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# MULTI LINKED RELEVANT FEATURE SET MARKING MODEL USING CONVOLUTION NEURAL NETWORK FOR DIABETIC RETINOPATHY GRADE DETECTION

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**ABSTRACT**

Diabetic Retinopathy (DR) is the most common cause of blindness in 12% of the population every year. One of the most effective ways to prevent vision loss and reduce health care costs is to screen for DR and monitor disease progression in the early stages, especially in the asymptomatic stages. Nonmydriatic digital colour fundus cameras are commonly used to take colour images of the retina in most screening programmes. Early diagnosis and treatment can significantly reduce the risk of severe vision loss. DR screening has been found to be a cost-effective method of reducing the burden on the health care system. The development of automated tools to aid in the detection and evaluation of DR lesions that has been a major focus of recent research. Patients who are diagnosed with retinopathy early on have a better chance of preserving their vision. The diabetic retinopathy grade severity level assessment is proposed in this paper that uses Multi Linked Relevant Feature SetMarking Model using Convolution Neural Network (MLRFSMM-CNN). The standard DIARECTDB1 datasets are used to obtain the colour retina images. Images of the retina are first analysed to identify lesions, such as blood vessels and haemorrhages, as well as exudate and microaneurysms, on the retina. This is followed by extraction of various relevant features, such as area of the segmented exudates, the quantity of microaneurysms in the segmented image, the mean and standard deviation of segmented lesions, to determine the grade severity level of the disease. The proposed model is compared with the traditional methods and the results represent that the proposed model performance is enhanced.

**Keywords:** *Diabetic Retinopathy, Feature Set, Feature Extraction, Convolution Neural Network, Grade Detection.*

## 1. INTRODUCTION

High blood sugar is caused by diabetes mellitus, which is better known as diabetes. Today, diabetes is the most serious problem facing by the world. The prevalence of diabetes is expected to climb from 2.8% to 4.4% in 2030 [1], according to data from the World Health Organization. Diabetic retinopathy (DR) is a direct result of a retina coronary artery [2]. Gloomy strings, longsighted, uneven sight, vitiated vision and empty patches in sight are all signs of DR. Mild, moderate, severe, and proliferative are all kinds of DR. DR can develop a number of different lesions. Microaneurysms [3] are the first DR alterations that can be seen in the clinical setting [4]. When capillary walls are weakened, blood leaks out. Small to big patches of whitish yellow hard exudates that form circular rings that are known as hard exudates. There are regions of greenish-white discolouration with fuzzy edges in the soft fluid nerve fiber sheet [5].

Insistently high blood sugar can cause a variety of health issues, including heart disease, eye disease, kidney and nerve damage [6]. One of the most common complications of diabetes is diabetic retinopathy [7]. Diabetes type I and type II can cause damage to the retinal blood vessels. Both nonproliferative (NPDR) and proliferation forms of

DR exist. The retina must be monitored in order to identify changes in NPDR [8]. Mild, moderate, or severe degrees of retinal impairment are identified by the NPDR's three stages [9]. Proliferative Diabetic Retinopathy (PDR) is characterized by the formation of new, fragile blood vessels on the retina's surface [10]. If these aberrant vessels bleed or scar, it might result in permanent vision loss. Figure 1 shows how the disease advances between mild NPDR to PDR [11]. It is possible to lessen the effects of DR by detecting and treating it early on.

By 2025, the number of people with diabetes is anticipated to rise form 382 million to 592 million worldwide [12]. Patients may experience blurred vision, flashes of light, and loss of visual acuity in the advanced stages of the disease [14]. Detecting DR at an early stage is critical to avoiding a worsening effect at a later time.DR is diagnosed using color fundus imaging. In terms of both time and money, manual examination can only be performed by specialists [15]. As a result, automatic analysis of fundus images requires the application of computer vision techniques. In order to find DR, many automated methods have been used. Hands-on engineering and edge learning are two types of computer vision-based techniques [16]. Built on extracted features, such as the contour of blood vessels and exudates, hemorrhagingmicroaneurysms and maculopathy of the retinal fundus picture[17] or their combinations, the hand-on engineering approaches were based. A more accurate classification is achieved by end-to-end learning. It is possible to detect DR using the Kaggle database [18], but no strategy can detect the mild stage. Early detection is critical in the fight against this deadly disease [19]. Male and female populations had the same level of impact on this disease. It was more prevalent in metropolitan areas. Diabetic retinopathy, which affects vision, affects 16.9 percent of diabetics between the ages of 30 and 50. According to the report, retinopathy affects 18.6% of those aged 60 to 69, 18.3% of people aged 70 to 79, and 18.4% of people aged 80 and up [19]. There was a 14.3% decreased prevalence inside the 50- to 59-year-old age group. The health retina and impacted retina is shown in Figure 2.Microaneurysms, soft and hard exudates, haemorrhages, neovascularization, and macular edoema are only some of the retinal abnormalities that may be caused by DR. The five stages of DR include mild DR, severe nonproliferative DR [21], severe nonproliferative DR, proliferative nonproliferative DR (PDR), and macular edoema (ME). Proliferative diabetic retinopathy develops when the eye is loaded with interstitial fluids and the vision is lost. Mild NPDR is the disease's first stage. Patients are frequently asymptotic in the early stages [22]. A variety of signs and symptoms may appear with the worsening of the condition. These can include hazy or blind areas in the vision as well as huge floaters and even sudden blindness [23]. Because of this, early detection and precise diagnosis and staging of the disease may lessen the risk of complications and loss of eyesight.

Ophthalmologists typically use a dilated eye exam to make the diagnosis of DR. These include fluorescent dye angiography, optical imaging (OCT), and fundus photography. Fluorescein angiography involves injecting a contrast dye intravenously and taking pictures of the blood flow and any anomalies in the arteries and veins. When using OCT, we can see the retina's structure, thickness, and edoema [24]. Because visual evaluation and manual measurement of changes in the retinal and layers are considered to be particularly demanding activities, retina specialists who have passed specific training in diagnosis and grading must currently do DR diagnosis [25]. Many diabetes patients wait until they are experiencing symptoms of vision loss before consulting a retina expert [26]. By then, their disease has progressed and is almost always irreversible due to a lack of access to eye care specialists with advanced training and tertiary eye care facilities [27]. Therefore, a therapeutically relevant reason exists for developing an accurate and non-invasive diagnostic method that can not only detect DR properly but also grade it in its early stages [28]. The proposed model introduces a DR level detection model using CNN that improves the accuracy in detection of DR [29].

## 2. LITERATURE SURVEY

There has been a great deal of research done on the DR classification system. It's been shown in several research studies that there are methods for detecting DR phases and severity. Numerous methods are available to identify DR, including single-stage detection and classification techniques. According to Kaur et al. [1], a CNN-based method is proposed where the architecture failed to detect the moderate stage and obtained 30% sensitivities and 95% specificity, indicating that the architecture failed to accurately classify the impacted stages. An imbalanced dataset is the main problem with their sensitivity results. For model testing, a balanced data has not yet been employed to detect differential reporting (DR). Willis et al. [3] suggested that a balanced dataset

improves training results. The training dataset employed by Kumaran et al. [4] yielded a 50.5 percent accuracy rate; however, the validation data was not balanced, resulting in a lower accuracy rate.

Using a dropout layer and a deep CNN, Yu et al. [6] able to accurately detect DR in the DRIVE dataset with an accuracy of 94%. For detection, they performed spatial feature analysis, although there weren't enough samples in the dataset. The retinal area was also used by Chaturvediet al. [7] to grade the DR disease staging system. Prognosis and therapy recommendations are made immediately by the suggested system. It's not typical practice to utilize Davis staging to grade DR, but this study used it. In that investigation, the low false rates are much lower than the probability of detection when the network misidentified some photos.

Deep learning classification methods have been shown to be extremely effective when taught with sufficient data in a supervised manner. Good results have been achieved by using several CNN models for transfer learning. Ensemble models, according to Komura et al. [8], are effective at detecting DR phases and DME, as demonstrated by Ting et al. [10]. Koriet al. [12] employed transfer learning and an ensemble polling technique to increase the accuracy of a model that had been pre-trained with transfer learning. Using transfer learning, Wang et al. [13] trained a Founding model that correctly categorized all stages of development. On the given dataset, they were accurate to within a 0.1 percent margin of error. As Tan et al. [17] did, they classified all stages of DR using transfer learning. All of them use backpropagation algorithm and an ensemble technique, but they didn't train and test a model on the balancing dataset.

Researchers have used a variety of strategies for identifying and classifying DR phases, as evidenced by the available literature. The severity of DR phases can be determined by using multi-classification. Detecting the early stages of DR for treatments is critical, as later stages are difficult to treat and can cause blindness, making early detection critical. The Kaggle database was utilized by Huang et al. [18] to identify the early phases. For the moderate stage, researchers developed models that are more accurate and more efficient than those now available. Classification error can be caused by an unbalanced dataset. Networks are able to accurately learn the possibilities in a balanced dataset if the examples in the categories are evenly distributed, however in a class imbalanced, the network exceed its high sampling class.

Using a standard KNN method with optimal filter on two classes, Nwankpa et al. [19] attained an AUC score of 0.927. A computerized Diabetic Retinopathy diagnostic system developed bySajana et al. [20] using the KNN algorithm and achieved a high level of specificity as well as high level of accuracy. In addition, Neural Network was used to classify three types of diabetic retinopathy by Lam et al. [21]. They classified Diabetic Retinopathy into mild, moderate, & severe stages with a validity of 82.6%, 82.6%, and 88.3%.

In fundus pictures with a visible threshold, Wang et al. [22] showed an automated diagnosis of Diabetic Retinopathy. True instances were detected 90.1 percent of the time, and false cases were detected 81.3 percent of the time. Multi-scale Amplitude Variation and Frequency Modulation-based decomposition was used by Kele Xu et al. [23] in order to distinguish among Diabetic Retinopathy and regular images of the retina. Jelinek et al. [27] developed an automated Eye Disease detection method with a specificity of 85% & specificity 90%. The Eye-Check method was created by Vishakhachandoreet al. [24] for the automated identification of Diabetic Retinopathy. With an AUC of 0.839, they were able to identify any abnormal growths.

In the last few years, learning algorithms are becoming increasingly common. Using CNNs, Pratt et al. [34] identified advanced stages of Diabetic Retinopathy that even outperformed human specialists in the field. The advanced stages of Retinopathy and vitreous enema were detected by Kori et al. [35] using an ensemble of ResNet and highly linked networks. An improved CNN model was developed by Torrey et al. [36] to detect retinal lesions in fundus pictures. Using an uneven weight map, Yang et al. [38] were able to detect 95 percent of lesions. Diabetic Retinopathy was successfully classified using VGG-16 and Inception-4 networks.

An algorithm developed by Mohammadianet al. [25] uses deep CNNs to detect DRs. An open data set called Kaggle was employed in this study. The labelled dataset is stretched, translated, flipped, and rotated in a series of steps. Finally, an automatic DR classification

system built on CNN's architecture is applied, and the system achieves 94.5 percent accuracy. Using deep CNNs, DinialQomariahet al. [26] developed an automated approach for revealing DRs. More than 35,000 photos are included in the dataset. Images are downsized to a 448x448 pixel size for this research. They also used a variety of data enhancing techniques. and finally, the authors were able to attain a precision of 81% for class 0 and 88% for class 1. NidhiKamothi et al. [28] provided a system for classifying DR through two categories: DR and No DR using the Kaggle dataset. It was decided to test the computation output against previously unseen data using a dataset consisting of 35,126 photos.

## 3. TABLES AND FIGURES

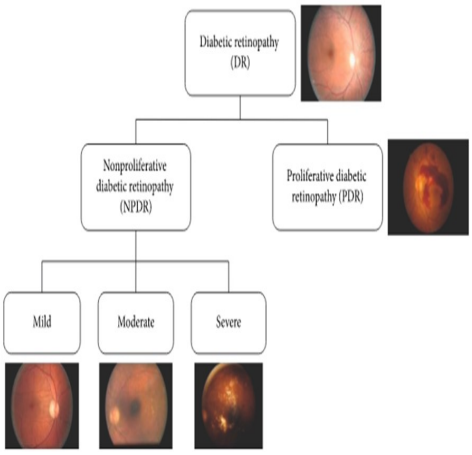


*Figure 1: Disease Advancements*

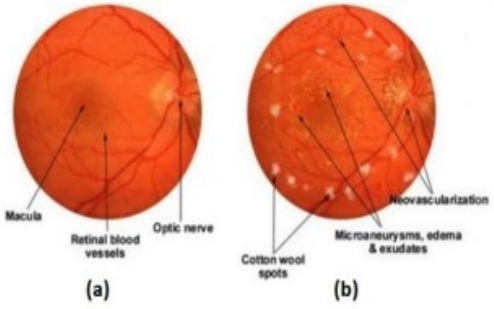


*Figure 2: Retinal Images. A Healthy Retina; B Diabetic Retinopathy*

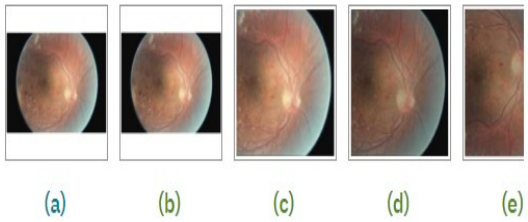


*Figure 3: Preprocessing Steps*

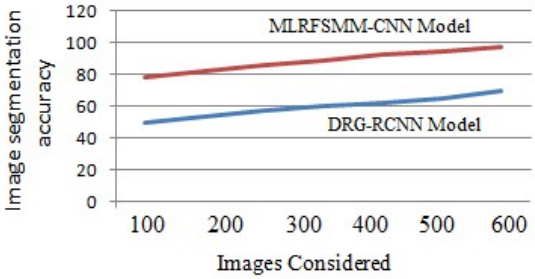


*Figure 4: Image Segmentation Accuracy*

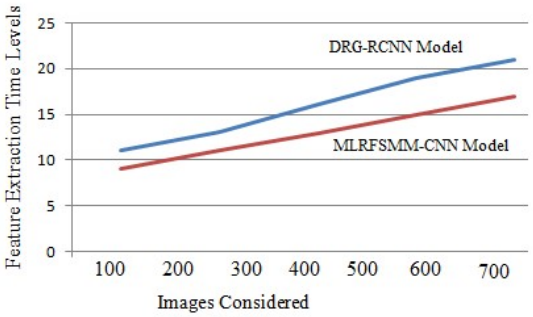


*Figure 5: Feature Extraction Time Levels*

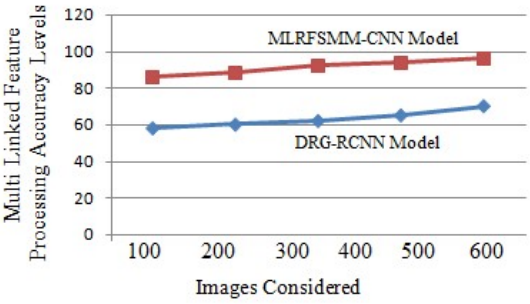


*Figure 6: Multi Linked Feature Processing Accuracy Levels*

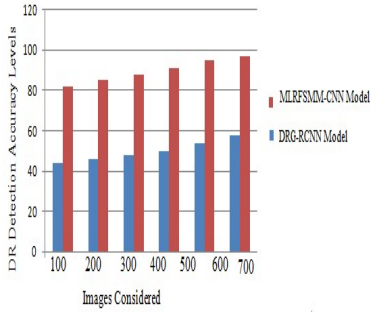


*Figure 7: DR Detection Accuracy Levels*

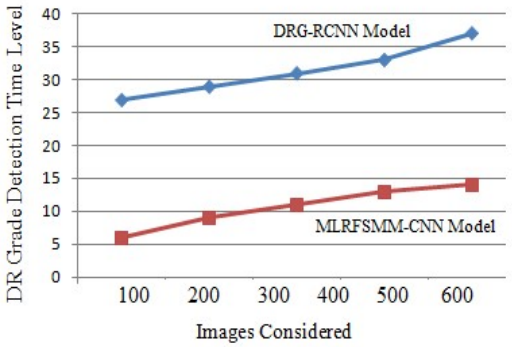


*Fig 8: DR Grade Detection Time Level*

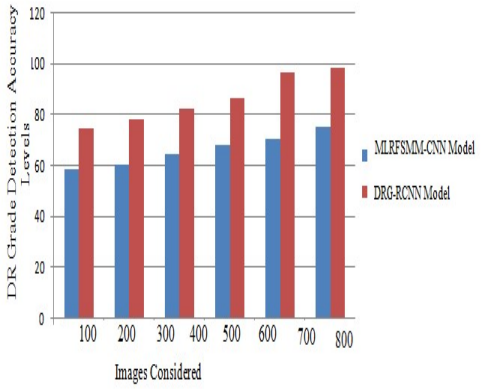


*Figure 9: DR Grade Detection Accuracy Levels*

## 4. PROPOSED MODEL

Microvascular complications in diabetes are common, and retinal imaging is the most extensively used screening tool because of its excellent sensitivity to identify retinopathy. Medical specialists currently use fundus or retinal scans of the patient's eyes to assess the severity and degree of diabetic retinopathy. As the number of people with diabetes rises, so will the amount of retinal images generated by screening programmes, putting additional strain on medical professionals and raising the overall cost of healthcare. Automated systems could help ease this, either as a supplemental tool for medical experts or as a stand-alone diagnostic tool. Deep learning algorithms have been tested in the automated identification of diabetic retinopathy. Automated systems based on deep training artificial neural network approach can detect the referable diabetic retinopathy, which is characterised as moderate or severe diabetic retinopathy. In addition to diabetic macular edoema and probable glaucoma and age-related macular degeneration, this technique has been used to study additional relevant eye issues.

Automated systems that can identify retinal pictures using clinical severity scales, such the proposed specialised medical diabetic retinopathy and diabetic macular edoema disease scales and are more likely to be useful in clinical settings. Deep learning systems may be hindered by the necessity for a large number of labelled photos in order for the model to learn. Researchers have shown that automated diagnosis and grading of macular degeneration can save time and resources with deep learning technologies. Ultra-wide-field fundus photography, on the other hand, provides up to 82% of the retinal surface for most automatic systems. The retinal image for DR detection in different levels are shown in Figure 3. Convolutional Layer is the initial layer, and it does heavy computing, making additional work easy. With an image input size of 64x64x3, this layer serves as an input layer. By changing the previous 3x3 matrix towards a more compact 3x3 matrix, the highest ranking function is isolated in the Max-pooling layer. Finally, the highest weighted function of the 3x3 matrix is turned into an asymmetric two-by-two matrix. Image matrix is reduced to a single dimension, which acts as dense layer inputs in the flattened layer. The dropout layer conducts a higher and more efficient operation that greatly boosts the network's normalising capabilities. The dropout rate is a hyperparameter that determines how many neurons are randomly removed and potentially restored during training. Finally, the dense layer serves as the final component of a deep convolutional neural classifier and is supplied by the qualities that were recently removed by the previous convolutional.

A Softmax or a logistic neuron, dependent as to whether the role is binary classification or multiclass classification, is the network's last output

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layer. The diabetic retinopathy grade severity level assessment is proposed in this paper that uses Multi Linked Relevant Feature SetMarking Model using Convolution Neural Network (MLRFSMM-CNN). Convolutional layer weights and biases are represented by M(p,q,L), N(s,p,q,L), and R(t), respectively. By subsampling the maps, the pooling layer reduces the amount of network parameters such as weights and biases while also improving the resilience of the recovered features. The process of DR grade detection is clearly explained in the algorithm.

Algorithm MLRFSMM-CNN

{

Input: Retina Image Dataset (RIMDS)

Output: DR Grade Prediction set

Step-1: Consider an Image from the RIMDS set and load in the memory frame for performing the image processing operations. The loading is done as

$$Img(i) = \sum_{i=1}^{K} getimage(RIMDS(K))$$

Step-2: The image loaded in the frame undergo segmentation process in which image is divided into multiple partitions and each segment will be used for edge detection for accurate blood vessel and retina detection. The segmentation is performed as

$$parti\ (\mathrm{Im}\ g(i)) = \frac{1}{size\ (\mathrm{Im}\ g(i))\sqrt{2\pi}} + l - \frac{I(x,y)^2}{2 * \max\ int\ ensity\ (\mathrm{Im}\ g(i))^2}$$

$$Seg(\mathrm{Im}\, g(i)) = \sqrt{\Sigma_{i=1}^{M} parti(\mathrm{Im}\, g(i)) + Th}$$

Step-3: The segments are considered and the edge detection is applied on each segment for accurate outline detection of the retinal so that pixels are extracted

$$FS(Seg[N]) = \frac{1}{\max range(Edge(seg(i)))}\left\{\Sigma_{i=1}^{N}\frac{\Sigma_{i=1}^{N} pixel(i,i+1)+grey(seg(i))}{\max(Edge(i,i+1)_N}\right\} + \frac{1}{\Sigma_{i=1}^{N}\left(\frac{\min(x,y)}{size(Edge(i))}\right)}$$

the range for accurate DR detection. The edge detection is applied as

$$Edge(Seg(i))_N = \left(\frac{1}{size(seg(i))} + \sum_{i=1}^{N} I(x,y) + sim(I(x,y))\right) + \max(sim(x,x+1))$$

Step-4: The features are extracted from the segments after edge detection. The features are used in the process of DR detection and the features are linked so that the sequence is followed during the training process for DR detection. The feature extraction is performed as

Step-5: The feature set generated will be marked with the upper boundaries as maximum priority for DR detection. The feature set marking is performed as

$$Lab(x,y) = \frac{1}{N}\sum_{i\in RIMDS_N, j\in RIMDS_N} FS(i) + sim(FS(i,i+1) + \mathrm{int}ensity(I)$$

Step-6: The training is performed based on the feature set that is marked with upper limits. The higher priority features are used in sequence to train the model for improved performance levels. The training of the model is performed as

$$Train\ (FS\ (i)) = \frac{\max(\ greylevel\ \ (Lab\ (i,j)) + Th\ +\ FS\ (i)}{\max\limits_{i\in RIMDS}\left\{\min(\mathrm{int}\ \ ensity\ \ (i,j)\left\{\frac{Lab\ (i,i+1)}{size\ (FS\ )}\right\}\right\}}$$

Step-7: The prediction of the DR grade is performed from the classified data based on the blood vessel impacted area and the calculation is performed as

$$\mathrm{Pr}ed\ \_Set(M) = \frac{1}{FS(i)\sqrt{2\pi}} + \Sigma_{i=1}^{N}\frac{\Sigma_{i=1}^{N}\max(FS(i)) + \min\mathrm{int}ensity(pixel(i,j)))}{Edge(i+1)_N}$$

Step-8: The error rate is calculated to identify the false positives in the model. The error rate is calculated as

$$Error\_rate = \frac{1}{size(\mathrm{Pr}ed\ \_Set)} + \sum_{i=1}^{M}\sum_{j=1}^{M}\log(\max(lab(i,j)) + Time(Train(FS(N)))$$

}

## 5. RESULTS

Vision loss occurs due to the retinal damage that occurs as a result of diabetes mellitus. It can lead to blindness if it isn't caught early enough. Because DR is irreversible, treatment is only able to maintain vision. There are several ways to prevent vision loss, but early detection and treatment can be extremely beneficial. When it comes to diagnosing DR retina fundus photos, ophthalmologists have to spend a lot of time, effort, and money compared to computer-aided solutions. For medical image analysis and classification, deep learning has recently become one of the most popular strategies for improving performance.The diabetic retinopathy grade severity level assessment is proposed in this paper that uses Multi Linked Relevant Feature SetMarking Model using Convolution Neural Network (MLRFSMM-CNN). The proposed model is implenmented in python and

executed in Anaconda Jupyter. The proposed MLRFSMM-CNNmodel is compared with the traditional Diabetic Retinopathy Grading Using ResNet Convolutional Neural Network (DRG-RCNN) model. The proposed model is compared with the existing model in terms of Image segmentation accuracy, Feature Extraction Time Levels, Multi Linked Feature Processing Accuracy Levels, DR Detection Accuracy Levels, DR Grade Detection Time Level and DR Grade Detection Accuracy Levels.

Automated DR detection approaches are more cost-effective and time-saving than manual diagnosis. In comparison to automated procedures, hand diagnosis is more likely to result in a false positive. Image processing techniques are applied in the proposed model to enhance image quality and then perform feature extraction. The image segmentation accuracy levels of the proposed and traditional models are shown in Figure 4. Fundus images are first classified using independent convolutional neural network models, which are then concatenated with a hidden layer for further classification. The same shape descriptor could extract many properties, such as compactness, roundness, and circularity, in this case. The feature extraction time levels of the proposed model are less than the traditional method. The feature extraction time levels of the proposed and traditional models are represented in Figure 5. Only the convolutional and pooling layers are used in CNN, which lacks a fully linked layer. Full-connected layers frequently have more parameters than conventional CNN's convolutional layers, so this option considerably reduces the number of parameters and improves the interpretability of neural networks. The multi linked feature processing accuracy levels of the proposed and traditional models are shown in Figure 6. The amount of processing time required to manually evaluate retinal fundus images is enormous. Because of this, clinicians increasingly rely on imaging and computer vision technologies as well as intelligent diagnosis tools as their next step. Image processing and contrast limiting equalisation techniques are two of the solution methods provided in this study. Next, a convolutional neural network is used to classify the results of the diagnosis. The DR detection accuracy levels of the traditional and proposed models are represented in Figure 7. The proposed model detects the DR grade accurately and in a less time than the existing model. The DR grade detection time levels of the proposed and traditional models are shown in Figure 8. The DR grade detection accuracy levels of the proposed and traditional models are depicted in Figure 9. The proposed model accurately identifies the grade in less time that shows the performance levels of the model.

## 6. CONCLUSION

Retinopathy is a term that refers to retinal microvascular injury caused by uneven blood flow, which can result in vision impairment. Retinopathy is a common ocular manifestation of diabetes or high blood pressure. Significant clinical ophthalmology issues are alleviated by the automatic detection and classification of DR and grade detection. It may be used to grade eHealth fundus photos in real time. Remotely located fundus cameras have been the principal tool in ophthalmic telemedicine, taking fundus images of diabetics and digitally transmitting them to ophthalmologists in distant locations. These photos, however, must still be examined by a professional, and the final diagnosis must be conveyed to the patient as soon as possible. Artificial intelligence has the potential to revolutionize the traditional method of diagnosing eye disease and to have a significant therapeutic impact on the promotion of ophthalmic medical services. The convolutional neural network (CNN), a key framework of deep learning in computer vision, has generated great results in terms of diagnosis and prediction in medical picture categorization. Deep learning with fundus images has emerged as a practical and cost-effective approach for the automatic screening and diagnosis of more serious diabetic retinopathy. The entropy image of luminance of fundus image was shown to increase detection capability for referable DR using a CNN-based approach. This study proposes using the feature components of a fundus shot to build an entropy image. This study proposes a Multi Linked Relevant Feature Set Marking Model based on a Convolution Neural Network methodology for reliable DR grade recognition utilizing a feature extraction model. The proposed model achieves 97% accuracy in detecting the grade level of the DR that improves the system performance.

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