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DIABETIC RETINOPATHY DETECTION USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES: A REVIEW

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Abstract:

One of the new global concerns to public health is diabetes. The World Health Organisation (WHO) predicts that diabetes will rank as the seventh leading cause of death by 2030 (WHO, Diabetes, 2020). Depending on the ophthalmologist's experience, the diagnostic process can be difficult or time-consuming, especially in environments with limited resources. Automated techniques are currently used to classify cases of Diabetes Retinopathy (DR). This study aims to offer an automated DR detection system based on preprocessing, feature extraction, and classification procedures. Deep Convolutional Neural Networks (DCNN) and Machine Learning (ML) approaches are applied.

The transfer learning method extracts features from a model that has already been trained. Different techniques like Convolutional Neural Networks (CNNs) for classifying DR images and Deep Learning (DL) such as Modified Alexnet, ResNet, Reinforcement Deep Learning (RDL), and DenseNet are widely acknowledged as one of the most popular methods for increasing performance, particularly when classifying and analyzing for DR images of patients. CNNs are a more well-liked and effective DL method for analyzing medical images. For this study, cutting-edge DR image detection and classification methods using DL approaches have been looked at and studied. The datasets used for RD detection, attribution, and classification have also been assessed.

Keywords: Diabetes Retinopathy, AI, Machine Learning, Deep Learning, CNN and Detection, Classification.

1. Introduction

Artificial intelligence's (AI) utility in medicine is constantly growing. In the upcoming years, AI has the potential to transform patient care by maximizing personalized medication and customizing it for each patient. AI in medicine was progressively adopted. A few specialties, like radiology, embraced AI right away. Others, such as pathology, are just starting to deploy AI in clinical settings [1].

A consequence of diabetes called diabetic DR causes the blood vessels in the retina to enlarge and leak fluid and blood [2]. Loss of eyesight could occur in severe DR cases. 2.6% of blindness worldwide is caused by DR [3]. Patients with diabetes who have had the disease for a long time are more likely to have DR. Routine retinal screening for diabetics is necessary to swiftly identify and treat DR and reduce the risk of blindness [4].

Recent results from the DL application for automated retinal image processing have shown specialist-level accuracy in DR severity diagnosis, significantly facilitating access to DR screening and enhancing diagnostic accuracy. However, this research's inherent weakness—the ambiguous quality of data annotation—has not been addressed [5]. The recent rise in interest in and initiatives to integrate AI into many industries is mostly caused by the emergence of DL. CNNs are an ML approach that accesses higher-level information from an image by employing many input layers, such as image processing. AI's feature mimics how the human brain processes data and develops patterns that may be applied to decision-making. Human brain neurons inspired AI. It can learn from unsupervised data. The most frequently used ML approaches in the biomedical field are deep learning or CNNs. These connected artificial neural networks adhere to mathematical models. Their broad range of applications enables the administration of 'big data' in genomics and molecular biology. They are most frequently used for visual image analysis [6].

Neural Networks (NNs) may swiftly gather data using the Internet of Things (IoT), image scanners, digital cameras, remote sensors, and electrical appliances. AI may be trained using both labeled and unstructured data. Artificial neural networks (ANNs) are used hierarchically in the ML process. As was already noted, ANNs employed in AI are designed to resemble human brains, with neuron nodes connected in a web-like pattern. It is as opposed to conventional computer programs, which construct analyses with data linearly. DL systems' hierarchical structure allows for nonlinear data processing by machines [7].

1.2 Machine Learning

Several ML techniques, such as XGBoost, Bagged Decision Trees (DT), Random Forest (RF), Extra Trees, Support Vector Machines (SVM), Logistic Regression (LR), and Multilayer Perceptron (MP), can be used to classify the collected characteristics. In this instance, generic descriptors are retrieved from one of the first layers of InceptionV3 and ML methods are used to achieve competitive classification accuracy. Furthermore, considering the quantity of preprocessing techniques employed, the complexity of the model, the quantity of parameters that must be trained, and the required computing and memory resources, our strategy provides satisfactory results. Researchers can compare the performance of several machine-learning techniques thanks to this work [8]. Most early studies on DR classification used ML techniques to classify retinal pictures after manually building ways to extract characteristics from the images. Proliferative DR can be identified using the proliferative DR detection techniques developed by Kasurde and Randive. The suggested paradigm is founded on straight vessel identification using morphological operations and structure components, straight vessel deletion, and acquisition of aberrant vessels [9]. Finally, the images undergo classification using vessel pixel statistics.

In this study, classification is carried out using a linear classifier (logistic regression), an SVM linear classifier, a boosting model (XGBoost), bagging models (bagged decision trees, random forest, and additional trees), a linear classifier (logistic regression), and a Multilayer Layer Perceptron (MLP). It is outside the purview of this study to provide a thorough description of the computations. The following is a brief explanation of the ML algorithms mentioned above. Extreme Gradient Boosting implements the Gradient Boosting Algorithm (GBA), also called XGBoost. It is a scalable machine learning approach for tree boosting that uses distributed and parallel computing to raise overall model performance. Similar to how boosting is described above, building new models that anticipate prediction errors or residuals from previous models before adding them together to produce the final prediction. XGBoost employs a gradient descent method to decrease loss when introducing new models.

1.3 Deep Learning

To identify patterns and acquire unsupervised features, DL, a subtype of ML, employs hierarchical layers of nonlinear processing stages [10]. A technique for computer-assisted medical diagnosis is DL [11]. Classification, segmentation, detection, retrieval, and registration of images are just a few of the DL applications used in medical image analysis. Recently, DR detection and classification have heavily relied on DL. It may still learn the features of the supplied data despite the integration of several disparate sources [12]. Numerous DL-based techniques exist, including sparse coding, autoencoders, CNNs, and Limited Boltzmann Machines (LBM) [13]. Due to the increased learned features compared to ML approaches, these methods perform better as the amount of training data grows DL techniques did [14].

2. Review of Literature

This systematic review or study showed that DR is one of the most common conditions affecting diabetic people and that patients with an early diagnosis can avoid losing their vision. Once the illness has been identified, the patient must undergo an evaluation every six months to track the disease's development [15]. The ophthalmologist will benefit more from an effective algorithm to identify and classify fundus images in eradicating DR-related vision loss. Numerous image systems have been created by researchers that can correctly identify diabetic retinopathy. The human eye's lens and optic nerves are two components of its structure. Segmenting the images of the fundus image's components or scanning the image for haemorrhages, lesions, microaneurysms, exudates, etc., can identify and classify DR.

Several metrics, including the area covered by blood vessels, anomalies in the foveal zone, and microaneurysms, can be calculated using the algorithm described by the authors [16]. The suggested method makes use of curvelet coefficients from angiography and fundus imaging. It uses the three-stage classification system of Normal, Diabetic Retinopathy (PDR), mild Nonproliferative (NPDR), and Proliferative Seventy patients participated in the trial. The suggested approach is completely sensitive. Based on the existence of microaneurysms in the DR images, the researchers in [17] and [18] have classified each image. Circularity and the position of microaneurysms are two features that are taken into consideration during feature extraction. The datasets Digital Retinal Images for Vessel Extraction (DRIVE), Accessibility Image of Republic of China (ROC), and the DiaRetDB1 is a public database for evaluating and benchmarking diabetic retinopathy detection algorithms, are used in this investigation. According to the authors ' methodology, sensitivity and specificity were 94.44% and 87.5%, respectively. Using Principal Component Analysis (PCA), the recommended method divides the fundus image from the optic disc images. By utilizing enhanced Major Depressive Disorder (MDD) assessment via enhanced k-nearest neighbor approach, electroencephalogram (EEG) data, and MDD classifier, the authors have raised the identification probability of exudates close to the area around the optic disc in the image by approximately 25–40%. Thirty-nine images were used in the study; using the advised method, they were split into four images showing a normal fundus and 35 images showing a fundus with exudates. Classifying the stages of DR as NPDR or PDR, academics have described how to assess fundus images using SVM, the Bayesian approach, and Perception Neural Network (PNN) in [19] and [20]. The DIARETDB0 database's 130 images were used. First, the DR images' blood vessel fragments, exudates, and haemorrhages have been divided. According to the given method, the accuracy obtained by applying the PNN, SVM, and Bayes classification techniques is 87.69%, 95.5%, and 90.76%, respectively. [21]'s author discusses validating the results of a trained SVM classifier. Public datasets DIARETDB1, DRIVE, and MESSIDOR stand for Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology (in French), have all been utilized for DR. Exudates and microaneurysms have been classified with an accuracy of 93% using blood vessel image segmentation. An accuracy of 96.73% has been attained, according to article [22], which also explains how to employ the local binary pattern texture characteristic to detect exudates. This study creates a dual classification system to clarify [23]. A bootstrapped decision tree is employed in this method for classifying the fundus images. The feature vectors are dimensionally reduced to create two binary vessel maps. The suggested technique yielded a 95% accuracy rate. The author of [24] has published a method for classifying DR images using the SVM classifier and the Gabor filtering technique. Before using the classifier, the input images are processed to the Circular Hough Transform (CHT) and CLAHE algorithms. The STARE database images have been shown to have a 91.4% accuracy rate. It is described [25] how Multilayer Perception Neural Network (MLPNN) is used to identify diabetic retinopathy. Nine statistical features are derived using the 64-point Discrete Cosine Transform (DCT). The neural network is given the statistical features that were like this obtained. It detailed how morphological operation uses the image's intensity as a threshold for segmentation [26]. The classification of DR images using CNN architecture and data augmentation approaches is covered in this article by [27]. The classification of DR severity uses five steps, and it is the Kaggle database. The generated accuracy is 75%. The researchers in [28] have suggested a strategy for organizing several error-dependent networks for picture classifying. The dataset used to evaluate the system contains remote-sensing photos of agricultural land in a village close to Feltwell, UK. A pixel-by-pixel classification process was used. The pixels were sorted into five distinct agricultural zones, including

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sugar beets, carrots, potatoes, barren soil, and stubble, based on the components of the feature vectors. The E1, E2, and E3 types of ensembles were created. The classification accuracy for the E1, E2, and E3 ensembles was 89.83%, 87.87%, and 90.46%, respectively. The authors of [28] used a recombined convolutional neural network to try and identify macular diseases using spectral domain optical coherence tomography (SD-OCT) images. For noise reduction during preprocessing, the Block-Matching and 3D filtering (BM3D) is an algorithm used primarily for noise reduction in images BM3D filter is used. The BM3D approach divides the image into 2D blocks, which are reconnected to create 3D blocks based on resemblance. From 18 layered residual networks, the low, mid, and high-level features are gradually recovered. The network has tested three kernel sizes—3 x 3, 5 x 5, and 7 x 7—. Recall, accuracy, and precision were used as performance metrics. With a kernel size of 3, the recombined residual network achieves a greater accuracy of 90%.

3. Materials and Suggested Techniques

3.1 Dataset description

The Messidor [29] dataset includes around 1190 color fundus images with comments. It was used to test and train the suggested Alexnet architecture. To FoV images taken at 45 degrees, a camera with three different charge-coupled devices and attached with a Topcon TRC-NW6 Non-Mydriatic Retinal Camera was used. The images that will be input were taken in 8 bp color at 1390 x 1040, 2160 x 1884, and 2216 x 1166 resolutions. According to the annotations provided for the relevant photos, each dataset has been divided into four distinct subsets: Healthy retina, DR stage 1, DR stage 2, and DR stage 3. The photos have been evaluated for the existence of microaneurysms and haemorrhages. Images of normal retinal tissue don't show any signs of microaneurysms or haemorrhages. Images with just a few microaneurysms are considered to be in DR stage 1. Images representing DR stage 2 contain more (between 5 and 15) microaneurysms and few (less than 5) haemorrhages. Figure 1 below illustrates images that indicate DR stage 3: more (more than 15) microaneurysms, more (greater than 5) haemorrhages, and just a few spots of neovascularization.

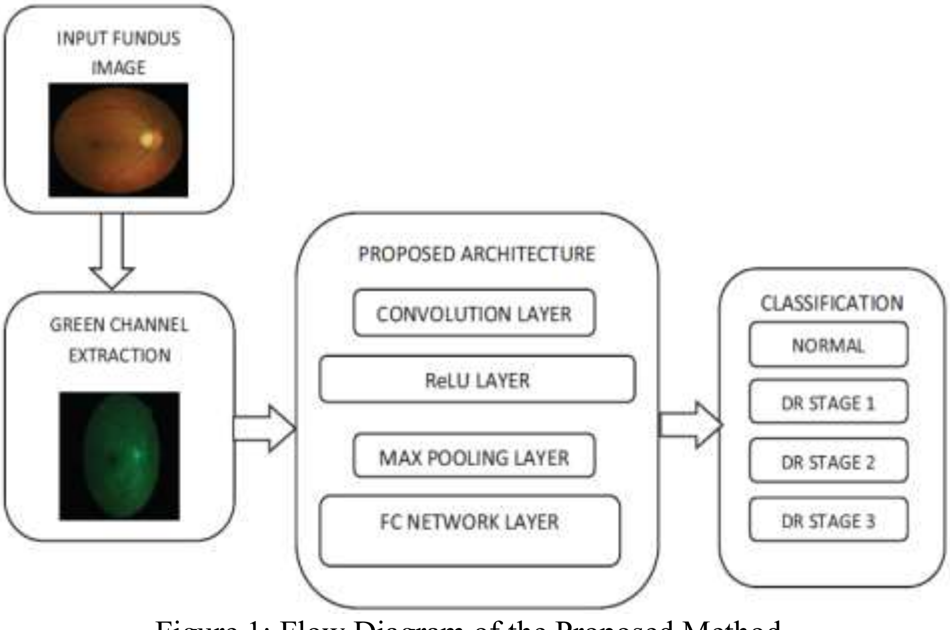

Figure 1: Flow Diagram of the Proposed Method

The current study aims to accurately classify the fundus images into the different stages of diabetic retinopathy. People who have diabetic retinopathy are becoming more and more common. The patients must be rapidly divided into the various stages of diabetic retinopathy. We have attempted to improve the classification accuracy in the current study's analysis of DR images by applying a modified Alexnet architecture. The Messidor Dataset (MD) was divided into four subgroups during preprocessing: Healthy retina, DR stage 1, DR stage 2, and DR stage 3. Each image in the MD contains

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comments in an Excel file. These nuances considerably contribute to the capacity to classify subgroups. The optic nerves and other retinal structures can be seen more clearly in the green channel. The photos are first converted into RGB channels. The green channel improves the input fundus image and boosts classification accuracy. DR classifies the fundus images into the corresponding phases, and improved images at various stages are provided to the modified Alexnet architecture.

3.2 Convolutional Neural Network

A Deep Learning Neural Network (DLNN) is a convolutional neural network. It was developed by modeling biological processes. It replicates how the multiple layers of the human brain operate. All image processing applications, such as face identification, pattern recognition, etc., have proved CNN to be highly effective. The planned design utilizes various levels to process pictures. The initial convolution layer receives the input image, and several stages of the defined architecture process the output. The convolutional layer partially removes the input fundus image before the input images are run through several filters. Unwanted pixels are eliminated by the maximum pooling layer, which uses the convolutional layer's output as input. CNN employs a variety of networks, including Le-Net, Alex-Net, Google-Net, Conv-Net, Res-Net (model numbers for Res-Net layers include 30, 50, and 110 152) and others. We used it in the current study because Alexnet design has a greater computing capability than other designs to solve complexity. CNN uses three-dimensional (length, breadth, and depth) variables. Following processing, the forecast is provided by the architecture's final layer. The top layer receives the input image. In an Alexnet design, there are typically eight layers: the first five are convolutional and maximum pooling layers, while the latter three are entirely coupled to the neural network.

Alexnet, one of the best CNN models, is frequently applied to solve picture categorization issues. The Modified Alexnet Architecture (MAA) for classifying images of diabetic retinopathy is shown in Figure 2. There is a list of the many procedures for carrying out the various tasks in the suggested Alexnet architecture. The input image must first be resized to 259 x 259 pixels, representing its width, height, and three-color channels representing its depth. An image's tiniest chunk multiplied by each neuron's weight yields the neurons' output.

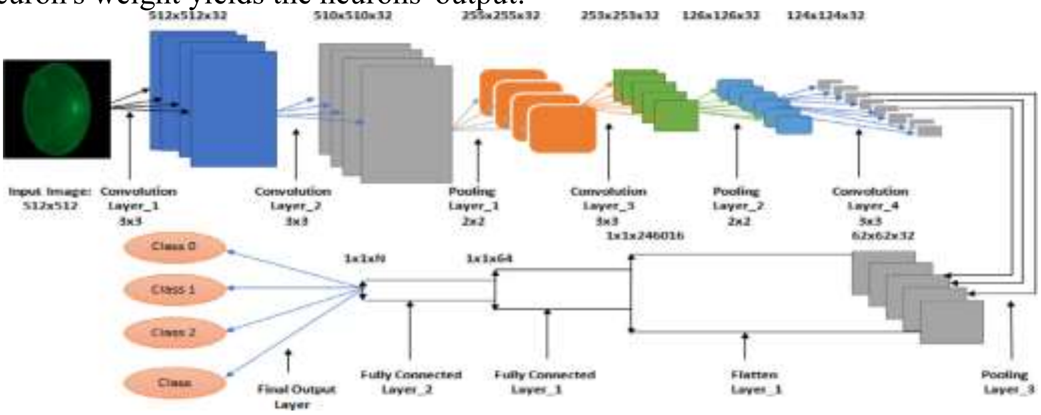

Figure. 2. Adapted Alexnet architecture for diabetic retinopathy image classification

. The entire distance is covered by repeating this process. This process takes place in the convolutional layer. Figure 3's Rectified Linear Unit (RELU) layer's second step employs an element-wise activation function. This layer gives The system nonlinearity, which makes all negative activations zero and applies the function f (k) = max (0, k).

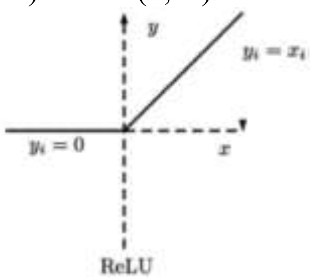

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Figure 3: RELU Activation function

The samples are lowered along the spatial coordinates into the pooling layer. Decimation is the term for this action. The Fully Connected (FC) layer determines the class scores for each image and provides the forecast as the final and most important step. The performance of the design is evaluated in terms of accuracy, specificity, sensitivity, and precision factor for all DR phases. The probability score for each prediction class is calculated, and the predicted class with the highest probability score is chosen. Seven hundred ten input fundus images were used to train the Alexnet architecture. 303 of these 710 images were utilized as the algorithm's input fundus images to assess the algorithm's performance. Such a sample size is necessary for perfect classification with low computing error. The values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) for each class of input images vary according to the confusion matrix results. All other legitimate predictions for other classes are considered to be true negatives concerning this class (healthy retina) if a healthy retina is thought to be a healthy retina. This result indicates a genuine positive value for that class. False positives happen when an input image of a healthy retina is wrongly thought to be a DR image at any level (DR stage 1, 2, or 3). On the other hand, a false negative is a DR input image of any stage (DR stage 1, 2, or 3) that is inaccurate.

$$sensitivity = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

$$specificity = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + False\ Negative + True\ Negative}$$

$$Precision\ factor = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Sensitivity measures how many correctly identified images out of all positively classified images are correctly classed. How accurately the algorithm predicts the other classes is measured by specificity. Accuracy quantifies the algorithm's overall prediction rate.

3.3 An Automatic DR

Other algorithms or methods, such as ML and DL, are employed in this article to classify DR. One of the main factors contributing to visual loss in people with diabetes worldwide is DR. Microvascular disease known as DR damages the retina of the eye. It results in arterial occlusion, cutting off the retinal tissues' principal source of nutrition. The author of this paper investigated an ensemble-based learning technique that incorporated several well-known classification algorithms into a complex diagnostic model. The suggested framework's accuracy rates are higher than any other widely applied classification techniques in the domain. The top 5 and 10 features from the Messidor dataset, as selected by InfoGainEval, were divided into four sub-datasets. Additionally, the accuracy scores for Wrapper SubsetEval. are 70.7% and 75.1%. To beat this disease, early diagnosis and treatment procedures are essential. A publicly accessible dataset trains and evaluates the DR's suggested model. The analysis makes use of calibration and grid search. This study compares the effectiveness of various ML techniques for researchers. The suggested model provides a reliable method for DR detection using a limited set of images. Transfer learning is a method utilized in the research for feature extraction that is distinct from other studies in the literature. It offers a data-driven, affordable solution with thorough preprocessing and fine-tuning procedures. [31]. This paper introduces a novel framework and technique for building an automated system that will allow us to investigate the damage of blood vasculature and recognize DR brought on by diabetes. The approach for screening and validating the DR was covered in this section. The engineering approach uses the following image processing processes once the retinal image has been entered into the system [32]. As illustrated in the figure below, the flow chart for it is relevant.

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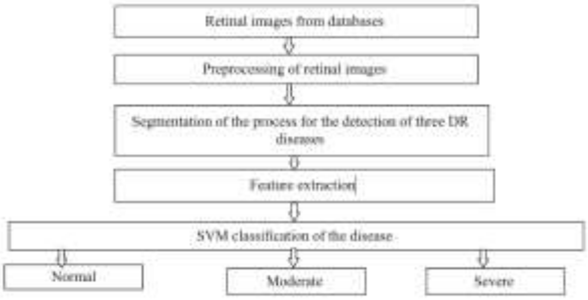

Figure 4: Flow chart of the automated system used for DR diagnosis

The author explains how following preprocessing to extract and select the most discriminant features in a two-stage novel approach for automated DR classification in this research suggested. Due to the low fraction of positive instances in the asymmetric Optic Disk (OD) and Blood Vessels (BV) detection system, preprocessing and data augmentation techniques enhance image quality and quantity. The first step uses two independent U-Net models based on transfer learning for OD and BV segmentation. A symmetric hybrid CNN-SVD model was created. This model detects DR by locating retinal biomarkers like MA (Micro Aneurysms), HM (haemorrhages), and exudates (EX). The proposed method was performed at the cutting edge on the EyePACS-1, Messidor-2, and DIARETDB0 tests, with average accuracy scores of 97.92%, 94.59%, and 93.52%, respectively [33]. CNN has been successfully used in diagnosing diabetic retinopathy and in several related fields. The effectiveness of current methods, an autonomous Deep-Learning-based system for stage diagnosis of DR by single imaging of the human fundus, is nonetheless constrained by the high cost of massive labeled datasets and contradictory reporting among various physicians. The multistage transfer learning method is also provided, which uses connected datasets with various labels. A screening tool for the early identification of diabetic retinopathy can be employed with the suggested approach. On the APTOS 2019 Blindness Diagnostic Dataset (13000 images), it has a sensitivity and specificity of 0.99 and is ranked 54 out of 2943 competing methods (with a quadratic weighted kappa score of 0.925466) [34]. Discuss creating and verifying a DL algorithm based on AI for identifying DR in retinal fundus images. The optic disc and macular were located, the vessels were segmented, lesions were found, and the degree of DR was graded on 500 fundus images with comprehensive labeling of DR lesions. CNN multi-level iteration and increased learning techniques were employed to increase the system's (Deep DR) accuracy in grading DR. The software was further trained using three open data sets. The hospitals' submitted fundus images were used to test the final grading results. [35].

The information in this article that is presented in the form of images with clearly visible lesion features can be utilized to train computer algorithms. Doctors annotated 2,000 fundus images from Shanghai Sixth People's Hospital's DR Database, which were then utilized to create and hone the software. The multi-level iterative CNN method and the enhanced learning strategy were used to create the automatic DR lesion marking, staging, and corresponding auxiliary diagnosis and recommendation systems of Clinical text report mining in Figure 5 and the automatic screening and auxiliary diagnostic system for DR in Figure 6. It is increased the accuracy of the systems.

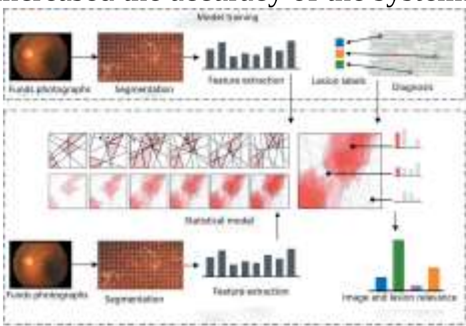

Figure 5: Clinical text report mining.

The processed image is shown in the following figure.

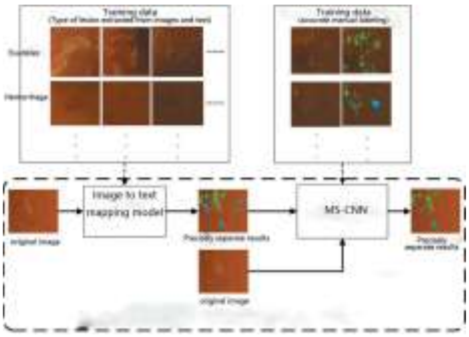

Figure 6: Automatic detection and supplemental diagnostic methods for DR

Four hundred patients had a thorough evaluation that included Fundus Fluorescein Angiography (FFA) and a mydriatic fundus examination to screen for patients who satisfied the international diagnostic guidelines for DR. Based on the results of FFA and mydriatic fundus examination, and two clinicians adjusted the results of the automatic screening. Increases the reliability and accuracy of system screening and additional diagnostics while giving the computer system instructions to use deep learning to update the self-model. To classify and predict diabetic retinopathy, several ML and DL algorithms have been used in this work; however, the bulk of them missed data preprocessing and dimensionality reduction, producing biased findings. A dataset on diabetes retinopathy was used in the current investigation, obtained from the University of California Irvine machine learning (UCI-ML) repository. After the raw dataset has been initially normalized using the Standard Scalar approach, the most relevant characteristics are extracted using PCA. The Firefly algorithm is also used to reduce the number of dimensions. The smaller dataset is classified using a DNN model. The suggested model is superior in accuracy, precision, recall, sensitivity, and specificity when the output is compared to results from existing ML models currently in use [36]. This study uses convolutional neural networks along with the necessary Pooling, Softmax, and Rectified Linear Activation Unit (ReLU) layers to classify DR fundus images according to the severity of the illness. On the Messidor Database, the suggested algorithm's performance has been verified. For images of healthy people, images of diabetic retinopathy in stages 1, 2, and 3, and healthy images, classification accuracy of 96.6%, 96.2%, 95.6%, and 96.6%, respectively, has been achieved [37]. Diabetes or affected patients demonstrated a noticeably greater proliferation of ocular nerves than healthy individuals. We used a CNN to train the classifier before doing classification. Convolutional and pooling layers, as well as squeezing, excitation, and bottleneck layers, one for each class, are all included in CNN's classification architecture. These layers also allow for classification between the two classes. We use the datasets DIARETDB1 (standard Diabetic Retinopathy Dataset) and the dataset provided by a medical facility, which consists of fundus images of both damaged and healthy retinas, to evaluate the performance of the recommended approach. According to experimental findings, the suggested strategy outperforms other well-known strategies regarding results. The model exhibited accuracy and precision of 98.7% and 97.2%, respectively, when evaluated on the DIARETDB1 dataset [38].

3.5 Segmentation-Based Detection of DR

The segment-based learning strategy for diabetic retinopathy is another DR technique for segmentation or classification of detection and identification. It significantly improves the accuracy of detecting the images of diabetic retinopathy and locating them inside lesions by learning classifiers and features from the data. To classify diabetic retinopathy images with improved accuracy, the pre-trained CNN is modified to produce segment-level DRE (Diabetic Retinopathy Estimation), and then integrating all segment levels of (DRM) is used. This method will allow diabetic retinopathy to be more precisely identified in retinal images. Preprocessing, CNN-based segment-level classifiers, integrating all segment levels of diabetic retinopathy, and integration comprise our method's four main parts. Figure 7 shows the general layout of our suggested approach. The methods presented are listed below [39].

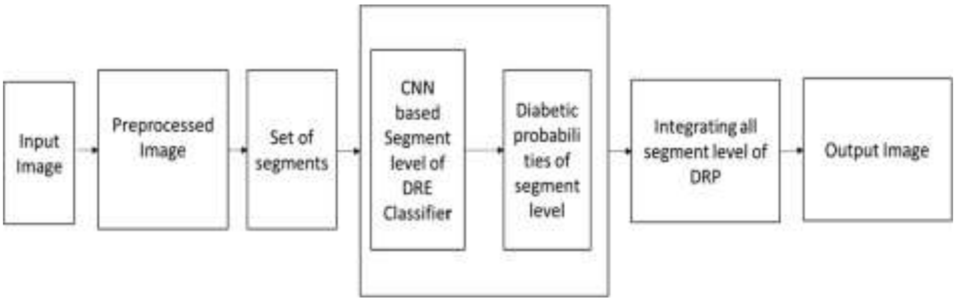

Figure 7: Segment Diabetic Retinopathy Level

The radial size of the FOV (field of vision) has been adjusted to match the retinal images. Set the radius size to pixels to obtain an image size close to the one utilized. Then, a cutting-edge technique is applied to equalize illumination and improve contrast. To deal with irregular diabetic retinopathy lesions, we finally developed a segment-based end-to-end learning technique. On the Kaggle dataset, the sensitivity and specificity for recognizing diabetic retinopathy images are 96.37% and 96.37%, respectively, with an area under the ROC curve of 0.963. These outcomes significantly outperform the current model. A DR detection and classification system is added in another part of the project. Our approach consists of two main stages: the first stage extracts texture features using local binary patterns (LBP), and the second stage analyses in-depth state-of-the-art deep learning techniques for detection and classification tasks. Deep learning methods include ResNet, DenseNet, and DetNet. According to preliminary studies, ResNet, DenseNet, and DetNet can achieve accuracy levels of 0,9635%, 0,8405%, and 0,9399%. Additionally, we assess each detection configuration's effectiveness [40].

4. Discussion Section

Ten to fifteen books, articles, and papers were reviewed for this inquiry. The DL-based experiments described in the paper changed the diabetic retinopathy screening system. With the recent rise in diabetic patients, there is a greater need than ever for reliable diabetic retinopathy screening technology. The issue of choosing trustworthy features for ML is resolved by using DL in DR detection and classification. However, it requires a large amount of training data. DR images to enhance the quantity of and prevent overfitting during the training phase, data augmentation was used in the majority of trials. The research served as the current work's basis. While 59% of them combined two or more public datasets, 94% of them used existing datasets to address the problem of data size and evaluate the DL algorithms on various datasets, as demonstrated in the magnitude of the training datasets required for DL in the medical industry is one of the challenges. The quantity, quality, and balance of the training data are all important factors that affect how well DL systems perform. To better remove the huge datasets, such as the public Kaggle dataset, it is required to increase the size of the present public datasets. They differ in that fewer studies chose to use pre-made structures with transfer learning, such as VGG, ResNet, or AlexNet, whereas fewer studies selected to create their own CNN structures. Transfer learning substantially accelerates and streamlines the design and construction process when compared to starting from scratch to create a new CNN architecture. However, the system that developed its own CNN structure outperformed those using the existing structures in terms of accuracy, which is astounding. Scholars should concentrate on this issue, and further research should be done to compare the two patterns.

As shown in Figure 7, most studies (73%) solely designated the fundus input image as non-DR, although 27% did so for one or more stages. However, only 30% of the most recent investigations identified the affected lesions, and 70% of them did not. An effective follow-up system for DR patients is made possible by an accurate DR screening system that can recognize different lesion types and DR stages, reducing the risk of vision loss. A technology gap that needed to be filled was the inability to detect the five DR stages and DR lesions reliably. This problem could be seen as the present challenge for researchers.

5. Research Gap of DR Detection through ML and DL Techniques

The classification and interpretation of medical images have benefited greatly from using ML and DL, one of the most well-liked methodologies, improving performance in many domains. In medical image processing, CNNs are more frequently employed as a DL technique and perform admirably. The most cutting-edge techniques for classifying and detecting DR color fundus images utilizing DL approaches have been analyzed and looked at for this paper. Additionally, the color fundus retina DR datasets have been examined. Several feature extraction approaches are advised to extract DR features for early detection. However, traditional ML) models perform feature extraction and classification less consistently and require more training time when used with larger datasets. DL is hence presented as a new ML domain. A smaller dataset can be handled by DL models with the aid of effective data processing methods. However, to improve the efficiency of feature extraction and image classification, they usually use larger datasets for their deep architectures.

This study and examination of cutting-edge DL algorithms in supervised, self-supervised, and Vision Transformer situations proposed the classification and detection of retinal fundus images. Consider the proliferative, nonproliferative, and referable classes in the DR. The article also describes the datasets for DR that may be used with retinal fundus images for segmentation, classification, and detection. The report explores research gaps in DR detection/classification and indicates several difficulties that require additional research and analysis. Early detection and treatment of DR can dramatically lower the risk of visual loss. Unlike computer-aided diagnosis procedures, ophthalmologists must manually diagnose DR retina fundus images, which takes time, effort, and money and is prone to error. Recently, DL has emerged as one of the most popular methods for performance enhancement, notably in the classification and interpretation of medical images. As a DL method, convolutional neural networks are increasingly used to analyze medical images and are quite successful. The most advanced techniques for classifying and detecting DR color fundus images have been evaluated for this paper. Additionally, the color fundus retina DR datasets have been examined. The preceding also emphasizes other difficult subjects that need further study.

The screening, segmentation, prediction, classification, and validation aspects of deep learning breakthroughs in DR analysis are all covered in this work. A sizable body of recent scholarly work has been produced in this area. Diagnosis of DR to assist the research community in creating more effective, dependable, and accurate DL models for the various challenges in the monitoring and a critical analysis of the pertinent reported techniques is conducted, with the associated benefits and limitations highlighted.

6. Conclusion

Automated screening methods drastically reduce the time needed to make diagnoses, saving ophthalmologists time and money and enabling patients to begin treatment sooner. Automated DR detection techniques are crucial for early DR detection. The phases of DR are determined by the sorts of lesions that develop on the retina. This article has reviewed the most recent automated deep learning-based methods for classifying and identifying diabetic retinopathy. We have presented the publicly accessible common fundus DR datasets and offered a quick description of DL methodologies. Due to CNN's effectiveness, most studies have chosen it to detect and classify DR images. This review has also included helpful methods for identifying and classifying DR using DL.

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