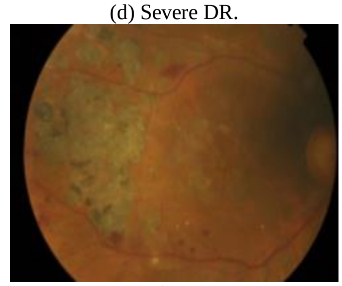

(e) Proliferative DR.

Fig. 4. Visual Outcomes of Classification.

TABLE IV. QUANTIFIED OUTCOME OF THE PROPOSED SYSTEM

CNN With Feature Enhancement			
Label	**Precision**	**Recall**	**F1**
0	98.60%	95.41%	96.98%
1	89.06%	91.93%	90.47%
2	97.34%	95.31%	96.31%
3	82.45%	100%	90.38%
4	89.23%	95.08%	92.06%

TABLE V. QUANTIFIED OUTCOME OF THE STANDARD CNN MODEL

CNN Without Feature Enhancement			
Label	**Precision**	**Recall**	**F1**
0	95.07%	88.40%	91.62%
1	68.23%	93.54%	78.91%
2	93.02%	83.33%	87.91%
3	74.54%	87.23%	80.39%
4	69.73%	86.88%	77.37%

For an effective analysis, the proposed system is also compared with the existing works done in a similar interest research area by Sikder et al. [39] and Pratt et al. [34] as shown in Table VI.

TABLE VI. NUMERICAL OUTCOMES OF COMPARATIVE ANALYSIS

Parameters	**Proposed**	**Sikder et al. [30]**	**Pratt et al. [33]**
Precision	95.65%	90.4%	82.3%
Recall	95.36%	89.54 %	86%
F1 score	95.42	89.97 %	83.95%

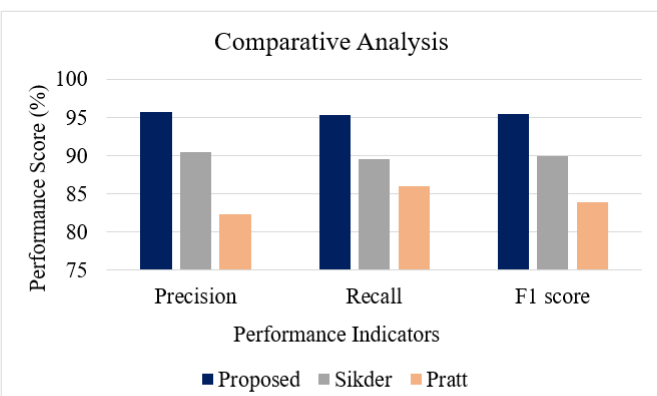


Fig. 5. Comparative Performance Metrics.

Based on the entire analysis, it can be seen that the proposed system exhibits significant enhancement in its classification performance in comparison to normal CNN and existing studies concerning the precision, recall, and F1 score (Fig. 5). The prime reason behind this outcome is as follows: The work of Sikder et al. [30] involves using conventional feature extraction techniques and an applied ensemble learning approach. Although the ensemble learning technique has its advantage in the suitable decision-making process in the classification task, the conventional feature extraction and image enhancement approach are not appropriate for applying to massive fundus images subjected to a higher degree of artifacts and impreciseness in feature generalization, unlike proposed scheme. At the same time, the work of Pratt et al. [33] has used a different approach unlike Sikder et al. [30]; however, they are more inclined towards classification without considering the need to enhance the primary input image first. Hence, the proposed system offers a better analysis of fundus images with classified states of DR and exhibits higher performance in different assessment cases. The proposed method identifies DR in an early stage and monitors its progression.

VII. CONCLUSION

This paper has presented a simplified and unique computational modeling to carry out multiclass classification of the stages of diabetic retinopathy from a given fundus retinal image. The achievement of the proposed scheme is that unlike existing literature on classification techniques, the proposed scheme performs a sequential image feature enhancement and representation extraction prior to classification, making the accuracy score much more reliable and improving the computational burden of training by CNN and adopting two-dimensional Gaussian blurring with specific size of window assists in the simplified feature extraction process. Further feature extraction via Sobel edge detection, color compression, and enhancing the image concerning blood vessel and haemorrhage assists in better analysis of lesion in fundus retinal image. Another significant achievement is towards its potential for categorizing different DR states based on their criticality. The CNN was used with seven convolution layers with a Maxpooling layer. The quantified achievement of study is that the study outcome shows that the proposed scheme offers approximately 6% improvement over existing work and approximately 12% over another existing scheme. The feature enhancement's introduction increases the CNN classification performance and reduces the surface of computational complexity by representing specific features in the training and pattern generalization phase. In future work, the proposed system can be extended toward analyzing failed test cases due to the poor visual quality of images, which can be addressed by integrating it with our on-demand preprocessing Framework. Also, further optimization will be carried out over CNN and customization will be applied to the feature enhancement technique.

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