International Journal of Knowledge Based Computer Systems
12 (1) 2024, 16-26
http://www.publishingindia.com//ijkbcs/

Early Detection of Diabetic Retinopathy by using Deep Learning

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Abstract: The eye disease diabetic retinopathy (DR) can cause blindness if not treated. Worldwide, 2.6 million persons lost their sight or had severe vision impairments in 2015 as a result of diabetic retinopathy. By 2020, experts predict that number will have jumped to 3.2 million. In high-income nations, diabetic retinopathy should be less common, but in low- and middle-income countries, finding and treating the condition early should be a top concern. Thanks to recent developments in deep learning, researchers have demonstrated that automated diabetic retinopathy screening and grading is a practical method to reduce manpower requirements. The Kaggle dataset was used to find the winners of the diabetic retinopathy detection contest. In the suggested DL-DRDC methodology, the feature vectors from the previously processed retinal fundus images were retrieved using the modified Efficient Net method. The DL-DRDC Mechanism extracts characteristics from previously studied retinal fundus pictures using a modified version of Efficient Net. The proposed GA evolution selects the best-fitting model from a model population pool in order to optimise deep CNN models. The research and the experimental findings show that the recommended approach operates more efficiently than the other basic models. This research offered a novel and better approach for the diagnosis and severity rating of diabetic retinopathy.

Keywords: Convolutional Neural Network (CNN), Deep learning, Diabetic retinopathy, Model, Patient.

I. Introduction

According to the National Diabetic Registry (NDR), over 2.6% of Malaysians over the age of 18 had diabetes in 2012. Life expectancy may be reduced if problems occur, and the disease needs continual monitoring. At this time, diabetes also has no known cure. Having a basic understanding of the ailment, its effects on the body, and successful management strategies is, therefore, crucial. The title claims that a deep learning neural network and fundus images were used to identify diabetes. The fundus picture was obtained using the Topcon TRC NW6 non-mydriatic retinography, which features a color video 3CCD camera and a 45-degree field of view. In a nutshell, a fundus picture shows what's within a human eye. So, this study demonstrates how to identify diabetic eye illness using fundus photos. Variations in visual clarity, blurred or distorted vision, eye discomfort, cataracts, delayed recovery from eye injuries, and eventually blindness are among complications that diabetics may face. Furthermore, blindness is one of the most terrifying consequences of diabetes for the eyes. The most fundamental definition of diabetic retinopathy is damage to the retina, an eye ailment. The retina, situated in the back of the eye, is the main culprit when it comes to light sensitivity. Because of this, damage to it could cause blindness. Type 2 and type 1 of the illness were both discovered. However, the most common form of diabetes is type 2, which affects an estimated 90% to 95% of people.

In 2010, diabetic retinopathy (DR) caused the blindness and visual impairment of 3.8 million people worldwide. Experts project that 191.0 million individuals will develop DR by 2030 due to the increasing incidence of diabetes. Despite the fact that the worldwide incidence of any DR was 27.0% from 2015 to 2019, the early phases of DR, including referable DR, do not exhibit any noticeable symptoms. By detecting and treating DR early, the chance of vision loss may be reduced by about 57%. This is because DR can progress to a quite advanced stage before it impacts vision. It is extremely important for individuals with diabetes, especially those in the middle age and older age groups, to attend screenings and follow-up sessions regularly. Many diabetic people don't have their required yearly eye exams because they're too painful, don't notice any problems, or can't get to a retina specialist quickly enough, according to a number of studies [1].

Byproducts of glucose metabolism, including abnormally high blood sugar levels, build up in blood vessels. After a patient has had diabetes for over a decade, diabetic retinopathy (DR) sets in. High blood pressure is the root cause of diabetic retinopathy (DR), which in turn damages the retina and its vascularization, potentially leading to blindness or even death. Only via laborious and costly fundoscopy procedures can ophthalmologists detect retinal vascular edema. Diabetes is a major cause of blindness, and there will be an estimated 552 million people living with the disease by 2030 [2].

The most effective way to curb vision loss is to catch it in its early stages and treat it accordingly. Abnormal development of blood vessels and eventual blindness may occur in extreme instances when the vessels enlarge, leak fluid, or obstruct blood arteries. Retinal DR is characterized by micro aneurysms, hemorrhages, and exudates. The degree to which a lesion is noticeable depends on its size, shape, and general look. A screening tool for DR in the field of ophthalmology is fundus photography. An automated evaluation approach may effectively and affordably prevent diabetes-related blindness.

Ophthalmologists use visual evaluations and examinations of the eyes to determine the existence and severity of DR. This is a laborious and costly procedure for many people throughout the world who have diabetes. With statistics among qualified ophthalmologists differing greatly, DR severity and early disease identification continue to be challenges. In addition, there is a lack of adequate ophthalmologists and detection equipment in undeveloped nations, where 75% of DR patients reside. There are worldwide screening programmes in place to combat the increase of avoidable eye disorders, but the prevalence of DR is too high for effective individual detection and treatment.

Damage to the retina, known as DR, may happen as a result of hypertension. It may harm the retina's blood vessels, leading to potential blindness or death. Only via laborious and costly fundoscopy procedures can ophthalmologists detect retinal vascular edema. It is necessary to find DR automatically by looking at retinal fundus pictures. It has been shown that deep learning models can detect DR more accurately than ophthalmologists. They become a practical choice because of this. One of the most used deep learning models, Convolutional Neural Networks (CNNs) are utilized often in medical image identification, prediction, and classification. The objective of this study is to construct a CNN model with an updated activation function that can detect DR automatically.

This new activation function is compared against earlier activation functions using the open-source datasets DIARETDB0, DRIVE, CHASE, and Kaggle. By including a novel activation function, the present CNN version has been enhanced and now yields remarkable outcomes [3].

II. Literature Review

S. Gothane *et al.* (2022) When insulin is insufficient, blood glucose levels rise, a symptom of diabetes. A diabetic's eyes, heart, nerves, and kidneys are all impacted. Among the complications, diabetic retinopathy stands out. Compared to human analysis, automated approaches for Diabetic Retinopathy detection are more competent, cost less, and provide greater flexibility. Diagnose medical conditions with the help of computers using the Deep Learning approach. The goal of this project is to develop an automated method for detecting diabetic retinopathy in its early stages. Artificial intelligence and deep learning could help doctors predict when a patient will go blind. Using a supervised learning approach, this project is now classifying fundus photos. Micro aneurysms, hemorrhages, exudates, and swollen blood vessels are some of the key indicators of diabetic retinopathy that may be improved upon using a variety of image processing techniques and filters for this purpose. Neural networks are then employed for classification purposes. Using ResNet architecture, it successfully categorizes fundus pictures 82% of the time [4].

K. Oh *et al.* (2021), Worldwide, an estimated 3.2 million individuals will be blind or severely visually impaired by 2020 as a result of diabetic retinopathy, up from 2.6 million in 2015. Low- and middle-income nations must prioritize early identification and treatment of diabetic retinopathy, even though high-income nations should see a decline in its incidence. Automatic screening and grading of diabetic retinopathy is efficient, saving workers and time, according to researchers. This was made possible by the current breakthroughs in deep learning technology. Even though ultra-wide-field fundus photos may capture as much as 82% of the retinal surface, conventional fundus photos are still used by the majority of automated systems. Our method for diabetic retinopathy detection employs deep learning in conjunction with ultra-wide-field fundus imaging. Our experimental results show that, when comparing early treatment diabetic retinopathy studies, a 7-standard field picture produced by ultra-wide-field fundus photography is statistically better than an optic disc and macula centered image [5].

F. Nawaz *et al.* (2021) One of the retinal diseases that may lead to permanent blindness is Diabetic Retinopathy (DR). It is challenging to diagnose DR in its early stages since there are no symptoms at the beginning level. When blood sugar levels are too high, DR sets in. Timely identification and continuous treatment are necessary to avoid blindness. The ophthalmologist's ability to assess their patients' problems might be substantially enhanced with the use of AI-powered automated detection. Using DL and RL with ML, this study seeks to build a system that can autonomously identify and rank diabetic retinopathy. A method used in artificial intelligence known as transfer learning is utilized to train the Inception-v4 deep neural network. Two distinct transfer learning configurations—fixed feature extractor mode and fine-tune mode—are employed during Inception-v4 training. Although the accuracy rates achieved by both setup strategies are fair, fine-tuning outperforms fixed feature extractor. Using fine-tune configuration mode, the team achieved 97.7 percent accuracy in disease grading and 96.6% accuracy in early DR detection, surpassing the state-of-the-art methods in the corresponding literature [6].

Hasan *et al.* (2021) A chronic condition, diabetes mellitus is rapidly becoming a global epidemic. The condition manifests as problems with the eyes, kidneys, and heart caused by an elevation in blood glucose levels. When blood vessels in the retina burst, a condition called diabetic retinopathy (DR) develops. This is an eye consequence of diabetes. Since it does not present any obvious symptoms when first developing, it is thought to be the main cause of blindness. Early identification and classification of DR patients is crucial for the provision of needed medical care. Recent advances in machine learning's algorithms have made it a powerful tool for use in computer-assisted diagnosis and other medical applications. In this article, the team aims to analyze the performance of DR detection and classification systems that utilize various machine learning algorithms. For the purpose of training and evaluating these algorithms, several publically available datasets including massive volumes of retina fundus and thermal photos are utilized. These algorithms proved they could spot warning signs and quantify the severity of DR. Looking at the systems the teamanalyzed, ResNet50, an algorithm for deep convolutional neural networks, appears to have achieved the greatest performance. Using a cascade of feature extraction kernels, the Resnet50 can process retinal images and derive wealth data. Our findings suggest that ML algorithms might be useful in assisting medical professionals in DR patients with accurate diagnosis and appropriate treatment [7].

D. Das and S. Biswas (2020) One medical complication of diabetes mellitus is diabetic retinopathy (DR). Because it mutilates the human retina, it causes serious blindness. Statistics show that 80% of the population, disproportionately those of working age, has been afflicted by this illness. Therefore, DR has recently emerged as a critical problem that requires prompt resolution in order to significantly reduce the prevalence of blindness among working-age individuals. Due to the time and inaccuracy associated with human diagnosis, many sophisticated technologies have been developed to identify DR early on. Furthermore, ophthalmologists cannot be made available 24/7 at every location. Therefore, a computer-assisted intelligent system that is highly optimized is needed for the early diagnosis of DR. For decades, scientists all throughout the world have put forth different models. This paper's goal is to provide a more in-depth analysis of previous efforts and new technologies related to DR detection. Herein, the team provides the current level of knowledge about the characteristics, etiology, symptoms, grades, and models for early detection of DR [8].

III. Research Methodology

A. Genetic Algorithm for Deep Learning Model Selection in DR Diagnosis

It takes learning millions of parameters to train the CNN model from the ground up for a specific issue. Excessive computing power and resource utilization are necessary for this. Therefore, less computation is needed when transfer learning is used. There is a plethora of CNNs that have already been trained for the categorization job. Nonetheless, they have been designed to accommodate a wide range of datasets and applications. This makes choosing the optimal model for DR severity categorization a challenging task. Consequently, the team provides an automated process to choose the optimal pre-trained model for DR severity categorization. What sets GA apart from previous efforts is its application to the problem of automatically selecting the optimal model from among many pre-existing CNN models. The team suggests using GA to automatically choose the CNN network topology from the pretrained model. The first set of data points used to train GA are the pre-trained CNN architectures. A subset of the population is chosen at random from the population to make up the GA model's population. Additional training for deep feature extraction is applied to the chosen people. A significant disadvantage of using GA is the enormous computational expense it entails. The LSTM classifier is used to categorise the deep characteristics that have been retrieved in order to lower it. Ranking the individual models within the current population is a good indicator of the reliability of the testing data. The final ultimate model emerges by several iterations of genetic functions, including selection, crossover, and mutation. In order to aid in the early detection of DR, this best-fit model will include features with deep representations. Fig. 1 depicts the planned work's structural design. Python with TensorFlow, a library built on top of Keras, was used to create the system that was presented. A server with a TeslaV100 card ran the algorithm [9].

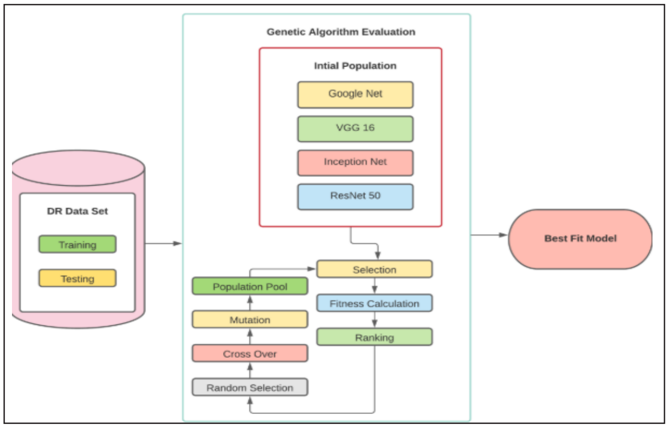

Fig. 1: Selection of Models using GA Evolution

- *Random Selection:* In order to incorporate genetic diversity, a small number of models with poor fitness scores are also included in the population, even though only the fittest models are preserved for the next generation. As a result, the global maxima are more easily reached by the optimum algorithm. To make sure of it, models with poor fitness are chosen at random using a 0.1 threshold. The number [0,1] is randomly allocated to each new generation of progeny.
- *Mutation:* A tiny fraction of each person's DNA may be changed at random to increase genetic variation. This haphazard alteration in a person's DNA is called mutation. You may randomly alter the bit position of a single gene at one of four locations. A mutation with a chance of 0.3 may only occur in one specific location in an individual's genes.
- *Crossover:* If there is still room for additional people in the population after retention, the process of crossover is used to fill it up. In order for crossover to take place, two separate models are chosen at random to serve as parents. The crossover point for the parent models is the midpoint of their length. Any person may take part in the crossover; there are no limits.

B. Proposed Methodology

A new "deep learning"-assisted DR detection and classification model is the Deep Learning Diabetic Retinopathy Detection and Classification (DL-DRDC) technique. Using retinal fundus photos, this DL-DRDC approach identifies and categorizes the different degrees of DR. The DL-DRDC system employs the CLAHE approach for its pre-processing stage. The most up-to-date DL-DRDC technique for DR detection using retinal fundus images is provided. You may see the whole DL-DRDC system's operation plan in the provided picture. The DL-DRDC approach is comprised of three separate steps. First, there is pre-processing. Then, there is feature extraction. And last, there is classification. The first step was to enhance the contrast levels of retinal fundus photographs using the CLAHE model. In the second stage, features were extracted from the pre-processed pictures using the modified Efficient Net approach. In the end, the processed retinal fundus pictures were appropriately classified using the Deep Neural Network procedure [10].

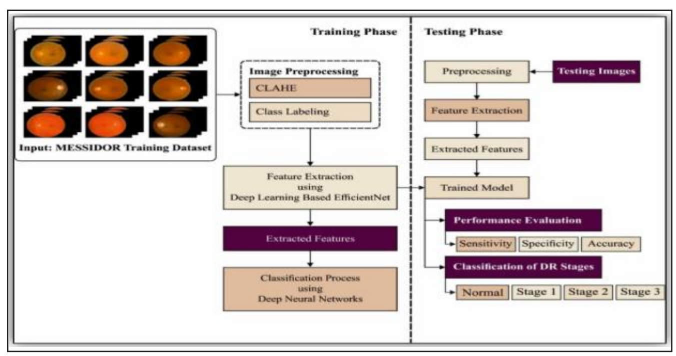

Fig. 2: A Comprehensive Overview of the Deep Learning Diabetic Retinopathy Detection and Classification System (DL-DRDC)

(i) CLAHE Method for Pre-Processing Images

To enhance their quality, the retinal fundus pictures undergo preprocessing. Reducing noise, shrinking the picture, and correcting the colors are common phases in this process. Statistical information about the picture is primarily what the histogram is intended to provide. In order to identify diabetic retinopathy, CLAHE is an important part of the preprocessing workflow. Retinal fundus pictures may be fine-tuned for more precise analysis and diagnosis by increasing contrast, which makes important characteristics more visible. In order to identify diabetic retinopathy, the preprocessing pipeline relies on CLAHE. By enhancing contrast, it makes key features in retinal fundus photos more visible, leading to a more precise evaluation and diagnosis of the disease.

(ii) Extracting Features using the Rationalized Efficient Net Method

Feature vectors are generated by passing the pre-processed, contrast-enhanced picture through the several levels of the Efficient Net model. A number of computer vision applications rely on feature extraction, such as segmentation, object identification, and picture categorization. In order for deep learning algorithms to make predictions or complete tasks, it is necessary to transform raw input data, such images, into a collection of representative features. One state-of-the-art framework for computer vision feature extraction is Efficient Net [11].

IV. Data Analysis

A. Selection of Neural Networks for Diabetic Retinopathy Diagnosis Based on Genetic Data

In Fig. 3, the confusion matrix that algorithm 1 produced on the DR dataset is shown. The confusion matrix illustrates exactly where the model is losing its bearings. This aids in the model's further fine-tuning. A deep learning system's TP, TN, FP, and FN may be discovered by creating an error or confusion matrix. The deep learning model's perplexion is well illustrated by the confusion matrix.

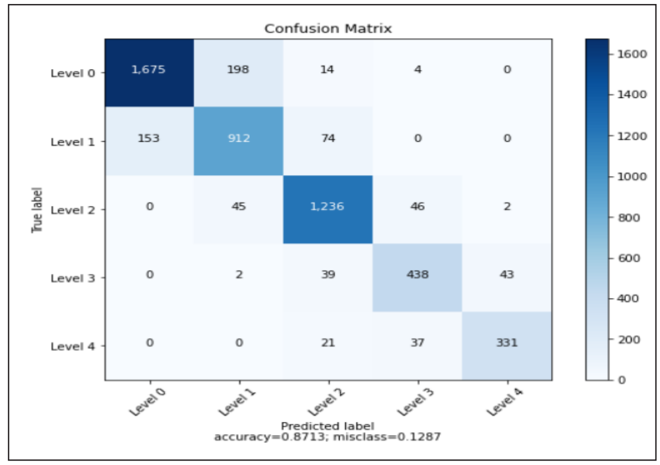

Fig. 3: A Model Selection Confusion Matrix Based on GA

Algorithm 1: The Use of Genetic Information to Select Neural Networks for DR Diagnosis

Input: Labeled fundus image dataset

Output: Optimized Neural Network for DR diagnosis

Initialization: Population, P = {DenseNet, ResNet50, VGG16, GoogleNet}

With_hold=0.3; Mutate = 0.3; Select_Random = 0.1

Steps:

i. For every, i ε P do
   a. Evaluate fitness function, F(i)
   b. Grade, G[i] = F(i)
ii. Arrange P with respect to non-increasing order of G[i]
iii. For x ε (0, with_hold* G.size - 1) do
   a. Parent.append(G[x])
iv. For every x in P calculate a random number and do
   a. If random(x)>Select_Random then
      i) Parent.append(G[x])
v. For every x in Parent calculate a random number and do |
   a. If random(x)>Mutate then

i) Flip x at position, Randint(0, x.size-1)

ii) Parent.append(G[x])

vi. size P.size- Parent.size

vii. If offsprings.size<size then

a. Select two parents, Pl and P2 from Parent at random and do

b. If P1 ≠ P2 then

i) offspring (P1[0, P1.size/2-1] + P2 [P1.size/2, Pl.size-1)

ii) offsprings.append(offspring)

iii) goto step vii

viii. Parent.append(offspring)

ix. Return parent

In the confusion matrix, you can find the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) calculations. Table I and Fig. 4, illustrate how well the Best-Fit model developed by GA Evolution performed when it came to early DR diagnosis. The model had an error rate of 11.35% for the train and 12.83% for the test [12].

Table I: Evaluation of GA Evolution's Best-Fit Model

Class	**Stage 0**	**Stage 1**	**Stage 2**	**Stage 3**	**Stage 4**
Accuracy	0.92	0.90	0.94	0.96	0.97
Precision	0.88	0.7	0.92	0.83	0.84
Recall	0.91	0.78	0.88	0.82	0.87
F1 Score	0.8	0.78	0.90	0.83	0.86

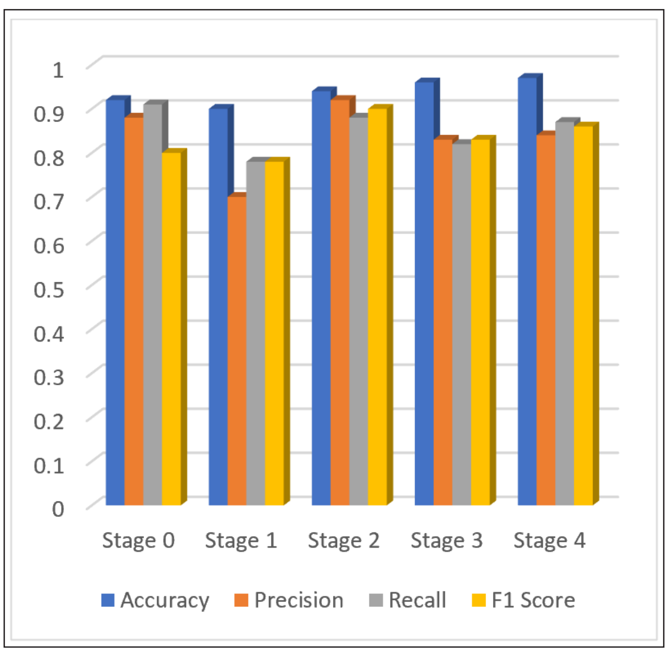

Fig. 4: Evaluation of GA Evolution's Best-Fit Model

The optimal model is chosen from the pool of available models using the suggested GA evolution for optimizing deep CNN models. Based on the analysis and experimental findings, the proposed technique is more efficient than the other basic models [13].

B. *Diabetic Retinopathy using Retinal Fundus Images for Deep Learning-Enabled Classification and Detection*

Kaggle data sets were used for training, whereas Messidor was used for experimental validation. One hundred and twenty fundus retinal pictures are available for DR classification in the Messidor dataset. It features pictures taken by three different ophthalmology clinics in France. Pupil dilation was not used in any of the photos. Following pupil dilation, 800 photos are captured, whereas 400 images are captured without. There are one hundred and twenty retinal fundus photos in this collection, arranged in the correct sequence of healthy, DR stages 0-4, and so on. A number of functionality measures are used to compute the results.

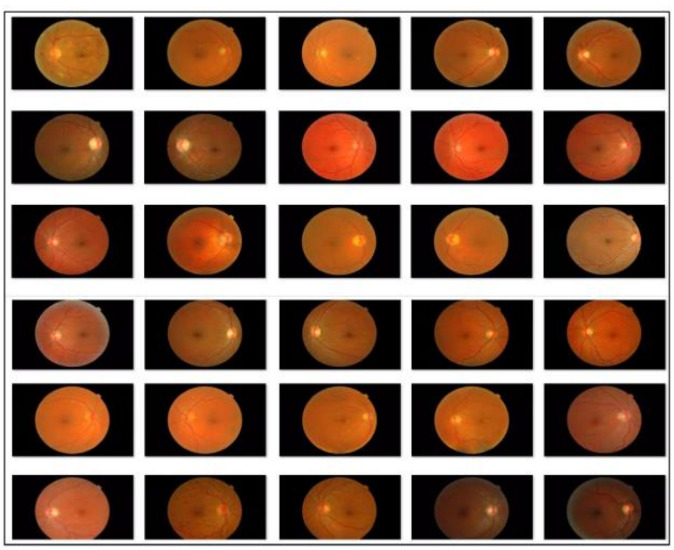

Fig. 5: Instance images

Fig. 5 shows the results of running the DL-DRDC technique on the data resource that was presented, and the resulting confusion matrices. Several DR phases monitored in separate runs have been described using the DL-DRDC approach. In terms of execution, the DL-DRDC model has classified 543 instances for the general stage, 150 instances for phase-1, 245 instances for phase-2, and 251 instances for phase-3. Table II illustrate how DL-DRDC performed in each of the experimental runs. Results across a number of parameters have been satisfactory using the DL-DRDC method. The first execution run of the DL-DRDC approach in the normal class achieved a 99% accuracy rate. An average accuracy rate of 99% has been achieved in explaining the DL-DRDC technique in the stage-1 class. There is now a 99% accuracy rate in describing the DL-DRDC technique in the stage-2 class. There has been a 99% success rate in explaining the DL-DRDC algorithm in the stage-3 class at the same time [12].

Table II: The Architecture of Efficient Net B0 Layers

Operator	Resolution	No. of Channels	No of Layers
Conv 3X3	224X224	32	1
MBConv1, k3X3	112 X 112	16	1
MBConv6, k3X3	112 X 112	24	2
MBConv6, k5X5	56 X 56	40	2
MBConv6, k3X3	28 X 28	80	3
MBConv6, k5X5	14 X 14	112	3
MBConv6, k5X5	14 X 14	192	4
MBConv6, k3X3	7 X 7	320	1
Conv1X1 &pooling &FC	7 X 7	1280	1

Table III and Fig. 6 show the average classification results from the analysis of the DL-DRDC method's executions. The DL-DRDC model generated effective DR diagnostic findings, as shown by several runs. In particular, the DLDRDC model has attained a 99% specificity, 98% rising sensitivity, 98% precision, 99% accuracy, and a 98% F-score throughout execution. After that, the DLDRDC method produced an F-score of 99%, sensitivity that increased by 99%, specificity that increased by 99%, precision that increased by 99%, and accuracy that increased by 99%. All of the DLDRDC model's metrics—F-score, accuracy, precision, specificity, and rising sensitivity—reached 99% by run-5.

Table III: Classification Results Analysis using the DL-DRDC Method

Number of Runs	Class	Sensitivity	Specificity	Precision	Accuracy	F1-Score
Run-1	Normal	99.4	99.4	99.4	99.4	99.4
	Stage-1	97	99.7	98.6	99.5	98.3
	Stage-2	99.1	99.3	97.5	99.2	98.3
	Stage-3	98.7	100	100	99.7	99.3
	Average	98.8	99.6	98.8	99.4	98.8
Run-2	Normal	99.7	99.4	99.4	99.5	99.4
	Stage-1	98	100	100	99.8	99
	Stage-2	100	99.6	97	99.5	99
	Stage-3	98.7	100	100	99.7	99.3
	Average	99.0	99.8	99.3	99.7	99.1
Run-3	Normal	99.6	99.7	99.6	99.7	99.5
	Stage-1	98.7	99.8	98.7	99.7	98.7
	Stage-2	99.2	99.6	98.4	99.5	98.8
	Stage-3	99.2	100	100	99.8	99.6
	Average	99.1	99.8	99.2	99.7	99.2
Run-4	Normal	99.4	99.7	99.6	99.6	99.5
	Stage-1	98.5	99.8	98.7	99.6	98.6
	Stage-2	99.5	99.6	98.7	99.6	99.1
	Stage-3	99.2	99.8	99.6	99.8	99.3
	Average	99.2	99.7	99.2	99.7	99.1
Run-5	Normal	99.8	99.6	99.6	99.8	99.6
	Stage-1	99.3	99.8	99.4	99.8	99.3
	Stage-2	99.5	99.7	99.2	99.8	99.3
	Stage-3	99.1	100	100	99.8	99.5
	Average	99.4	99.7	99.5	99.8	99.4

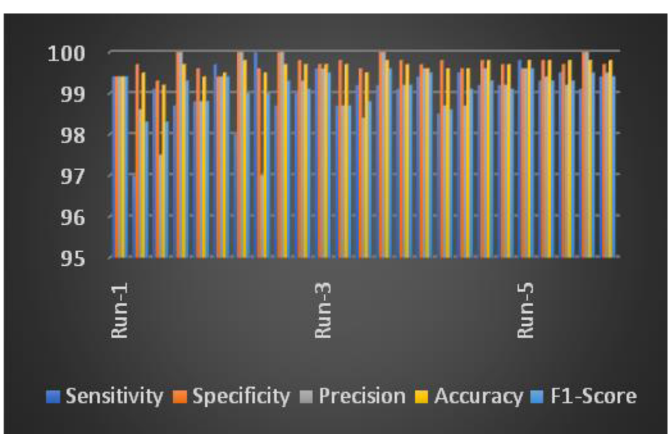

Fig. 6: The Results from Several Runs of the DL-DRDC Model

The majority of deep learning models used for DR detection are convolutional neural networks (CNNs), which sort out pixels that represent blood vessels from those that do not. This study presented a state-of-the-art DL-DRDC method for diabetic retinopathy (DR) severity rating systems. With the help of Efficient Net with DNN for picture categorization, deep learning models were able to provide prompt and accurate diagnoses. Retinal pictures were made more contrasty using the CLAHE method. Using the results of the class probability calculations, DNN chose the class with the best score. A thorough and effective method for identifying diabetic retinopathy, the proposed model included integrated pre-processing, segmentation, feature extraction, and classification phases [14].

V. Conclusion

In summary, a person's eyes are among their most vital organs. People are more likely to get Diabetes Mellitus (DM) due to modern lifestyle choices. DR will occur as a result of the chronic predominance of DM. While a full solution for DR is still in the works, it is now manageable with early diagnosis. Therefore, certain studies are conducted for computer-aided DR diagnosis in order to detect the disease at an earlier stage. Diabetic Mellitus (DM) has been on the rise due to modern lifestyle changes. Diabetes develops when the body either does not generate enough insulin or develops resistance to it. When blood glucose levels rise due to DM, regular blood flow becomes impossible. The kidneys, nerves, and eyes are among the most affected organs. As a result of diabetes being so common over the long term, a condition known as Diabetic Retinopathy (DR) may develop. Using deep learning methods, the DR may be detected early on. Convolutional Neural Network (CNN) design is a labor-intensive process. To choose the Convolutional Neural Network model that has already been trained, an automated Genetic Algorithm (GA) is used. A lot of deep learning models have been drawn by hand. They provide a function, to rephrase. The serious problem of diabetic retinopathy, which can cause blindness and frequently begins to manifest with no outward signs of illness, is the subject of this study. Treatment efficacy and vision preservation depend on prompt diagnosis and precise severity categorization. The four main components of the proposed comprehensive framework—preprocessing, optical disc removal, feature extraction, and classification—utilize the most recent advancements in deep learning.

Acknowledgement

Gratitude is extended to my advisor, for their guidance and support. Thanks also to my colleagues in the [Prestige Institute of Engineering Management & Research, Indore] for their assistance and feedback. Acknowledgment is made to the creators of the open-source tools and datasets used in this project. Thanks again to everyone who has always been there for us, but especially to our family and friends.

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