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Detection of Diabetic Retinopathy Using RESNET-50

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Abstract—One of the most common causes of blindness in the elderly, especially in the elderly, is diabetic retinopathy. Retinal vascular disease is the main cause of this condition. Caution Indicators are usually not indicated. Diagnosis of diabetic retinopathy in the early stages can be made by examination. The DR classification system presented in this study is based on complex and deep learning (DL) techniques, especially convolutional neural network (CNN). The proposed approach can help ophthalmologists in making early decisions. This allows classification of DR that considers normal eyes as well as mild, moderate, severe, and progressive disease. The results obtained for DR classification using color retinal background images based on the ResNet50 model show that the classification accuracy is in the range of 70

Index Terms—Diabetic Retinopathy, Convolutional Neural Net-work, Resnet-50, Retina, Deep Learning

I. INTRODUCTION

. Diabetes is a widespread and devastating epidemic in Indian society. This leads to an increase in the prevalence of diabetes, which causes diseases such as DR. 463 million people worldwide suffer from diabetes; India ranks among the top three countries in terms of diabetes. In recent years, it has increased from 108 million to 463 million, with half of the population living in Brazil, Indonesia, the United States, China, and India . According to the Lancet study, China, India, and the United States are the three countries with the highest prevalence of diabetes. The study focused on diabetic retinopathy, which is associated with vision loss. High blood glucose levels cause diabetic retinopathy (DR), which damages the small blood vessels of the retina. This causes the macula to thicken and enlarge as a result of excess fluid, blood, cholesterol and other lipids in the retina [1]. In the process of blood supply to the retina, the retina begins to develop new, sharp, delicate blood vessels knowown as IrMAs (Intraretinal Microvascular Abnormalities) . Increased intraocular pressure in the eye can cause damage to the optic nerve in the eye. Therefore, DR is damage to blood vessels in the retina due to diabetic complications, which in this case can lead to irreversible blindness. A potential method for early detection of retinal disorders is retinal examination [2]. Since diabetic retinopathy is initially asymptomatic, most patients are not aware of these symptoms until they are emotionally affected. Consequently, early detection and routine screening of diabetic retinopathy is important to prevent future complications and manage disease progression. Exudates that are embedded in the fundus and indicate that the patient has or has developed DR are the main indicators of dry eye disease (DR) [3]. Finding lesions on fundus images can also help in the early diagnosis of diabetic retinopathy. [4] Ophthalmologists often use fundus color imaging to diagnose diabetic retinopathy (DR). These images show hemorrhages, soft and hard exu-dates, and microaneurysms (MA), small red dots that resemble small chambers caused by the localization of capillary walls. There are four stages. Diabetic retinopathy can experience: (i) proliferative retinopathy, which is suspected in the early stages and is related to the development of micro-aneurysms (MA).
(ii) Degenerative, nonproliferative, intermediate retinopathy, in which the blood vessels supplying the retina are enlarged and deformed, reducing their ability to transport blood. (iv) proliferative diabetic retinopathy (PDR), an advanced stage of the condition where new blood vessels proliferate due to retinal growth factor. These blood vessels fill the eye and grow along the inner layer of the retina in the vitreous gel. To solve this problem, the main goal of the paper is to use machine learning to generate the best model. This is done using convolutional neural network (CNN), deep neural network (DNN) and classical neural network (NN). The ideas of the biological brain are transferred to the neural network. Because biological neurons are more complex than this artificial model, the results are often difficult to apply, but some researchers have succeeded. Neural networks have worked well, but as the complexity and volume of data has increased, the need for deeper methods has arisen, giving rise to the idea of deep learning. A hierarchical attribute learning technique has been developed before deep learning, a 50-layer deep convolutional neural network architecture called ResNet-50. It is known for its high efficiency in computer vision problems due to the residual connections that allow the creation of very deep models. Residual connections make optimization simpler by reducing the problem of increasing gradients. ImageNet's pre-trained ResNet-50 is often used for training and modified for different workloads.

II. LITERATURE SURVEY

Depending on the research focus and area of interest, scientists have made significant contributions to the field of di-

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abetic retinopathy. Research on machine learning and medical science shows that scientists have proposed and implemented several machine learning methods, but currently there is no research that compares different deep learning methods in relation to diabetic retinopathy. Considering the findings and development of various machine learning algorithms for DR, the work completed so far represents a novel approach. Raman et al.] Developing a computer-aided detection mechanism to detect retinal imaging abnormalities and detect the presence of abnormal features from retinal fundus images is the focus of Raman et al. [5]. The proposed method uses machine learning techniques for image enhancement, noise filtering, blood vessel detection and optic disc detection, extraction of exudates and microaneurysms (MA), feature extraction, and several stages of diabetic retinopathy such as mild, mod-erate, severe, NPDR (classification) . .Proliferative diabetic retinopathy) and PDR (proliferative diabetic retinopathy). [6] Singh and Tripathi used different analysis approaches such as image processing for automatic and early detection of diabetic retinopathy. Research Soomro et al. proposed thresholded static wavelet transformation for morphological processing as an image enhancement method [7]. CLAHE (Contrast Limited Adaptive Histogram Equalization) in addition to retinal fundus imaging for vascular enhancement. [8] In their study, Zhao et al. presented a unique feature to detect fluorescence leakage in angiograms. Only two open issues of the International Journal of Grid and Distribution Computing were used to validate proposed methodology. Diabetic Retinopathy and Febrile Retinopathy are two databases available. Soomro et al. Analysis or PCA is used. In addition, univariate classification and back-propagation neural networks were used to classify images as diabetic or non-diabetic. Akram Usman et al. [9] based on a hybrid classification that identifies retinal lesions by preprocessing, extracting lesions from candidates, generating features, and classifying them. This extends the m-Mediods-based modeling methodology by combining it with the Gaus-sian mixture model to create a hybriid classifier to improve classification accuracy. Digital color retinal imaging, Winder, R. John et al. considering the use of algorithms for automatic detection of retinopathy. [10] conducted a survey. The research rival algorithm has five steps in this process: preprocess-ing, optic disc localization and segmentation, retinal vascu-lar segmentation, macula and fovea localization, retinopathy localization and segmentation. Halim, Muhammad Salman et al. [11], advanced techniques for the automatic extraction of anatomical information from retinal images are reviewed to help in the early diagnosis of glaucoma. Winder, R. John, et al. [12] conducted a study using an algorithm to automatically detect retinopathy by viewing digital color retinal images. The competing algorithms in the study are optic disc processing, localization and segmentation, retinal vessel segmentation, macular and foveal localization, and retinopathy localization and segmentation in five process steps. An advanced technique to automatically extract anatomical information from retinal photographs to aid in the early diagnosis of glaucoma is precisely explored in the work of Haleem, Mohammad Salman et al. [13]. Gardner and colleagues investigated whether a neural network could identify diabetic features in stock images and compared the system to a set of ophthalmological examinations from stock images. duty shows the presence of arteries, exudates, and hemorrhages. In addition, the study is more accurate in detecting diabetic retinal disorders compared to ophthalmologists. In their research, Roychowdhury et al. Enable Adaboost to manage features that help reduce the number of features required

III. Methodology

A. Description of the Data

An optical device called a fundus camera records images of the retinal fundus. The Diabetic Retinopathy Detection 2015 challenge dataset, available at https://www.kaggle.com/ sovitrath/diabeticretinopathy-2015-data-colored-resized, is used to classify DR. The data set contains high-resolution photographs of the retina under different imaging conditions.

B. Approach

Deep Convolutional Neural Networks (CNN) have shown remarkable achievements in automatic feature extraction and categorization. We used the ResNet-50 Architecture which won the ILSVRC competition in 2015

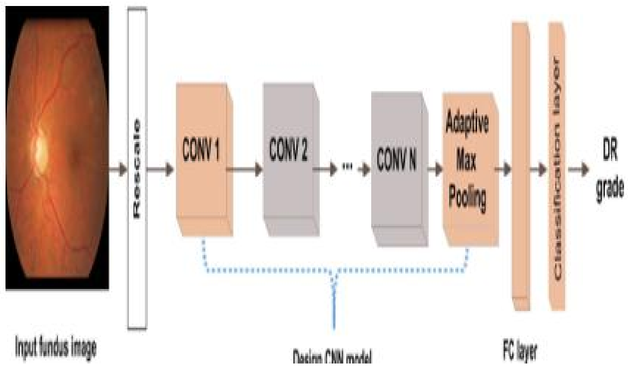

Fig. 1. Overview of proposed method

Figure 1 represent the overall structure of model that defines this mapping. A CNN model represents the structure of images and its applications, it has been used for DR diagnosis. The

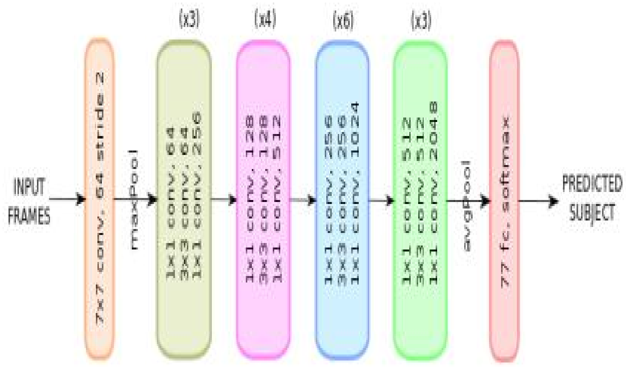

Fig. 2. Block Diagram

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image classification. The RESNET model architecture allows the training error to be reduced with a deeper network through connection skip.

C. Measure of Performance Evaluation

. The photos in this collection came from different models and types of cameras and their quality was quite inconsistent. Both labels and photos contained noise. Several images con-tained artifacts: either overexposed, underexposed, or out of focus. The main goal of this project was to create an algorithm that can work in the presence of fluctuations and noise. As shown in Figure , the ResNet architecture consists of residual blocks.

As shown in Figure , the ResNet architecture consists of residual blocks.

IV. Results and Discussions

In this study, we evaluated the efficiency of using ResNet-50 architecture to detect diabetic retinopathy, an important step for early diagnosis and treatment of potentially blinding disease. We developed and optimized the ResNet-50 model by carefully selecting and using a collection of retinal images that included both normal and diabetic retinopathy cases.

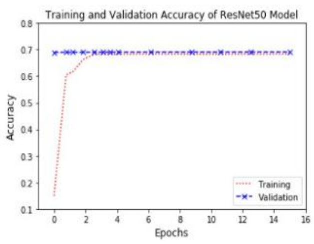

Fig. 3. RESNET-50 PLOT

The figure 3 shows that whole RESNET-50 network archi-tecture is quite extended, in order to meet space limitations, a small part of network from which it becomes evident that layers can have input from multiple layers and output to multiple layers.

We carefully review every aspect and put in place a comprehensive training plan that includes data augmentation techniques to improve the generalization and robustness of the model. After thorough evaluation, our proposed approach has shown encouraging performance indicators. The good accuracy rate of the model is demonstrated by results showing its ability to correctly classify retinal images and differentiate between normal and diabetic retinopathy cases. In addition, our approach showed good specificity and sensitivity, indicat-ing that it can detect diabetic retinopathy while reducing false positives. The advantages of our proposed ResNet-50-based method have demonstrated the effectiveness of the diagnosis of diabetic retinopathy compared to conventional methodologies. In particular, our approach not only outperformed previous methods, but also demonstrated robustness and generalizability across patient demographics and imaging scenarios, indicating that it can be used in real-world scenarios. In addition to quan-titative measurements, qualitative analysis enhances our results figure 2 represents an innovative neural network created for with a powerful visual representation that explains the model's[3] ability to detect small retinal anomalies typical of diabetic retinopathy. In addition, we have carefully considered ethical issues related to patient privacy and justice, demonstrating our commitment to the appropriate use of AI in healthcare.

In summary, our findings provide strong evidence for ResNet-50 in the detection of diabetic retinopathy, opening a promising path for automated screening and early intervention. Our proposed approach using deep learning is a major advance in improving patient outcomes and clinical workflow for the treatment of diabetic retinopathy.

V. Conclusion

We have developed an automated system utilizing deep learning to analyze retinal fundus images and identify early-stage diabetic retinopathy (DR) cases, guiding them for further assessment by ophthalmologists. Due to limited database avail-ability and the deep convolutional neural network's extensive parameter space, we employed a two-stage training approach. Initially, we evaluated three state-of-the-art CNN models pre-trained on ImageNet. Since ImageNet's natural images differ structurally from retinal fundus images, we adapted the pre-trained CNN model's architecture by reapplying the CONV1 layer filter using lesion Regions of Interest (ROIs) from the annotated E-opta database and subsequently fine-tuning them using ROIs. Secondly, recognizing the high-level feature encoding nature of the fully connected (FC) layer and its extensive parameter count, we substituted the FC layer with a Principal Component Analysis (PCA) layer. This adjustment aimed to streamline model complexity and prevent redun-dancy, enabling the extraction of diverse features from fundus images. We then introduced a classification layer to predict the DR level of fundus images. Ultimately, our experimentation re-vealed that ResNet152 with restarted CONV1 and a PCA layer (ResNetGB) achieved superior performance compared to state-of-the-art methods across various DR diagnosis scenarios, including DR rate, normal vs. DR, and challenging databases such as EyePACS and Messidor. Notably, the ResNetGB model operated without preprocessing or refinement steps. However, it struggles to accurately predict the DR level of fundus images with very low contrast and saturation. This limitation highlights an area for future research, focusing on improving the model's reliability in such conditions. Overall, our automated system holds promise in aiding students in the early diagnosis of DR patients, potentially leading to timely interventions and management strategies.

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