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Deep Learning Framework for Early Detection and Risk Analysis of Diabetic Retinopathy

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Abstract: Retinopathy is a common and possibly sight-threatening disease that needs to be diagnosed correctly and quickly. This study examines how deep learning models, like ResNet-50 and a Simple CNN, can detect retinopathy in retina images. We use a dataset of Kaggle Diabetic Retinopathy Detection Training Dataset (DRD) retinal images, process them so they are all the same size, and train the models on a deep learning system at the cutting edge. We aim to compare how well these models work on a test dataset regarding accuracy. The results show that ResNet-50 does better than the Simple CNN baseline in all evaluation measures. It is more accurate and knows more about the features of retinopathy. The model is 94.6% accurate, which shows that it could be used in clinical settings. However, neither model can be generalized, especially since it needs to be tested on more patients from different groups.

Keywords: Retinopathy detection, deep learning, ResNet-50, Simple CNN, medical image analysis, automated diagnosis.

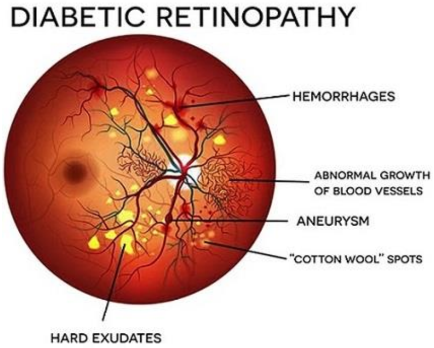
I. INTRODUCTION

The retina functions as a special kind made up of tissue positioned at the posterior part of eye that is important to see. It is like the "light-sensitive film" inside the eye. The retina is like a camera's film. It's essential for making the pictures you see out of light. But if the person is affected by diabetes, the high amounts of sugar in your blood can hurt the retina. This can cause a disease called diabetes retinopathy, which affects the eye. It's like a secret, silent threat. At first, we might not even realize that our eyesight is bad. But over time, it can cause significant vision problems and even blindness in some people [4], [8].

DR, or Diabetic Retinopathy is a disorder that can cause people with diabetes to lose their sight. Diabetes causes long-term changes in the body's metabolism, which can impair the retina, the light-responsive tissue situated at the eye's posterior. DR can receive worse if it isn't detected and treated [5], [9]. If it isn't detected and treated, it can go from mild to severe and cause vision loss or blindness. Deep learning models can identify the risk of DR worsening, which lets doctors make treatment plans for each patient and step in exactly when needed [10].

Damage to the blood vessels, eye tissue, and scar tissue that forms in later stages can make it impossible to regain your vision. Diabetic retinopathy can be found by having to check the eyes regularly [11]. During these exams, the eyes are usually made bigger so the retina can be looked at in detail. The diagnostic tests such as Optical Coherence Tomography (OCT), and eye angiography can employed to get detailed pictures of the retina's blood vessels and structure and find any problems. Tonometry and visual field tests can also be used to check eye pressure and peripheral vision. The eye care professional evaluates based on the results of these tests and suggests treatments or other steps to take. Diabetic retinopathy must be detected early through regular screenings to treat it well and prevent vision loss. Figure 1 shows the image of diabetic Retina [12].

Deep learning plays a vital role in aiding retinopathy detection by utilizing neural network models, particularly Convolutional Neural Networks (CNNs), which allow for the analysis of large datasets of retinal images [13]. These models demonstrate exceptional performance in identifying anomalies and patterns related to diabetic retinopathy (DR), enabling timely detection, reliability, adaptability, and instantaneous screening. Deep learning serves as a valuable adjunct to the efforts of healthcare practitioners, offering the prospect of enhancing the effectiveness and precision of diabetic retinopathy (DR) diagnosis and treatment [14]. In this paper a new deep-learning neural network framework is proposed classify patients with diabetic retinopathy (DR) against those without DR. Our architecture's primary objective is to assist ophthalmologists in their diagnostic process.



(Source: https://www.lifelinecelltech.com/role-monocytes-diabetic-retinopathy-pathogenesis/)

Figure 1: Diabetic Retina

The following sections of the paper are organized as follows. Section II offers a review of the relevant literature in this domain. The architectural design under consideration is outlined in Section III. The dataset utilized for the experiments is elaborated upon in Section IV. The experimental findings are provided in Section V. The conclusion and potential avenues for future research are outlined in Section VI.

II. LITERATURE SURVEY

Thippa Reddy Gadekallu et al. introduced a deep neural network (DNN) combined with Principal Component Analysis (PCA) and Grey Wolf Optimization (GWO) to enhance the model's parameter optimization. The primary procedures encompassed in this process include data standardization, dimensionality reduction, hyperparameter tuning, and deep neural network (DNN) training. The performance assessment criteria include accuracy, recall, sensitivity, and specificity [1],[6].

Wei Zhang et al. proposed an automated method known as DeepDR, which aims to identify and assess the severity of DR by analyzing images in fundus databse. The DeepDR system employs transfer learning and ensemble learning techniques, leveraging a fusion of neural networks to accurately identify and assess the existence and extent of diabetic retinopathy (DR). This method is built upon a collection of DR images labeled by clinical ophthalmologists, ensuring its high quality and reliability [2], [7].

Zhentao Gao et al. proposed automating diabetic retinopathy (DR) diagnosis due to the considerable screening requirements of individuals with diabetes. This study involved the creation of data set consisting of fundus images tagged with indicated diagnosis approaches. The dataset was used to train deep convolutional neural networks (CNNs) for evaluating the severity of diabetic retinopathy (DR) in fundus images [3], [8].

III SIMPLE CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) have greatly transformed the domain of medical image processing. They are widely utilized in several applications, including disease diagnosis, anomaly detection, and treatment planning. Convolutional neural networks (CNNs) facilitate the automated extraction of complex patterns and characteristics from several medical imaging techniques, such as magnetic resonance imaging (MRI), X- rays, computed tomography (CT) scans, and histopathological sections. This technology facilitates the work of radiologists, pathologists, and medical

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professionals by offering precise and efficient instruments for detecting and diagnosing illnesses, tumors, fractures, and other medical disorders. Convolutional Neural Networks (CNNs) can boost healthcare results, mitigate human error, and augment early disease identification, facilitating more efficient and accurate medical treatment. Figure 2 depicts Retinopathy detection using Convolutional Neural Network. Figure 3 represents left and right resized images.

Steps in CNN:

- A sequential model is constructed by incorporating convolutional layers and max-pooling layers.
- The input images undergo a resizing process to achieve dimensions of 224x224 pixels while maintaining three color channels according to the RGB color model.
- The ReLU activation functions are utilized for the convolutional layers. In contrast, a softmax activation function is employed for the output layer, given that the task involves multi-class classification.
- A dropout layer is incorporated into the model architecture to mitigate the risk of overfitting.
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- The model is configured with the sparse_categorical_crossentropy loss function and the Adam optimizer

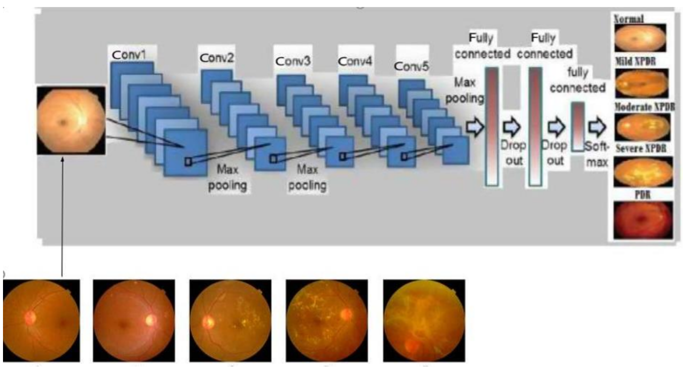

Figure 2: Retinopathy detection using Convolutional Neural Network

	
Left-resized 224x224	Right-resized 224x224

Figure 3: Left and Right Resized images

The identification and marking of lesions or anomalies, such as tumors or lesions in retinal images, is necessary. A binary mask is generated for each identified lesion. A binary mask refers to a monochrome image that shares the dimensions of the source image. Within this mask, The pixels located within the region of the lesion are assigned a white color, indicated by a pixel value of 1. The pixels located outside the region of interest are assigned a black color, indicated by a pixel value of 0.

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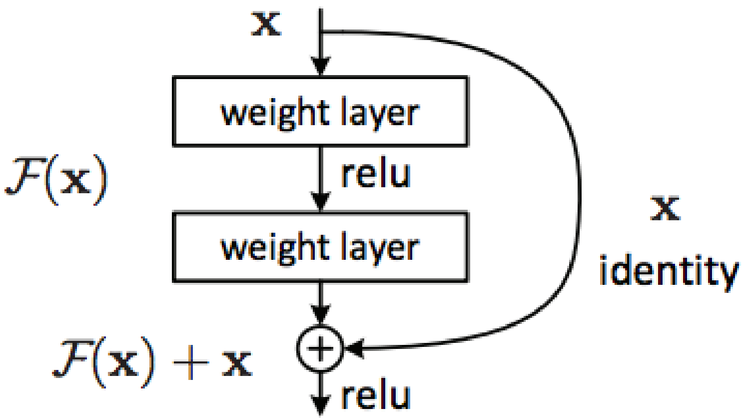
Figure 4: Binary mask of retina image

IV. RESIDUAL CONVOLUTIONAL NEURAL NETWORK (ResNet-CNN)

The prevalent pre-trained models in the field include ResNet, VGG, Inception, and MobileNet. In this paper ResNet architecture is considered for detection of Retinopathy. The ResNet architecture is a deep learning model that combines the concepts of Convolutional Neural Networks (CNNs) with residual connections. The vanishing gradient problem may arise when training deep neural networks, particularly concerning gradient-based optimization techniques like stochastic gradient descent (SGD). Consequently, the weights pertaining to the initial layers within the network undergo minimal or negligible updates, thereby resulting in their limited influence on the overall learning process. This phenomenon can result in a decrease in convergence speed and suboptimal performance in deep neural networks. The vanishing gradient problem, which poses a challenge to the training of deep neural networks, was effectively mitigated by ResNet with the use of skip connections or residual connections. In the context of a conventional feedforward neural network, the output of a layer is transmitted directly input to subsequent layer. Within a residual block, the input is combined with the output of a subsequent layer.



(Source: https://blog.devgenius.io/resnet50-6b42934db431)

Figure 5: ResNet Architecture

In mathematical terms, when representing the input to a residual block as x and the corresponding output as F(x), the computation performed by the residual block may be expressed as F(x) + x. This allows the network to acquire knowledge of residuals or alterations to the input, rather than attempting to comprehend the complete transformation from input to output. Figure 5 depicts ResNet architecture. All algorithms are trained using the output variable 'Y'; however, ResNet is trained using the function F(X) as the output. In more accessible terms, the ResNet architecture aims to optimize the discrepancy in between output and input by attempting to achieve F(X)=0, so ensuring that the output Y is equal to the input X. The following are Steps in ResNet:

1. Input: The input for ResNet-50 is an RGB image with dimensions of 224x224 pixels.
2. Initial Convolutional Layer: The input picture undergoes a first convolutional layer with 64 filters (kernels) measuring 7x7 pixels. This is followed by normalization and activation function ReLU. Max-pooling uses 3x3 pixel window and a stride of 2 leads to a reduction in the spatial dimensions.
3. Residual Blocks: ResNet-50 is composed of a total of 16 residual blocks, which are organized into four distinct phases or blocks. Each stage of the process consists of a varying number of residual blocks, and the number of filters within each stage also undergoes modifications.
    - In Stage 1, the model employs three residual blocks, each consisting of 64 filters.
    - Stage 2 consists of four residual blocks, each containing 128 filters. The initial block incorporates a projection shortcut for the purpose of aligning dimensions.
    - In Stage 3, the model employs six residual blocks, each consisting of 256 filters. The initial segment encompasses a projection shortcut.
    - In Stage 4 of the model architecture, three residual blocks are employed, each consisting of 512 filters. The initial segment encompasses a projection shortcut.
4. Each residual block within a stage follows a similar pattern:
    - The utilization of a 1x1 convolutional layer results in a reduction of the filter count to a bottleneck dimension.
    - The 3x3 convolutional layer performs operations on the bottleneck representation.
    - The utilization of a 1x1 convolutional layer results in an augmentation of the filter count to match the initial dimension.
5. ReLU and batch normalization are utilized in the convolutional neural networks (CNNs) post-processing steps following each convolutional layer.
6. Global Average Pooling (GAP): The final residual block, GPA is utilized.
   Figure 6 depicts Retinopathy detection using ResNet-CNN.

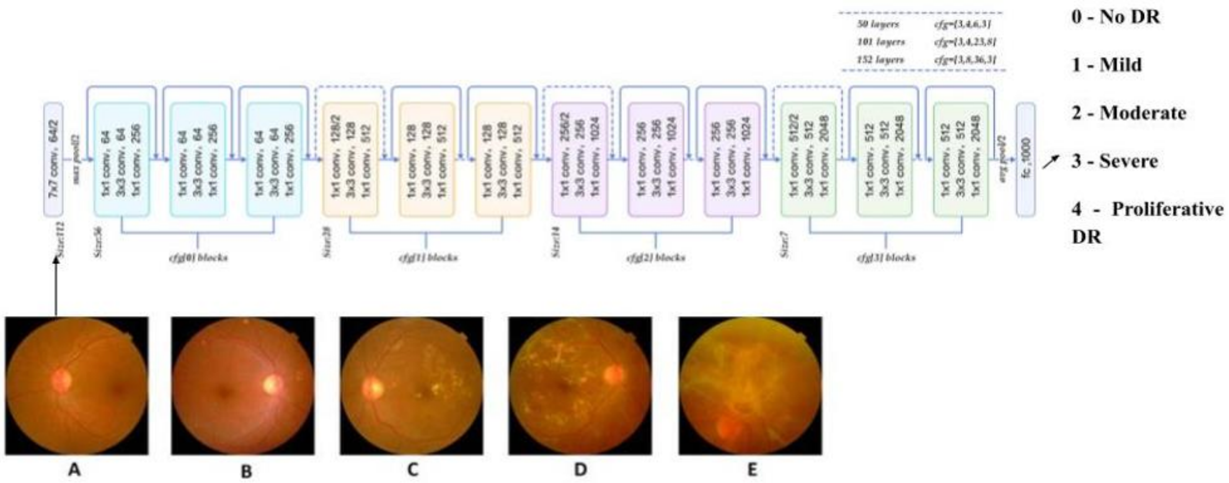


Figure 6: Retinopathy detection using ResNet-CNN

V. DATASET

Diabetic retinopathy is a prevalent eye condition that impacts individuals who have had diabetes for an extended period. One of the hardest things about treating diabetic retinopathy is that it often has few or no signs until it has gotten to a point where there aren't many good ways to treat it. At the moment, identifying diabetic retinopathy is a manual process that takes a lot of duration. Digital color fundus images of the retina need to be examined at and evaluated by doctors who have been trained to do so. The identification of diabetic retinopathy (DR) by clinicians is facilitated through the observation of lesions that are linked to the vascular abnormalities induced by the disease. The dataset used in this research is obtained from the Kaggle Diabetic Retinopathy Detection Training Dataset. The collection comprises a total of 35,126 images. A left and right field accompanies each subject. The images are assigned a subject identifier, indicating either left or proper orientation. The presence of diabetic retinopathy in each image has been assessed by an expert using a scale from 0 to 4, detailed below.

0 – Absence of DR
1 – Mild DR
2 – Moderate DR
3 – Severe DR
4 - Advanced DR

VI. EXPERIMENTAL RESULTS

This section presents experimental outcomes of DR problem utilizing ResNet and Simple CNN architectures. We conducted a thorough evaluation to determine the efficacy of these models on a data set of retinal photographs. The models are evaluated based on their accuracy. On the test set, the metrics were computed to evaluate the models' ability to classify retinal images by severity.

Throughout the training process of our retinopathy detection models, the loss graph illustrates both the training and validation losses over several epochs. The blue line corresponds to the training loss, reflecting how effectively the model aligns with the training dataset. It begins relatively high and decreases as the model learns to make more accurate predictions over time. Validation Loss (Orange Line): The orange line indicates validation loss, which assesses the ability of model that generalize to unexplored data. Similarly, it begins at a relatively high level but declines during the initial epochs. The convergence of training and validation loss indicates that model training has been successful. Figure 7 depicts the graph representing training loss and validation loss.

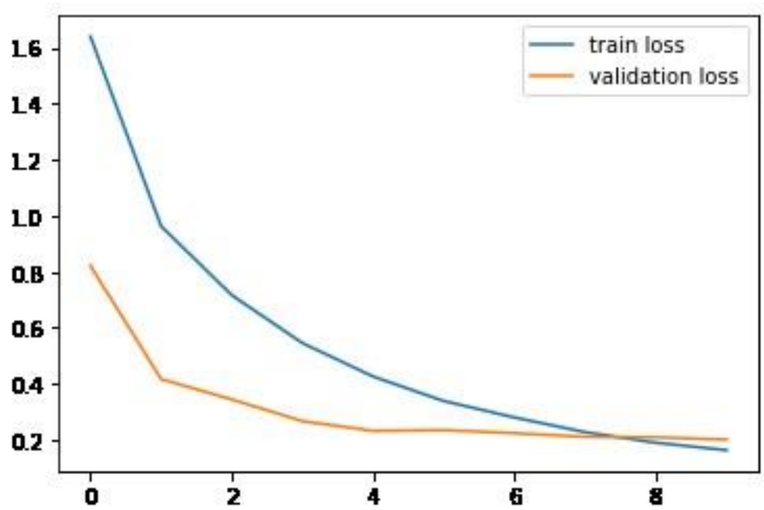


Figure7: Graph of Training loss and validation loss Vs Epochs using ResNet

Across multiple epochs, the accuracy graph depicts the training and validation accuracy of our retinopathy detection models. Both training and validation accuracy are initially comparatively low, but steadily improve as the model is trained with data. Figure 8 depicts the graph representing training accuracy and validation accuracy.

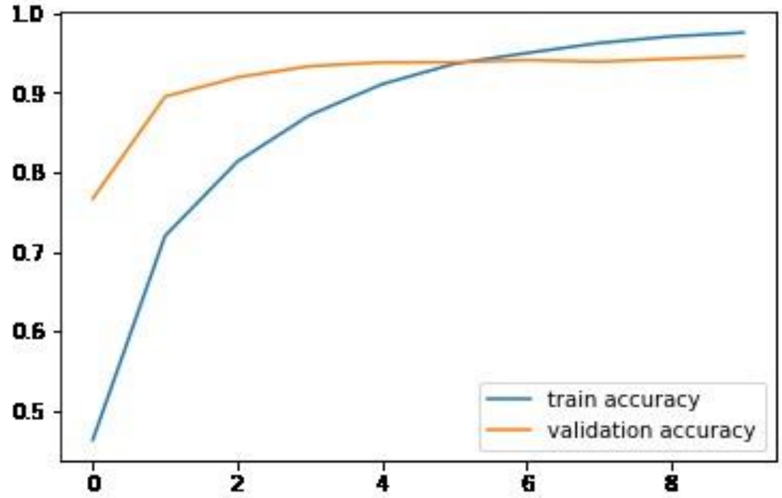


Figure8: Graph of Training accuracy and validation accuracy Vs Epochs using ResNet

Table 1 and 2 summarizes the performance of the ResNet-50 and Simple CNN models.

Name of Model	Total no of parameters	Training parameters	Non-training parameters
CNN	197322	197322	0
ResNet	23,587,712	23,534,592	53,120

Table1: Comparison table for Parameters in CNN VS ResNet

Model	Epochs	Train accuracy	Loss in train data	Test accuracy	Loss in test data
CNN	10	0.3925	1.6905	0.352	1.721
ResNet	10	0.9460	0.2015	0.9386	0.2318

Table2: Comparison table for accuracies and loss in CNN VS ResNet

The experimental findings indicate that the ResNet-50 model exhibits superior performance in terms of accuracy when compared to the Simple CNN model. The ResNet-50 model had a high accuracy rate of 0.94, hence substantiating its efficacy in the identification of retinopathy.

VII.CONCLUSION

In conclusion, our work has shown that deep learning models, and ResNet in particular, are useful for detecting retinopathy. Through careful testing and review, we've shown that ResNet does better than the Simple CNN baseline by being more accurate and able to generalize better. hese findings hold promising implications for the field of medical image analysis, suggesting that state-of-the-art deep learning architectures can significantly enhance the accuracy and reliability of retinopathy diagnosis. We believe our work provides the groundwork for advancing the field of retinopathy detection and holds promise for enhancing patient outcomes and healthcare delivery.

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