[1]Ms. Kinjal Patni *,

[2]Dr. Shruti Yagnik ,

[3]Dr. Pratik Patel

Advancements in Diabetic Retinopathy Detection: Innovations in Machine Learning and Deep Learning Techniques

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Abstract: - Diabetes, a widespread health issue affecting people of all ages, leads to high blood sugar levels and can cause serious complications if unmanaged. One such complication is Diabetic Retinopathy (DR), which damages the retina's blood vessels, potentially resulting in vision problems or blindness. Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), is increasingly utilized to detect DR stages by analyzing medical images, particularly fundus images that capture the back of the eye and are crucial for DR diagnosis. This study explores the effectiveness of various AI algorithms, especially deep learning-based methods, in extracting features from fundus images for DR detection, classification, and segmentation. We identify limitations in current models and propose new approaches to reduce processing times and costs in medical diagnostics, making the technology more accessible and aiding in preserving vision for patients with DR. Our research is the first to investigate the impact of complexity on processing times and costs in healthcare applications using diverse deep learning techniques. We provide a comparative analysis of ML and DL methods focusing on accuracy, sensitivity, specificity, and real-time challenges, aiming to assist academia and industry in developing improved frameworks and overcoming existing limitations.

Keywords: Diabetic retinopathy, Artificial intelligence, Deep learning, Machine-learning, Datasets, fundus image.

I. INTRODUCTION

Every manuscript About 101 million Indians has diabetes, and another 136 million are in pre-diabetes, according to a recent study by the **Madras Diabetes Research Foundation** and **Indian Council of Medical Research.** It is estimated to affect the global population with diabetes mellitus (DM) to be 463 million and is responsible for 22.27% of global blindness due to Diabetic Retinopathy [1]. Diabetes, also known as diabetes mellitus, is a long-term condition that alters how your body uses glucose, or sugar, as your cells' main source of energy. You get glucose from the food you eat, and the hormone insulin controls the amount of it is in your blood. When there are issues with insulin synthesis, action, or both, it results in diabetes and raises blood glucose levels.

The layout of the paper is as outlined: An overview is provided in Section 1. Diabetic retinopathy, different types, stages and symptoms, concepts of Machine Learning and deep Learning are discussed. In section 2, a review of the literature was done to gain thorough understanding about the research that has already been done. In Section 3, Methodology is described. In Section 4, Research Scope is Define. In Section 5, the paper is concluded in part 5 and section 6 gives the studied inferences a direction.

1.1 DIABETIC RETINOPATHY

Diabetic retinopathy is an ocular condition resulting from diabetes mellitus that impacts the retina, the light-sensitive tissue located at the rear of the eye. It is a typical diabetic side effect brought on by high blood sugar levels damaging the small blood vessels in the retina. If diabetic retinopathy is not identified and treated right away, it can cause vision issues and, in extreme circumstances, even blindness. Diabetic retinopathy is a diabetes-related eye disorder characterized by damage to the blood vessels in the retina, which can lead to visual loss if not treated swiftly. Usually, it progresses in phases, beginning with moderate non proliferative retinopathy, in which little blood vessel bulges appear, and ending with severe stages, in which there is substantial artery blockage and the development of aberrant blood vessels. Prolonged high blood sugar, hypertension, and cholesterol problems

[1] ***Corresponding author: Research scholar from Department of Computer Engineering, Indus Institute of Technology and Engineering, Indus University, Ahmedabad, Gujarat, India:** kinjalpatni11@gmail.com

[2] Associate Professor from Department of Computer Engineering, Indus Institute of Technology and Engineering, Indus University, Ahmedabad, Gujarat, India: shrutiyagnik.ce@indusuni.ac.in

[3] Assistant Professor form Department of Computer Science & Engineering, Parul Institute of Engineering & Technology, Parul University, Waghodia, Vadodara, Gujarat, India: pratik.patel2988@paruluniversity.ac.in

are important risk factors. Regular ocular examinations are essential for early detection, since prompt therapies such as injections or laser therapy can help preserve vision and avert significant problems.

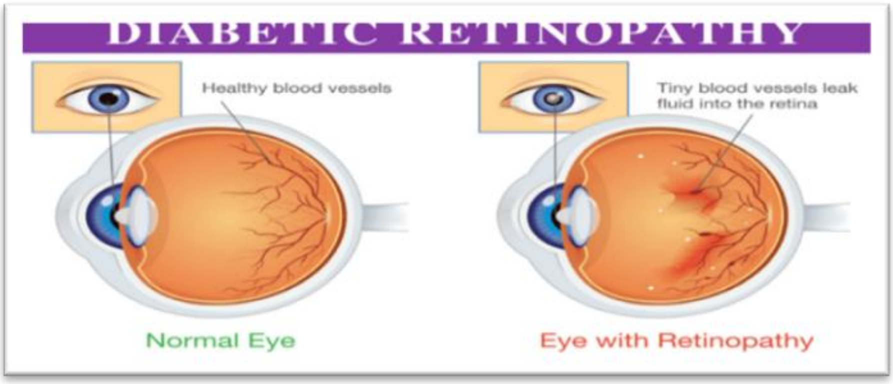

Figure 1: Difference between Healthy Eye and Eye with Diabetic Retinopathy [2]

Here we mentioned some Sign and Symptoms of Diabetic Retinopathy [2]: -

1. Fluctuating vision
2. Blurred vision
3. Vision loss
4. Impaired color recognition
5. Dark spots or strings floating through your vision.

1.2 TYPES OF LESIONS IN DIABETIC RETINOPATHY

The information describes some of the common signs or lesions associated with diabetic retinopathy (DR), a diabetes-related eye disease. These signs are typically observed during retinal examinations and can provide important diagnostic information. Here's a brief explanation of each of these signs:

1. **Microaneurysms (MA):** It is tiny bulges or outpouchings in the retina's small blood vessels. They are a hallmark sign of diabetic retinopathy and are commonly found in the macular area, which is responsible for central vision. Microaneurysms often appear as red dots on the retina and are typically less than 125 micrometres (µm) in size. They have sharp margins and can be early indicators of retinal damage due to diabetes.

2. **H**

emorrhages (HM): Hemorrhages are spots of bleeding in the retina. There are different types of hemorrhages associated with diabetic retinopathy.Blot Hemorrhages: These are larger, irregularly shaped hemorrhages that are typically greater than 125 µm in size. They occur due to leakage from damaged capillaries. Superficial Hemorrhages: These are hemorrhages that happen on the surface of the retina and are also associated with capillary leakage.

3. **Hard Exudates:** Hard exudates are bright yellow or white deposits that often occur in the macular area. They have sharp margins and result from the leakage of lipid-rich fluids, such as plasma, from damaged blood vessels. The accumulation of lipids in the retinal tissue can lead to vision problems.

4. **Soft Exudates:** Soft Exudates are either grey as well as white. Patches on the retinal surface. They are caused by the swelling and damage of nerve fibres in the retina due to insufficient blood supply. Soft Exudates are signing about retinal ischemia (lack of blood flow) and may indicate more advanced diabetic retinopathy.

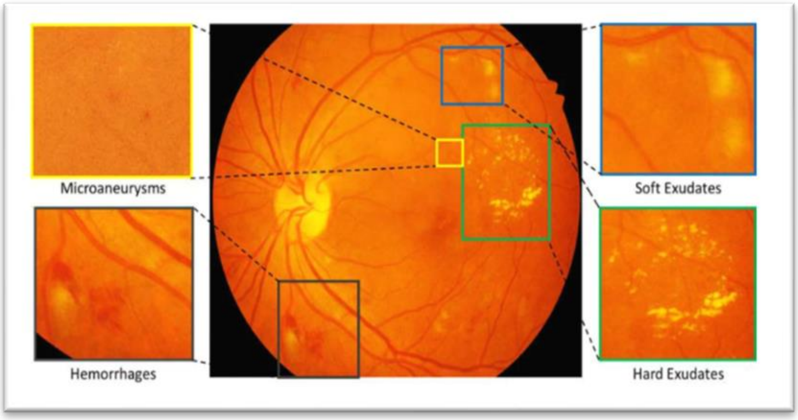

Figure 2: Define Types of lesions on a retina image [3]

1.3 STAGES OF DIABETIC RETINOPATHY

The **4 Stages** of Diabetic Retinopathy are: -

1. **Mild NPDR:** Highlighted by tiny areas of microaneurysms—a type of swelling in the retinal blood vessels. Macular it, or swelling in the retina, can result from tiny amounts of fluid leaking in. [5].
2. **Moderate NPDR:** It happens when the retina's blood flow is impeded by the growth of small capillaries, which leads to a buildup of blood and fluid in the macula (macular wounds) [5].
3. **Severe NPDR:** In this moment, a greater portion of the retina's blood vessels obstruct, significantly reducing the amount of blood flowing to the afflicted area. In response, the body sends signals to generate new blood vessels in the retina. [5].
4. **Proliferative Diabetic Retinopathy:** In the retina, new blood vessels are growing at this advanced stage. Because of their fragility and propensity to leak, these new vessels can cause floaters, blurriness, limited field of vision, difficulties reading, difficulty recognizing distant things, and even blindness. [5]. The Below mention figure Define the Phases of Diabetic Retinopathy [4].

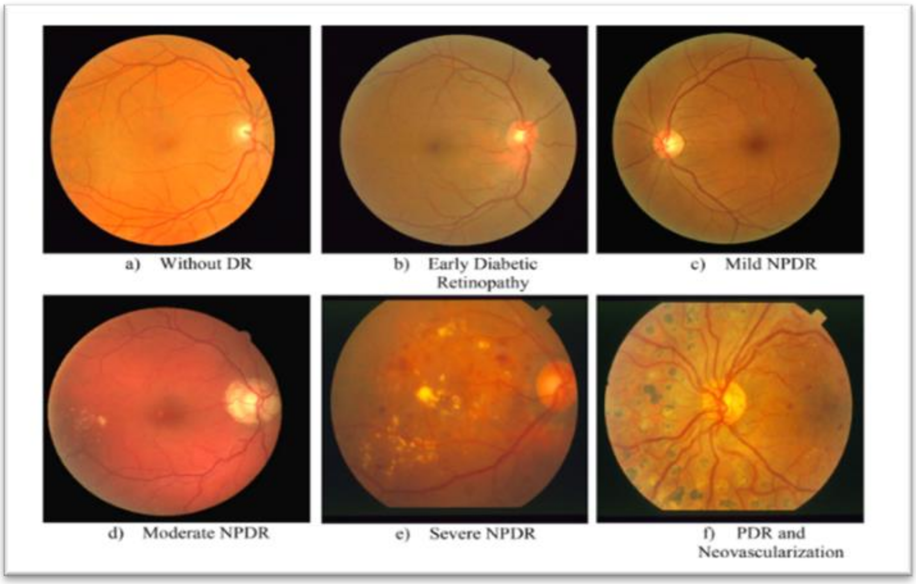

Figure 3: Phases of Diabetic Retinopathy [4]

1.4 MACHINE LEARNING AND DEEP LEARNING

Machine learning is a branch of artificial intelligence (AI) that focuses on developing models and algorithms that let computers learn from data and produce predictions or decisions without the need for explicit programming. In the field of medicine, machine learning has been widely applied, particularly in the diagnosis and treatment of diabetic retinopathy (DR). Image segmentation is the process of identifying and separating various structures within retinal images. Algorithms for machine learning can be applied to this. Using machine learning in the treatment of diabetic retinopathy serves as an example of how technology can be used to improve patient outcomes, facilitate early detection, and streamline healthcare procedures.

It is true that machine learning includes deep learning. Focusing on multiple-layer neural networks. Because it can automatically learn hierarchical representations from data, it has become more and more popular. Deep Learning models are characterized by their multilayered, hierarchical architecture. This hierarchical representation permits them to spot complex patterns and features in the data. Applications in Medical Image Analysis: Deep Learning has found extensive use in medical image analysis. It can be applied to tasks such as classification, localization, segmentation, and detection of abnormalities in medical images. In the context of diabetic retinopathy, Deep Learning has demonstrated impressive results. DL models have demonstrated promise in automating the detection and classification of diabetic retinopathy from retinal images. Diabetic retinopathy is a common eye disease among patients with diabetes. Convolutional neural networks (CNNs), deep Boltzmann machines (DBMs), autoencoders, deep neural networks (DNNs), recurrent neural networks (RNNs), deep belief networks (DBNs), and generative adversarial networks (GANs) are a few examples of the various Deep Learning techniques that are available. Depending on the particular requirements of the medical image analysis task, any of these methods can be used. It's true that having a larger amount of training data can significantly enhance the Deep Learning models' performance. More data allows these models to learn both low-level and high-level features effectively, which is crucial for tasks like medical image analysis. To be sure, the most widely utilized Deep Learning architecture in medical imaging is the Convolutional Neural Network (CNN). CNNs are well-suited for tasks involving grid-like data such as images and have shown remarkable success in image classification and segmentation tasks.

1.5 CONTRIBUTION OF RESEARCH

The most common cause of blindness worldwide is diabetic retinopathy. A consequence of diabetes called diabetic retinopathy makes the blood vessels in the retina swell and leak blood and fluids. The appearance of various lesion types on a retinal image serves as a detection method. These lesions include: 1. hard exudates (HE), 2. Microaneurysms (MA), 3. Soft exudates (SE), and 4. Haemorrhages (HM). Diabetic Retinopathy is categorised into the following Stages based on the Lesions: 1. Absent DR, 2. Proliferative Diabetic Retinopathy; 3. Moderate NPDR; 4. Severe NPDR; 5. Mild NPDR. Deep learning and machine learning functions in diabetic retinopathy research has led to the development of automated systems for the Detection and classification of retinal abnormalities. These technologies could boost diagnostic accuracy and increase the effectiveness of screening Diabetic retinopathy. These techniques make it easier to identify retinal abnormalities linked to diabetic retinopathy early on, allowing for prompt treatment and lowering the risk of vision loss. Ultimately, the goal of applying a systemic algorithm is to mitigate the worldwide burden of diabetes-related vision impairment by enhancing clinical management techniques. Current investigations continue to tackle novel issues and look for creative ways to treat and prevent diabetic retinopathy.

II.LITERATURE REVIEW

The literature review on diabetic retinopathy is presented in this section includes a number of relevant deep learning and image processing model methodologies for predicting the disease with precision applying trained models. This literature review's main objective is to highlight the uses of the various algorithms and approaches used to identify diabetic retinopathy disease.

Yerrarapu Sravani Devi, Singam Phani Kumar [6], the paper focuses on deep learning-based diabetic retinopathy detection. It talks about data augmentation techniques with a transfer learning model. In order to prevent vision loss, the paper primarily emphasizes the early detection technique of diabetic retinopathy.

Samyak Shah, Shikha Punjabi, Shweta Chavan et all [7], The authors of this study state that CNN provides the most promising results, using retinal images to predict normal and abnormal conditions. For image detection, OpenCV image pre-processing packages are utilized. When it comes to scan interpretation, computer vision and machine learning techniques outperform healthcare professionals in the detection of diabetic retinopathy.

Nandhini s, Sowbarnikkaa S et all [8], In this paper author used CNNs and transfer learning—in which CNNs are utilized in DR for both feature extraction and classification. An author proposes applying the DenseNet-169 method to identify DR early on. Will highlight that an ensemble algorithm for improved DR detection may be used in future work.

R.B.Jayanthi rajee, S.Mohamed Mansoor Roomi et all [9], The authors' work on using deep learning models to diagnose retinal diseases can be summarized up. The author suggests using the Inceptionv3 architecture, which has the accuracy to identify five different retinal diseases. In retinal diseases, early detection is essential to preventing visual impairment.

Penikalapati Pragathi and Agastyaraju Nagaraja Rao [10], In order to identify diabetic retinopathy, this paper proposed an integrated approach using machine learning algorithms and achieved high performance. The dataset obtained from the UCI ML repository is utilized in the suggested methodology. As the author suggests, a very useful integrated approach of machine learning algorithms for identifying diabetic retinopathy and averting blindness is the moth-flame optimization technique.

Ghulam ali, Aqsa dastgir et all [11], DR is becoming more recognized as a cause of visual loss in individuals of working age. Diabetes-related vision loss must be avoided by receiving treatment and early detection. This study proposes a novel CNN network for the diagnosis of diabetic retinopathy. The proposed technique uses Inceptionv3 and Resnet50 in an end-to-end mechanism to extract features from diabetic fundus images. A combination about the features extracted from both models; they are put into the suggested IR-CNN model for DR classification.

Sheena Christabel Pravin, Sindhu Priya Kanaga Sabapathy et all [12], The author of this work proposed an effective DenseNet model for extracting features from retinal images. Images of the retina were classified into five groups by the model during training: healthy, mild, moderate, severe, and PDR. In terms of total accessible parameters, computational time, test precision as well as additional assessment criteria, a suggested effective DenseNet may perform better than them. Ophthalmologists can therefore use The Model to diagnose DR precisely. Several retinal datasets will be the subject of experiments in future work.

Srilaxmi Dasari, Boo Poonguzhali et all [13], This article Focuses on existing methods for diabetic retinopathy classification. EML-DRGC system proposed by the author. Diabetic retinopathy should be automatically diagnosed with high specificity and high accuracy using the EML-DRGC design.

Shalini R, Sasikala S [14], the learning model proposed by the author, which depends on an Improved Grid Search Convolutional Neural Network (IGSCNN), demonstrated early stages accuracy. The CNN algorithm was selected because the convolutional layers automatically extract features. This paper discusses a number of deep learning models, including CNN, UNet, and GAN. Image processing for hemorrhages, exudates, and microaneurysms classification. Both the CNN tuned model and the CNN normal model were examined in the suggested work.

Nida Nasir, Neda Afreen [15], the authors of this paper describe how transfer learning is used to classify DME and DR according to their grading. Prior to automated features, quantification and grading in DR were done by hand. Therefore, several machine learning techniques, including SVM and KNN, were used for that. By classifying DR and DME using a severity grading scheme on the benchmark dataset that is accessible to the public IDRiD, the artificial neural network ResNet50 model attains higher training and testing accuracy.

A. Aruna Kumari, Avinash Bhagat et all [16], In this article, feed-forward neural networks with ResNet technology were proposed for automated decision making. When pre-processing and classifying the images, both sequential and non-sequential images were analyzed concurrently. Through precise DED disease detection, it can improve the delivery of healthcare. PCA is used to reduce dimensionality in the representation of image data.

Pranajit Kumar Das, Suree Pumrin [17], the author can use CNN models like LeNet-5, AlexNet, and VGGNet for DR classification. Convolutional Neural Network (CNN) models based on transfer learning are used to classify two stages of Diabetic Retinopathy from retinal color fundus images. The pre-trained network of VGG16, InceptionV3, and MobileNet models is used in two stages of DR classification. To help with diagnosis, a deep learning-based interpretable DR classifier is suggested. The original Messidor and Messidor-2 datasets, which are further separated into training and testing sets, make up the dataset used in this study.

Dhruvin Rajesh Dungrani, Harsh Rajesh Lotia et all [18], The principal aim of this project is to make the model accessible in rural areas to enable health care providers to use it for early detection of diabetic retinopathy and possibly prevent irreversible vision loss. This work focused on the automated detection, grading, and segmentation of diabetic retinopathy using CNNs. A three channel 2-dimensional sequential 3-layer convolutional neural network works better for retinopathy stage prediction.

Sarvat Ali and Shital Raut [19], the authors of this study state that deep learning algorithms provide improved accuracy in the early detection of diabetic retinopathy. By employing GAN to create images for data augmentation and then training the model on the combined dataset, the accuracy and scores of the current model can be further improved. Additional fundus image datasets, such as Eyepacs, Idrid, and others, should be used to assess the model. Lesion segmentation, classifying the degree of DR and distributing the model for screening across mobile or web platforms could all be accomplished with more research.

M. Vamsi Krishna1 B, Srinivasa Rao [20], in this study Several models, including VGGNet, GoogleNet, ResNet18, and AlexNet used. Authors can address overfitting problems by utilizing data augmentation techniques. The proposed methodology classifies the various DED disorders (normal, DME, cataract, glaucoma, and diabetic retinopathy) using fundus pictures. The proposed work uses combined datasets from multiple sources to implement classification. It also proposes a Hybrid DL technique for the detection of diabetic retinopathy.

Dolly Das, Saroj Kumar Biswas et all [21], 26 DL networks are compared in the study in order to extract and classify DR features. Using 26 state-of-the-art DL networks in the proposed comprehensive model, a thorough analysis of these architectures is applied to fundus images to determine the optimal DL architecture for DR feature extraction and fundus image classification. Out of all the models, VGG-16 has the lowest training accuracy, while DenseNet201 has the highest. Again, EfficientNetB4 has the highest validation accuracy, and VGG-16 has the lowest validation accuracy.

Thumma Dharani, Medikonda Padma Prasamsa et all [22], However, due to Due to the dataset's small number of fundus images, the model cannot reliably identify the severe stage of DR. An effective way to identify this stage is to increase the number of images associated with it. In addition, a number of deep neural network architectures other than ResNet's can produce higher accuracy; these can be explored in further research.

Bina Kotiyal and Heman Pathak [23], Using DL techniques, this study proposed a novel pipeline for binary classification of DR. The preprocessing of the IDRID dataset is completed before it is sent to the pipeline. The performance of the InceptionV3, Xception, and VGG19 is evaluated here. AUC score, f1-score, and accuracy are the performance metrics that are taken into account. For the DR image problem, InceptionV3 has been found to perform the best.

Yasashvini R., Vergin Raja Sarobin M et all [24], Inside this section Several deep learning models, such as ResNet151 and Inception V3, were used. Even though CNN performed better than the conventional algorithms, overfitting was avoided and the desired ac Future iterations of the algorithms' parameters can be precisely adjusted to achieve better outcomes, and additional effective optimization strategies utilized to increase the model's accuracy curacy was only reached when transfer learning algorithms like ResNet and DenseNet were applied.

Akshita L, Harshul Singhal [25], this paper focuses on the inefficiencies in the diagnosis of diabetic retinopathy, and the author suggests DCNN. The importance of effective classification schemes for DR is emphasised in the paper. In each iteration, the model employs a four-layered, deeply connected convolutional neural network. Since the provided models only covered a small amount of data, they can be expanded by using a larger dataset. This will enable the model to be trained through fewer iterations and increase testing accuracy. Additionally, the suggested system can be implemented on sophisticated platforms like field programmable gate array devices or mobile phones.

G. Kalyani, B. Janakiramaiah et all [26], In this paper, in order to identify diabetic retinopathy, we developed a convolution layer, primary capsule layer, and class capsule layer capsule network. The first two layers are used for feature extraction, while the class capsule layer assesses the likelihood of a particular class. In all four phases, the CapsNet that was created correctly detects the issue. The suggested CapsNet's performance is contrasted with that of an existing technique—modified AlexNet—that is a part of the CNN methodology. d, the suggested CapsNet performs well in the early identification of diabetic patients' retinopathy issues.

D. Raghu Raman, S. Nishanthi et all [27], An EfficientNet-B7 model was proposed in this study to classify diabetic retinopathy. When combined with augmentation techniques and EfficientNet-B7 models for training, the preprocessing methods yield better quality input images. Future research can also look into how well the suggested technology predicts other conditions like glaucoma and macular degeneration.

Gaurav kumar, Shraban chatterjee and Chiranjoy chattopadhyay [28], the author of this paper uses deep learning models to diagnose diabetic retinopathy. DRISTI helps oculists make quick, accurate diagnoses of DR. Testing across datasets demonstrates the robustness of the model.

Nandeeswar Sampigehalli Basavaraju, Shanmugarathinam Ganesarathina [29], This research paper proposes a new k-means based ensemble model to enhance the color retinal fundus image DR detection performance. The segmentation and classification phases are the two main components of the suggested k-means based ensemble model.

K. Nirmala, K. Saruladha and Kenenisa Dekeba [30], this study talks about a number of techniques, including feature extraction, segmentation, and classification. Created a deep CNN model to categories images of diabetic retinopathy. Utilising the CNN framework, retinal fundus images are evaluated for exudates. Future developments in feature analysis and diverse deep learning technique analysis may expand on this work.

Valarmathi Srinivasan and Vijayabhanu Rajagopal [31], The MSA-ResNetGB model was presented in this paper to identify and classify RF samples according to DR severity levels. Many models, including CNN structures, EfficientNet, and Xception-based models, were discussed. With great accuracy, the MSA-ResNetGB model classifies DR severity grades. Makes use of the MSFP model, MSA strategy, and encoder network.

Shubhi Gupta, Sanjeev Thakur & Ashutosh Gupta [32], the optimized hybrid machine learning approach for smartphone-based deep learning detection has been presented in this article. Nonmydriatic camera on a smartphone for DR detection in remote locations. The author can compare the performance of DR recognition using different DL structures. In the future, in order to achieve the highest detection rate possible, the classification stage may be expanded using improved ML and DL techniques along with new, distinct optimization algorithms.

Mahmoud Ragab, Abdullah S. AL-Malaise AL-Ghamdi et all [33], The authors of this article stress the significance of early detection of an effective treatment. The present work implements diabetes classification using a deep neural network, i.e., a convolutional neural network. The experimental results indicate that the proposed deep learning model is accurate and effective. To improve the work for an automated diabetes analysis, deep learning algorithms and methodologies can be added.

B. Sumathy, Sandeep Gupta et all [34], In this study Boosted trees, logistic regression, K closest neighbor, support vector machines, and bagged trees are some of the classifiers that were applied to the dataset in order to create the model. To choose the best features and prevent overfitting, K-fold cross-validation and hold-out validation techniques have been applied in conjunction with classification algorithms. 90.1 percent accuracy was highest for boosted trees.

Yarragudi Madhu Sudhana Reddy, Ramaswami Sachidanandan Ernest Ravindran [35], based on retinal fundus images, the authors of this paper have proposed a four-stage automatic DR screening system that determines and grades the stage of DR. This study mentioned achieving high accuracy with k-NN, GMM, and SVM classifiers. This study created a comprehensive DR diagnosis system that took into account every potential characteristic seen in retinal images. Additionally, the developed achieved a maximum accuracy, demonstrating its effectiveness. It was only tested on a small however, the quantity of retinal images. In the future, it can be utilized to test the robustness of different retinal images with different DR statuses.

Common issues across the reviewed studies include the reliance on small or limited datasets, which can affect the model's generalizability and accuracy in real-world settings. Many models face challenges with overfitting due to insufficient training data, and some approaches struggle with high computational costs and extended processing times. While deep learning models like CNNs and transfer learning techniques show promise, they often require significant fine-tuning and extensive computational resources. Additionally, the effectiveness of these models can vary depending on the quality of the images and the specific characteristics of the datasets used. Future research needs to address these limitations by incorporating larger, more diverse datasets, exploring alternative deep learning architectures, and improving the models' ability to generalize across different populations and settings.

Table 1: Present Technique for Detecting, Classification as well as Identification Diabetic Retinopathy

Authors & Refernce	Technique	Task	Dataset	Benefit /Achievement
Yerrarapu Sravani Devi,Singam Phani Kumar [6]	IR (Inception V3, ResNet50) & CNN Model	Diabetic retinopathy identification through data augmentation.	APTOS-Blindness dataset	With synthetic data, the suggested model, ResNet50, can strengthen and enhance the classifying model's performance.
Samyak Shah, Shikha Punjabi et al. [7]	Fully Convolutional Networks	Diabetic retinopathy Detection and Classification.	The National University Hospital in Singapore provided the dataset that was used to train the model, and ANOVA was used to obtain the statistics.	When compared to DenseNet-169, the suggested method, DNM, has an accuracy ratio of 90.02% for the early detection and classification of diabetic retinopathy.
Nandhini S, Sowbarnikkaa S et al. [8]	DiaNet Model (DNM)	Multistage Classification and automatic operation Diabetic Retinopathy Detection.	APTOS and EyePACS	When compared to DenseNet-169, the suggested method DNM has an accuracy ratio of 90.02% in order to identify and categorise diabetic retinopathy early on.
R.B.Jayanthi rajee et al. [9]	Based on Inception v3, transfer learning	Diabetic retinopathy Classification.	There have been 3294 retinal images used.	The performance of the proposed method is compared with other pre-trained models to illustrate its efficacy. Additionally, this work makes it easier to make decisions about common disorders without consulting ophthalmologists.
Penikalapati Pragathi and Agastyaraju Nagaraja Rao [10]	Moth-flame optimisation, machine learning (ML), and support vector machines (SVM).	Detecting diabetic retinopathy through an integrated machine learning approach.	UCI ML repository	Combining SVM, PCA, and moth-flame optimisation techniques is known to improve classification performance and yield precise class labels.
Ghulam ali, aqsa dastgir et al. [11]	InceptionV3 Resnet50 convolutional neural network	Diabetic Retinopathy Classification from Fundus	OCT fundus images	When compared to the current model, the proposed model (IR - CNN) produces encouraging results.

	(IR-CNN)	Images		
Sheena Christabel Pravin, Sindhu Priya Kanaga Sabapathy et al. [12]	DenseNet	Diabetic Retinopathy Screening	Kaggle dataset used	Therefore, ophthalmologists may utilise the suggested model as a medical tool to help them accurately diagnose DR. It can help with early and accurate DR screening.

III.METHODOLOGY

3.1 GENERAL FRAMEWORK

The Scheme discussing an identification and reduction of early-stage diabetic retinopathy (DR). If left untreated, diabetic retinopathy, a common complication of diabetes, can damage the eyes and result in blindness. The Scheme is designed to identify preliminary stages of diabetic retinopathy along with subsequently reduce the occurrence or progression of diabetic retinopathy.

Implementing such Scheme can have significant positive impacts on individuals with diabetes by enabling early intervention and appropriate management strategies to prevent or mitigate the effects of diabetic retinopathy. The successful management of numerous medical conditions, including diabetic retinopathy, depends heavily on early detection and prompt intervention.

The Scheme could potentially use various data sources, imaging techniques, or other relevant information to achieve its goal of early identification and subsequent reduction of DR occurrence. The detection and classification of diabetic retinopathy (DR) using fundus images involves a structured framework that begins with data acquisition, where a diverse dataset of labeled fundus images is collected from various sources. Following this, preprocessing steps enhance image quality through techniques like augmentation and noise reduction, while segmentation isolates key areas of interest. Feature extraction then occurs, utilizing both traditional methods (such as texture and shape analysis) and advanced deep learning approaches like convolutional neural networks (CNNs) to automatically identify relevant features.

The model development phase employs various classification algorithms, including traditional machine learning techniques and deep learning architectures, potentially utilizing transfer learning for improved performance. After training the model on the prepared dataset, evaluation metrics such as accuracy, sensitivity, and area under the ROC curve are used to assess its effectiveness. Finally, the developed model can be deployed in clinical settings to assist healthcare professionals in the timely detection and classification of diabetic retinopathy, ultimately aiding in patient management and treatment decisions.

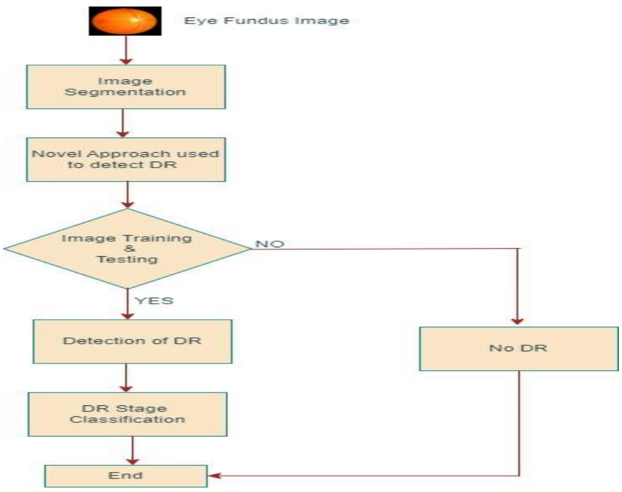

Figure 4: General Framework for Detection & Classification of Diabetic Retinopathy using Fundus image.

3.2 DATASET

The efficacy of the DL studies discussed here is greatly affected by the datasets that are being used. The quality of these datasets and the accuracy of their descriptions are two factors that affect the outcomes of these kinds of studies. Consequently, it will be useful to have a list of a few commonly used fundus image datasets for DR segmentation and lesion detection. A list similar to this is shown in Table 2.

These studies frequently use publicly available datasets from sources like Kaggle, DRIVE, IDRiD, MESSIDOR, DIARET DB1, and APTOS, among others. The MESSIDOR dataset was made available to the public in 2008 and was a component of the MESSIDOR project. Groundtruth for diabetic macular edoema (DME) and DR is provided by the Indian DR Image Dataset (IDRiD). It has annotations for the optic disc, DR lesions, and DR grading. A sizable collection of high-resolution retinal images captured in a range of imaging circumstances can be found on Kaggle.

Table 2: Datasets used for Diabetic Retinopathy Fundus images/Lesion Detection

References	Dataset Name	No of Image	No of Class
[6]	APTOS 2019	18590	Class 0 to 4 stages of DR
[7]	National University Hospital, Singapore	930	-
[8]	APTOS, EYEPACS	5590, 80,000	0 to 4 DR classes
[9]	Kaggle	3294	6 distinct classes
[10]	UCI ML repository	30,000	Two class
[11]	open-source dataset	44,119	five distinct classes of DR
[12]	Asia-Pacific Tele-Ophthalmology Society (APTOS)	13000	Class 0 to 4
[13]	Messidor	1200	which are classified into 4 categories
[14]	Kaggle	5556	five different classes
[15]	IDRiD	516	5 DR classes
[16]	Kaggle	5672 sequential and 7231 non-sequential Images	5 DR classes
[17]	Messidor and Messidor-2 dataset	1200 fundus color images & 1748 fundus color images	5 DR classes
[18]	DRIVE, local hospitals	40, 200	5 DR classes
[19]	Eyepacs dataset along with Aptos dataset	3762	-
[20]	DRISHTI-GS, Messidor-2, Messidor, and retina datasets	1748	5 DR classes
[21]	Kaggle's EyePACS dataset	35,126	5 DR classes
[22]	Kaggle APTOS 2019	5590	classes from 0 to 4
[23]	IDRID dataset	192	5 DR classes
[25]	EyePACS	17,540	5 DR classes
[26]	Messidor	1200	Grade 0 to 3 stages of DR

3.3 SEGMENTATION

In deep learning, segmentation is the process of breaking up an input image into regions or segments that have meaning. In order to essentially create a detailed map of the objects or regions present, the objective is to give each pixel in the image a specific label or category. For image segmentation tasks, deep learning—more specifically, convolutional neural networks (CNNs)—has shown to be very effective.

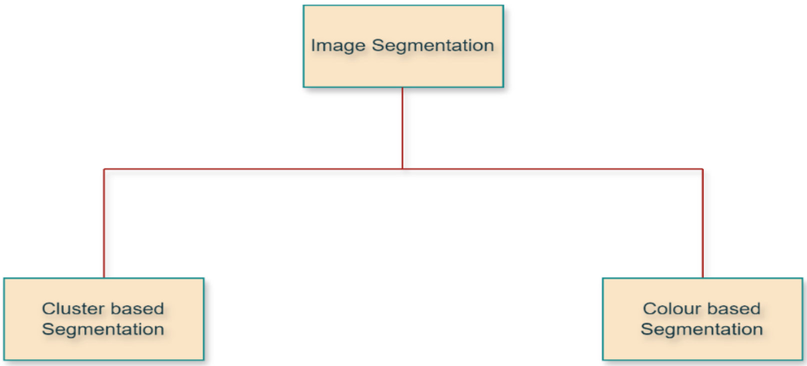

Figure 5: Methods of Segmentation

3.3.1 Cluster Based Segmentation

A method called clustering-based image segmentation divides an image's pixels or regions into clusters according to how similar they are. In contrast to semantic segmentation, which labels every pixel, clustering techniques combine pixels that share similar attributes. One of the most popular algorithms for this is K-means clustering. The purpose of the goal of K-Means clustering is to shorten the squared total distances between each cluster member and the cluster center.

The K-means clustering algorithm consists of the following steps: i) initialize K; ii) choose K points at random; iii) use the closest centroid for each data point to create K clusters; iv) after the calculation, place the new cluster centroid; v) rename the closest centroid for each data point; and vi) proceed to step 4 if there is any reassignment; if not, the design is complete.

3.3.2 Colour Based Segmentation

A method used in image processing called "color-based segmentation" divides an image into discrete areas according to the colour information of its pixels. When objects or regions of interest in an image have distinguishable and separable colour characteristics, this segmentation method is especially helpful.

Steps in Colour Based Segmentation: i) Colour Space Selection: Based on the properties of the image and the types of objects or regions that need to be segmented, select a suitable colour space. ii) Thresholding: To specify the colour range that corresponds to the objects of interest, set colour thresholds. Pixels that fall into this colour range are regarded as belonging to the target area. iii) Image Preprocessing Utilise preprocessing methods such as smoothing or blurring to improve colour features and lower noise. iv) Post – Processing (Optional): Use post-processing techniques like contour smoothing, connected component analysis, erosion, and dilation to improve the segmentation results.

3.4 Models

A mathematical representation or architecture aimed to recognize patterns and generate predictions from data is referred to as a "model" in deep learning. Usually, these models are neural networks, consist of layers of interconnected nodes, or neurons that process input data and produce predictions as an output. The term "deep" refers to the fact that deep learning models frequently consist of numerous layers, which enable them to acquire hierarchical data representations.

Examples of Transformers are used for natural language processing tasks, Recurrent Neural Networks (RNNs) handle sequence data, and Convolutional Neural Networks (CNNs) recognize images, among other deep learning models. The type of data and the task at hand determine which deep learning model is best. To determine which model works best for a given problem, practitioners and researchers experiment with various architectures and hyper parameters.

Table 3: Present Name of Model with Number of Layers used for Diabetic Retinopathy

References	Model Name	No of Layers	Accuracy
[6], [15], [19], [24]	ResNet	50	91.1%, 98.5%, 98.02%, 93.18%
[7]	Fully Convolutional Network	14	95.76%
[8], [12], [24]	Densenet	169	87.95%, 98.40%, 96.22%
[8]	DiaNet	-	90.02%
[9]	Inceptionv3	11	89.11%
[11]	Inception-V3, ResNet50 and CNN Model	15	96.85%
[14], [24], [25]	Convolutional Neural Network	5	77%, 75.61%, 91.52%
[16]	ResNet Feed-Forward Neural Network	172	94.90%
[18]	VGG	16	Training ACCU: 91.4% Testing ACCU: 91.72%
[22]	ResNet	152	97%

3.5 PARAMETERS

3.5.1 CLASSIFICATION PARAMETERS

In machine learning, classification is the process of dividing a given set of data into discrete categories. Classification, a type of supervised learning, is used to predict, from past observations, the categorical class labels of new instances. The confusion matrix is used in machine learning to assess how well a classification model is performing.A scenario where the task is to classify instances into one of two possible classes or categories is referred to as a two-class classification model. For instance, medical diagnosis (disease present or not present), sentiment analysis (positive sentiment or negative sentiment), spam detection (spam or not spam), etc.

A confusion matrix gives an overview of how well a machine learning model performed on a set of test data. It is a means of displaying the proportion of instances that are accurate and inaccurate in light of the model's predictions. It is widely used to evaluate the performance of classification models, which aim to give a categorical label to every instance of input.

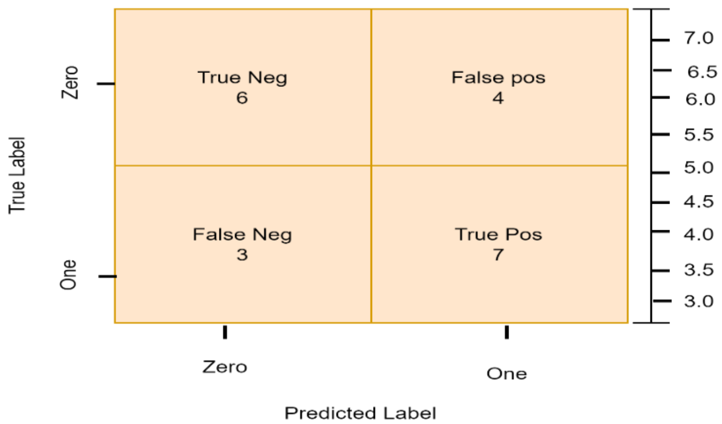

Figure 6: A confusion matrix plot

To understand the terms correctly, let me use the simple binary classification problem. Assume that the product reviews from an e-commerce website are included in our dataset. There are two labels for each review: positive (1) and negative (0). It is our responsibility to categories reviews as positive or negative. Assume for the moment that, by combining different NLP techniques, we have developed a model—good or bad—that can, in some manner, predict the labels. For example, the CSV file snap below displays a sample of our actual and predicted labels after our model made a prediction.

Metrics based on Confusion Matrix Data

In our case,
The Total worth of TP: 7
The Total worth of TN: 6
The Total worth of FP: 4
The Total worth of FN: 3

The number of instances that the model generated on the test data is shown in the matrix.

- True positives (TP): Appear once the model accurately predicts a positive data point.
- True negatives (TN): Appear once a negative data point is correctly predicted by the model.
- False positives (FP): Appear once a positive data point is mistakenly predicted by the model.
- False negatives (FN): Appear once a negative data point is miscalculated by the model.

Table 3: Comparing our sample product review predictions to the real, true labels

review	true_label	predicted_label
sample review 1	0	1
sample review 2	0	0
sample review 3	1	0
sample review 4	1	1
sample review 5	1	1
sample review 6	0	1
sample review 7	1	1
sample review 8	0	1
sample review 9	0	0
sample review 10	0	0
sample review 11	1	0
sample review 12	1	1
sample review 13	0	0
sample review 14	1	1
sample review 15	0	0
sample review 16	0	1
sample review 17	1	0
sample review 18	1	1
sample review 19	1	1
sample review 20	0	0

Note: A review in this dataset has a value of 1 and is classified as either positive or negative. Based on the (true_label) calculation, there are ten reviews that are positive (1) and ten reviews that are negative (0). Our machine learning model has generated predictions, which are shown in the following column (predicted_label). The values do not match the true labels exactly (true_label).

EVALUATION METRICS

Evaluating the effectiveness of machine learning models is the objective of evaluation metrics. Below is a brief description of the performance evaluation metrics that are used in research.

1. **Accuracy**: - The accuracy of the model is used to gauge its effectiveness. The ratio of all accurate cases to all instances is used to compute it.

$$\frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

The accuracy calculation formula

For the above case:

Accuracy = (7+6)/ (7+6+4+3) = 13/120 = 0.65.

Which means the accuracy is 65%.

2. **Precision: -** It is a gauge of a model's ability to forecast positive outcomes. Its definition is the ratio of the model's total number of positive predictions to the number of actual positive predictions.

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

The Precision calculation Formula

For the above case:

Precision = 7/ (7+4) = 7/11 = 0.636.

3. **Recall /Sensitivity: -** A classification model's recall measures how well it can locate each relevant instance within a collection of data. This refers to the ratio of true positive (TP) cases to the sum of false negative (FN) & TP cases.

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

The Recall or Sensitivity calculation Formula

For the above case:

Recall = 7/ (7+3) =7/10 =0.70

4. **F1 – Score: -** A classification model's overall performance is measured using a F1-Score. It is the harmonic mean of precision and recall.

$$\frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$

The F1-Score calculation Formula

For the above case:

F1-Score: = (2* 7)/ (2*7+ 4 + 3) = 14/21=0.667

IV.Future Enhancement

The medical field is set to experience significant technological advancements in the future. Currently, early treatment is often not accessible due to the high level of skill required for manual diagnosis by professional ophthalmologists, especially in remote or densely populated regions like India and Africa. Automated disease prediction systems will save time and enable people to take preventative measures early. Future improvements in algorithmic parameters will lead to better outcomes and increased accuracy, helping to preserve patients' vision and reduce the time and cost of medical diagnostics. Deep learning-based image processing methods are crucial for detecting anomalies in diabetic retinopathy. Potential improvements include refining the use of deep learning techniques. While convolutional neural network models are commonly used in research for diagnosing diabetic retinopathy from retinal fundus images, the need for ophthalmologists to analyze and interpret these images remains costly and time-consuming. Enhancing existing deep learning models by combining dynamically sized frameworks could improve performance, reduce training requirements, and lower computational costs. This approach may make the use of deep learning models more efficient and effective for diagnosing diabetic retinopathy.

V.Conclusion

This paper introduces an effective model for identifying and assessing the severity of diabetic retinopathy. The proposed approach includes three main steps: categorization, identification, and detection of diabetic retinopathy using various techniques. The ResNet50 model, when combined with synthetic data, shows impressive accuracy according to our analysis of different diagnostic methods. Given that diabetic retinopathy affects about 22.27% of the global population, there is a pressing need for automated detection, especially for the working-age population. The importance of automatic diagnosis of diabetic retinopathy is underscored, reflecting its global impact. The Convolutional Neural Network (CNN) used is a highly advanced pre-trained model with a complex architecture. Current literature supports the need for advanced technology and a systematic approach to early detection of DR. The integration of Artificial Intelligence (AI), particularly Deep Learning (DL) and Machine Learning (ML), shows promise in enhancing the quick identification and management of diabetic retinopathy. This technology has the potential to significantly improve vision preservation for diabetic patients by enabling timely interventions. The paper concludes by stressing the need for ongoing research and advancements to further enhance the accuracy and accessibility of AI-based solutions for diabetic retinopathy.

Conflict of Interest

The authors have no conflicts of interest to declare.

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Ethical and informed consent for data used

Not applicable

Data availability and access

Not applicable

Funding section

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