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Detection of Diabetic Retinopathy using Deep Learning: A Review

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Abstract. Throughout the globe, 1.6 million people annually fall prey to dia- betes. And an alarming total of 422 million people throughout the world have been diagnosed with diabetes, most of the contribution to this number being from low and middle-income countries. Diabetic retinopathy is the number one cause of blindness in the world. It generally affects people from ages 25 to 65.It occurs when the blood vessels present in the retina get damaged by hyper - glycemia or prevents blood from passing through the eyes. It is crucial to treat diabetic retinopathy early. If left untreated, it eventually leads to blindness. The proposed methodology is to use Convolutional Neural Networks with ResNet inorder to diagnose diabetic retinopathy. Fundal cameras are used to obtain retinalimages. The aim is to detect and prevent this disease, where it is challenging to perform medical tests. As per the research study, the images will be prepro- cessed, segmented, enhanced, and then the extraction of features such as micro aneurysms and hemorrhages will occur. Based on this, the disease will be clas- sified into mild, moderate, severe, or proliferative. In the future, this model mayalso be used to detect other conditions, such as glaucoma and macular degener- ation.

Keywords: ResNet, diabetes, convolutional neural networks, micro aneurysms,hemorrhages, retinal images.

I. INTRODUCTION

The eye is one of the most crucial organs in our body. The front of the eye is called cornea. Light passes through the cornea and lens; the lens focuses the light onto a light-sensitive lining called the retina before exiting the back of the eye through the optic nerve, enabling us to see the things around us. The number of casualties occur - ring annually due to diabetes has a number as high as 1.6 million. And an alarming to- tal of 422 million people throughout the globe have been diagnosed with diabetes, most of the contribution to this number being from low and middle-income countries. Diabetic retinopathy is the number one cause of blindness in the world. There are blood vessels that travel through the retina and exit the back of the eye through the middle of the optic nerve; over time, uncontrolled high sugar levels can affect these blood vessels; as a result, they might leak blood or other fluids, causing swelling and damage to the retina. There are almost no symptoms or very mild symptoms in the early stages. As Diabetic retinopathy progresses, some of the signs that may occur are floaters, blurry vision, or dark spots in your field of vision. It can be categorized intofour stages, namely: Mild, moderate, severe, and proliferative.

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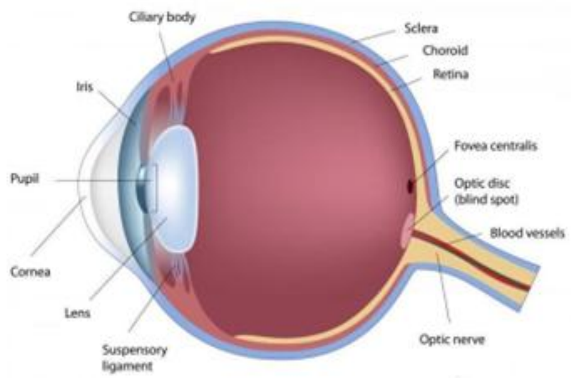

Fig 1: Structure of Human eye

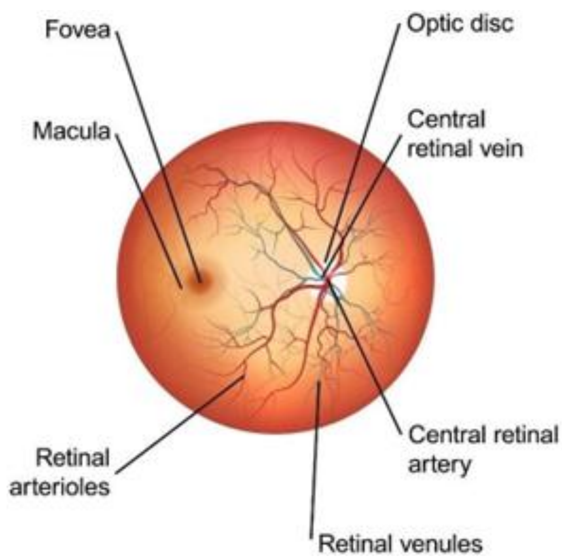

Fig 2: Normal Retina

In the first stage of Diabetic Retinopathy, there are almost no symptoms. The forma- tion of microaneurysms categorizes the first stage. They are formed because of the weakening of capillaries and an increase in the blood flow. They are tiny little red dots appearing throughout the retina. They are difficult to perceive when you look at the Fundus and more perceptible during fluorescein. Moderate non-proliferative Diabetic Retinopathy is the second stage of this disease. There are blocked blood vessels, and hemorrhages start forming inside the retina; Their appearance resembles that of a flame or a red coloured dot. Such spots are a larger form of microaneurysms. The damage to retinal capillaries also increases vas- cular permeability, resulting in the leakage of proteins and lipids from the capillaries into the retinal tissue.

This is called hard exudates, and it appears as waxy yellow-col- ored flecks on the retina. The number of blocked blood vessels increases in the third stage; hence the retina fails to receive sufficient blood flow. In addition to the lesions in the stages mentioned above, this stage has cotton wool spots or soft exudates. They are made up of axonal debris and result from vessel occlusion. They're more prominent around the optic nerve and are greyish white in color. They're billowy like clouds, and they don't havedistinct margins.

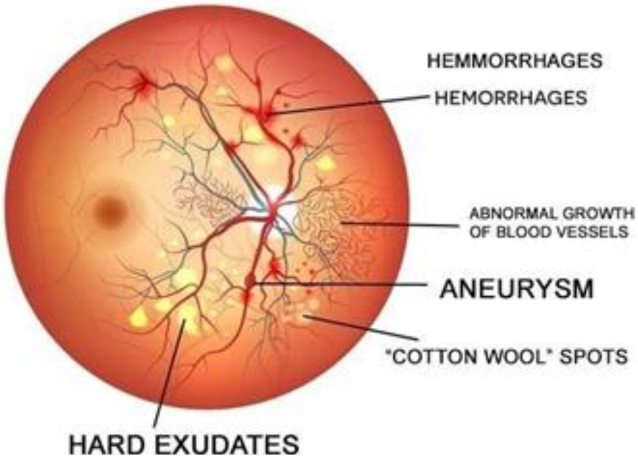

Fig 3: Diabetic Retinopathy

The final stage is also known as Proliferative Diabetic retinopathy. All the damage in the previous stages of Diabetic retinopathy leads to ischemia, which means a lack of oxygen supply to the retinal cells. The retina tries to bring more oxygen by creating new blood vessels. However, these are not correctly formed, irregular in shape, and highly sensitive and fragile, which can leak and burst, leading to permanent vision loss.

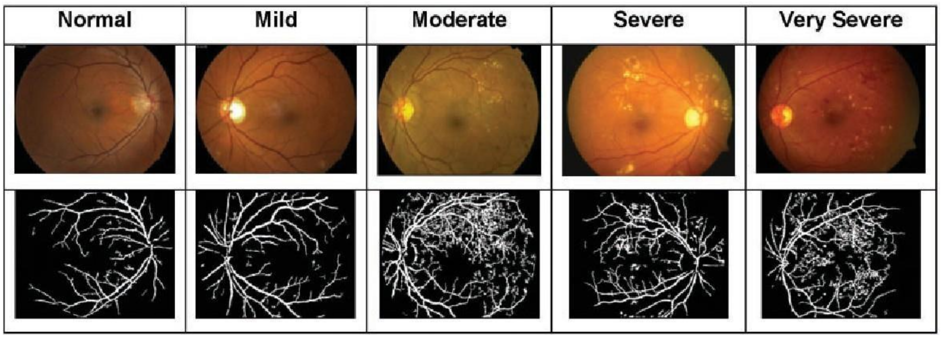

Fig 4: Stages of Diabetic Retinopathy [21]

Patients who have diabetes should have a regular dilated eye exam to look for signs ofthe disease. They should have good glycemic control as it can decrease the risk of hy- pertension. To avoid delay or development of diabetic retinopathy, one should take proper medication, a proper diet, have a planned schedule for exercise, control blood pressure, avoid having high cholesterol, avoid alcoholic beverages or products, and prevent smoking. Hence, timely diagnosis, regular check-ups, and proper control of one's blood sugar level through a healthy diet, adequate exercise, and regular medica- tion play a vital role in effectively managing diabetic retinopathy.

II. LITERATURE SURVEY

Many researchers have used various methods over the years for the detection of dia- betic retinopathy. The following paragraphs give a quick insight into the works com- pleted to date. In "Diabetic Eye Disease Detection Using Machine Learning Techniques," Sharma [1] uses supervised machine learning techniques to classify whether the input image has diabetic retinopathy or not. Image pre-processing techniques and pooling tech- niques have been used to resize the images to the same size. They've used Convolu- tional Neural Networks and Support Vector Machine to classify the image into Posi- tive and Negative categories. The positive category indicates the existence of diabetic retinopathy, and the negative category points out its absence. Sudha et al. [2] used Convolutional Neural Networks (CNN) to classify diseased im- ages into normal, beginning, mild, and severe using extracted features such as Mi- croaneurysms and Hemorrhages and detected their location in the image as well. To measure their model's accuracy, they used Binary cross-entropy, overfitting, and un- der fitting as their parameters. They used only 20-50 images and achieved an accu- racy of above 95% with low loss and limited overfitting. In "Automated Diabetic Retinopathy Detection Based on Binocular Siamese-like Convolutional Neural Network," Zeng et al.

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[3] uses a Siamese-like architecture that accepts binocular images, i.e., two fundus images at a time as input instead of one. One image was of the right eye, and the other one was of the left eye. It uses a Deep convolutional neural network to detect the presence of diabetic retinopathy in each eye. The model achieved 70.7% specificity and 82.2% sensitivity which is much greater than the monocular model. S. Qummar et al. [4] in "A Deep Learning Ensemble Approach for Diabetic Retinopa- thy Detection," used five deep learning models, namely Xception, Resnet50, Incep- tionv3, Dense121, Dense169 for classification of different stages of Diabetic Retinopathy. It is observed that the proposed model provides better results than other state-of-the-art methods. Qureshi et al. [5] surveyed "Recent Development on Detection Methods for the Diag- nosis of Diabetic Retinopathy". He established a method for detection by early screening through CAD tools. CAD tools are the one which can control the expansion of DR. He made use of automated DR screening algorithms which helped in detecting the variation in fundus through digital images. They discussed computerized methods to understand the fundus's framework and classification. These methods provided bet- ter accuracy, and in the future, it should also perform well against high-resolution im- ages. Kaur et al. [6], in "Neural Network Technique for Diabetic Retinopathy Detection," used the Neural Network approach for the classification of the infected area from the image. They used the Canny Edge detection algorithm for optical disk segmentation and blood vassal extraction for classifying diseased images. Compared to the SVM classifier, the proposed model shows better performance in specificity, accuracy and sensitivity. It is also observed that with the use of Neural Network, the results were optimized up to 5%. Li's [7] work was demonstrated using "Automatic Detection of Diabetic Retinopathy in Retinal Fundus Photographs Based on Deep Learning Algorithms," He aimed to achieve diabetic retinopathy detection in fundus images using deep transfer inception v3 network. He completed his goal as the proposed work showed an accuracy of 93.49%. This approach was able to detect DR with excellent accuracy and sensitivity. Issac et al. [8], in "Automatic computer vision-based detection and quantitative analy- sis of indicative parameters for grading of diabetic retinopathy," put forward a proce- dure for the classification of bright and red lesions from images. A quantitative analy- sis is carried out to resolve the extremity of the disorder. The technique resulted in good accuracy and sensitivity in detecting DR. This work has been globally accepted in determining the severity as light, medium, or critical. Both bright and red lesions are crucial for comprehensive DR detection. In the paper "Enhancement and Feature Extraction of Fundus Images," [9] Chavan uses OpenCV and Visual studio to analyze fundus images, various image pre-process- ing techniques such as color space conversion, noise removal, soothing, and thresh-olding. The feature extraction was done using the blob detection algorithm and mor-phological operations. The analysis was done on a very small dataset. The accuracy for detection of Macula was 85.71%, Exudates was 60%, and Hemorrhages was 83.33% Kumaran et al. [10], in "A Brief Review of the Detection of Diabetic Retinopathy in Human Eyes Using Pre-Processing & Segmentation Techniques," discusses the work done by various researchers in the field of diabetic retinopathy. The paper throws light on different pre-processing techniques and segmentation techniques used by re- searchers. It also explains about multiple stages of diabetic retinopathy and their de- tection. In the paper "Non-proliferative diabetic retinopathy symptoms detection and classifi- cation using neural networks," [11] Mohammad A. Has made use of an algorithm based on morphology for detecting lesions in Non-Proliferative Diabetic Retinopathy, Where the first step is to extract a set of features from the lesions that are detected, on which they then apply artificial neural networks so as to segregate them into severe, moderate and mild, respectively. The algorithms used are resilient backpropagation and Bayesian regularization, which exhibit an accuracy of 89.9% and 96.6%, respec- tively. Karami et al. [12] proposed an automatic DR detection approach for digital fundus images based on a dictionary learning approach using the K-SVD Algorithm. Based on the experiments performed and achieved outcomes, it was observed that 70% accu- racy was achieved for normal images, and 90% accuracy was achieved for diabetic images when the proposed technique was tested on 30 colour fundus images. Carrera et al. [13] in "Automated detection of diabetic retinopathy using SVM" pro- posed a novel approach using Support Vector Machine (SVM) to detect Diabetic Retinopathy from retinal images at an initial stage so that one can control it. The ex- perimental results achieved 94% of predictive capacity and 95% of maximum sensi- tivity. This research focused only on the detection of hard exudates and did not detect soft exudates. Shirbahadurkar et al. [14] proposed a method for recognizing DR by overcoming the disadvantage of the previously defined models. He manufactured an automated sys- tem that will detect the fundus images. His invention involved segregation in two stages. The primary stages involve simple classification as DR and one as non-DR. The next stage is the differentiation of lesions, which are considered to be potential. Three elements calculated the performance of the machine, namely sensitivity, speci-ficity, and accuracy. Gulshan et al. [15] presented his application through the paper titled Development and Validation of a Deep Learning Algorithm for the Detection of Diabetic Retinopathy in Retinal Fundus Photographs. He created an algorithm which automatically detects di- abetic retinopathy as well as macular edema in fundus images. The significant param- eters used by him were sensitivity and specificity. Using high specificity operating point, 90.3% of sensitivity, and 98.1% of specificity was obtained.On the other hand, the sensitivity found was 97.5% using high sensitivity operating point, and the speci- ficity was 93.4%. Further research is necessary to admit whether this method can im- prove the conditions in the given department. In the paper "Review on: Detection of Diabetic Retinopathy using SVM and MDA," [16] Shveta conducted an in-depth study about Support Vector Machine (SVM) and Multilinear Discriminant Analysis (MDA) to analyze and detect the presence of dia- betic retinopathy.

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She will compare the findings with the other current techniques us- ing various metrics such as Accuracy, Sensitivity, Specificity, time, Peak Signal to Noise Ratio (PSNR), and Area under ROC Curve (AUC). A. P. Bhatkar and G. U. Kharat [17] , in "Detection of Diabetic Retinopathy in Retinal Images Using MLP Classifier," recognize the issue of DR and put forward a method to identify the shortcomings. They primarily focused on MLPNN (which is a NN classifier) to differentiate the retinal pictures as normal or abnormal. The validation showed a radical accuracy for segregation of categories as normal and abnormal. Dutta et al. [18] proposed a model titled an efficient image processing based tech- nique for comprehensive detection and grading of nonproliferative diabetic retinopa- thy from fundus images. He makes use of a useful diagnostic tool for detecting and bracketing the extremity of diabetic retinopathy. Detection primarily focuses on ab- normalities. Various abnormalities are exudates and red lesions. The ranking is done according to these abnormalities' location. The overall method represented an overall accuracy of over 90%. In "Image processing and classification in diabetic retinopathy: A review," Ahmad et al. [19] concluded that Diabetic Retinopathy must be identified and rectified in the initial stages. They put forward a methodology proposing the same and made use of digitalized image formulating techniques for segregation. The model provided a few outstanding outcomes with perfect accuracy. Mitchell et al. [20] postulated the concept of diabetic retinopathy in his paper. He concluded that ophthalmic imaging modalities play a vital role in screening and moni- toring of diabetic retinopathy. Retinal photography interpreted by trained readers de- termined a high sensitivity of about 61-90% and high specificity of about 87-95% to detect diabetic retinopathy.

III. PROPOSED WORK

1.1 Data Process Diagram

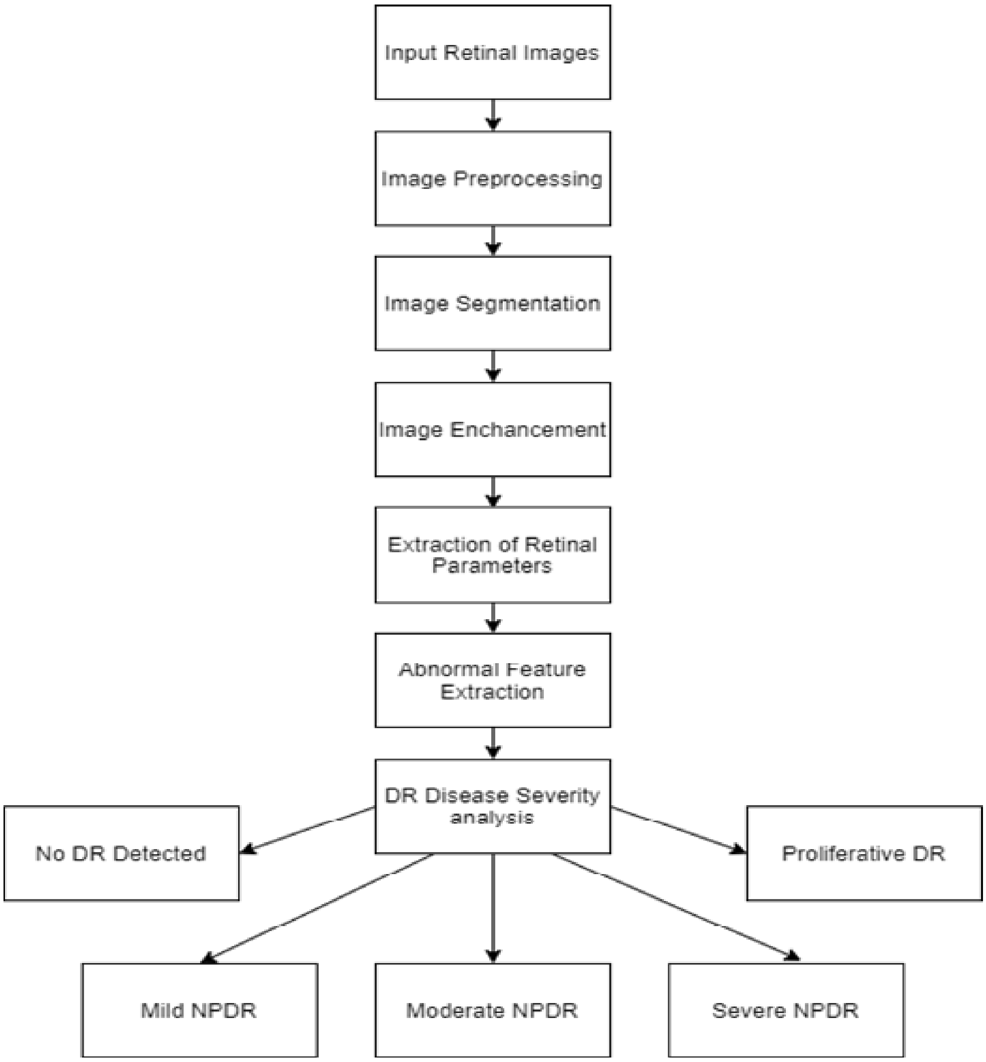

Fig 5: Flow chart for detecting Diabetic Retinopathy

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Input Retinal Images: The first and foremost step is to acquire images from the data-base or the hospital zones.

Image Preprocessing: The second stage is the preprocessing of the acquired image. That is the first rule concerning analyzing the retina colored images & the following concepts for performing the same. Trimming the image, Green channel uprooting, In-tensified image contrasting, Noise removal by filtering, Filter involving Gabor, Keel- ness Measure, Measuring Intensity, GL extraction, Invariance concepts.

Image Segmentation: When the preprocessing is done, the attributes are drawn out by using different methods. This process involves obtaining distinctive blood vessels from the image using image manipulation techniques. The procedures carried out on the image are: Separation, Edging, Flattening, Operations involving morphology.

Image Enhancement: When the data to the algorithm is large and cannot be consid- ered, it is assumed to be excess; by then, it might reduce the quality of the image ob - tained. So, when extracting an image, we primarily focus on important aspects, the end goal is to get the required results with tiny structures of the images instead of evaluating the entire image details. The fundus images which are captured can be ex- tracted using several methods. They are namely Semantics followed latency analysis, Partial values evaluation using the least square method, Principal Component Analy- sis, pattern recognition, image size reduction, and many more.

Extraction of Retinal Parameters: In the research work, we are considering work- ing with Artificial Neural Networks. We will use it for uprooting the attributes of the retinal nerve fibers. There are some directives in the segmentation and location of the images which can be abridged. Removal of Noise, Contrast intensification, Process of recognition, Localization of nerve fiber, Segregation of the nerve fiber, Vascular tree classification, Localization of fovea area, Drawing out abnormal areas attribute, Dif- ferent types of DR classification, classifiers performance evaluation.

1.2 ResNet Architecture

Deep Learning is known to be learning a hierarchical set of representations such that it learns low mid and high-level features. Deep neural networks can adapt to more complex data sets. It's better in generalizing previously unseen data because of its multiple layers. Different algorithms use Deep Learning's fundamental expertise and use diverse datasets to train and test these algorithms. One of these algorithms is ResNet50. Deep Neural Networks are challenging to train due to the vanishing gradi- ent problem while updating the weights because as we want to update the weights, we need to use backpropagation. We use the chain rule of calculus; during that, the weights may become extremely small while reaching the earlier layers because of the repeated multiplication. In neural networks, we can improve the accuracy by having more layers in our model, but after a certain point it is observed that the accuracy scales inversely with increase in depth. Due to this, the more layers we add to the model after the point of saturation, the higher the training error is. ResNet is a deep network in which the problem of vanishing gradient isn't present. It uses the concept of skip connection, which solves the vanishing gradient problem. ResNet adds the original input to the output of the convolution block. And as some of the layers are being skipped, the value will not reach a very small value. Suppose X isthe input, Y is the output, in other networks, we learn from Y, but in Residual Net- works, we learn from F(X). The target is to make F(x)=0 to make X=Y, the identity function, to increase overall accuracy. ResNet 50 means that there are 50 layers present in the network. There are two types of blocks present:

Identity block: When the input and output of the network are the same

Convolutional block: When the input size and the output size are not simi- lar, then a convolutional layer is added in the shortcut path, whose task is to

make the input size similar to the output size. There are two techniques for matching the output size: Padding the input volume or Perform 1*1 convolu-tions.

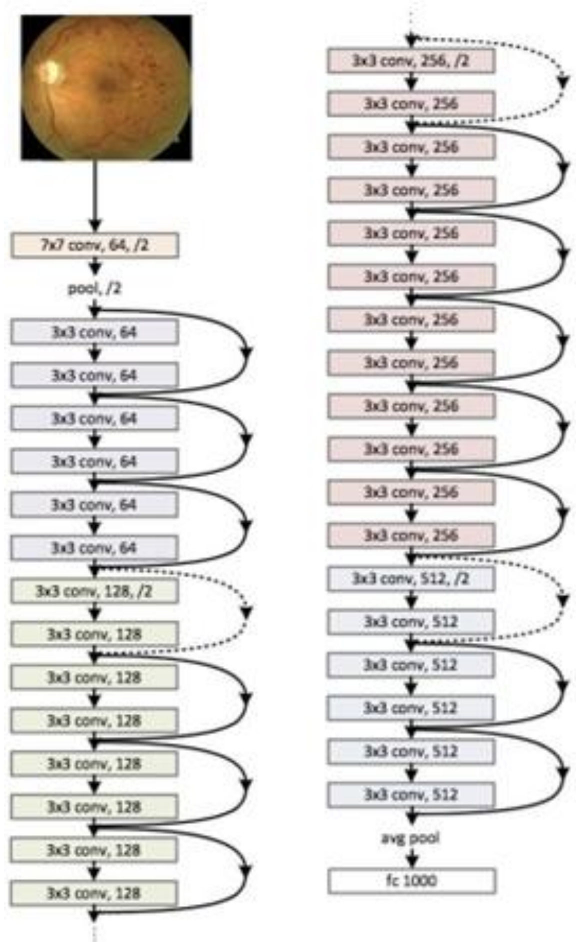

Fig 6: ResNet50 Architecture

In the ResNet50 architecture, we have the convolution layer, followed by a max-pool-ing layer. We have a specific mix of multiple convolutional blocks, and identity blocks followed by average pooling, flatten, and a single dense layer. The formula for calculation of output size is

$$s + \frac{n+2P-f}{} \quad s \; \frac{1*n+2P-f}{} \quad 1$$

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ResNet is less complicated as compared to the old VGG networks while still being much deeper. There is no need to have many parameters because you don't learn that much per layer, but the layers' succession gains you much more than having single massive layers. More parameters can lead to overfitting, and fewer parameters mean less training time

IV. CONCLUSION

Diabetic retinopathy is the number one cause of blindness in the world. The paper de- termines a prospective solution against the disease of Diabetic Retinopathy. For this reason, we have suggested the use of ResNet as it showed promising results when used with medical image datasets, giving an accuracy of more than 90%. Further re- search is required to ensure that this particular model can be implemented in clinical settings, increasing the health care rate against this specific disease. Knowledge should be spread among people regarding this disease, and they should be encouraged to get themselves examined. The proposed model can help doctors diagnose Diabetic Retinopathy more effectively and can be used to identify other ophthalmic diseases more automatically. By using this project, we can bring down the process of diabetic retinopathy detection down from 14 days to 1 hour.

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Neha Sharma, has completed her Bachelor's degree in Computer Application (BCA) from Panjab University. She is currently pursuing a Master of Computer Application (MCA) from Panjab University. While graduation, she has taken part in many quizzes and competitions in her college life. She has completed several virtual internships with companies like J.P Morgan and Walmart and has gained a lot of knowledge from online courses in the field of Deep Learning and Artificial Intelligence. She has a keen interest in the field of Machine Learning and Data Science and aspires to invent new technologies that can change people's lives in the blink of an eye.

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