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Detection of Retinal Neovascularization Using Optimized Deep Convolutional Neural Networks

S. Lavanya[1], P. Naveen[2]

[1]Computer Science and Engineering, St. Joseph's College of Engineering, Anna University, Chennai, India

E-mail: [1]lavanyasaravanan0998@gmail.com, [2]navee4@gmail.com

Abstract

The most common disease that is found among people across the world is Diabetes and it is predicted to increase more in the upcoming years by The World Health Organization (WHO). People who are diabetic for a longer period are more likely to have Diabetic Retinopathy (DR), an eye disease which can lead to blindness and this cannot be reversed. One of the severe stage problems of DR is Retinal Neovascularization (RN), i.e., outburst of retinal blood vessels. Residual Network (ResNet) has an effective technique called Skip or Residual Connections which solves the problem of vanishing gradient during backpropagation. ResNet50 has 50 layers which is a deep network that omits signal representations and learns from residual representations leading to predict RN with 88.97% accuracy.

Keywords: Diabetic Retinopathy, Retinal Neovascularization, Residual Network

1. Introduction

Retinal Neovascularization is an eye disease which is caused due to increase in the blood sugar levels- diabetes for a long period of time. People who are diabetic for more than three years are more likely to have Diabetic Retinopathy (DR) which leads to abnormal growth or outpouchings inside the eye. There are four stages of DR, Non-Proliferative Diabetic Retinopathy (NPDR) which includes- Mild, Moderate, Severe and Proliferative Diabetic Retinopathy (PDR). There are several techniques that are available to find DR at an early stage. DR cannot be reversed but projecting to proper medications can lower blood sugar levels. If a person suffers from DR for a long period of time, then there are chances that the person may lead to vision loss. While PDR may have lot of problems in the eye like presence of microaneurysms, outpouchings of cells and growth of abnormal blood vessels but

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the growth of abnormal blood vessels in the retina may cause bleeding inside the eye and blocks the vision. There are certain methods and techniques available to detect DR at an early stage which includes using Support Vector Machine (SVM), Convolutional Neural Networks (CNN), Deep CNN. But there are very few methods that are available to detect neovascularization in the retina. Resnet50 is used to train the network and predict the presence of RN accurately.

1.1 Advantages of using ResNet50

Traditional Convolutional Neural Networks algorithms face the problem of vanishing gradient while updating the weights during backpropagation, with each iterating training step the current weight with respect to the error function of the partial derivative multiplies large in numbers to compute gradients of the first layer in the n-layer network. The output of the first layer is given as input to the other layer, during this process the value gets decreased or many times becomes zero which cannot be given as input in the first or front layer of the neural network. The data here travels in a normal way without being modified which leads to a situation where the other layers will not receive any input and the training that has to happen with the layers is not completed because of this problem of vanishing gradient for updating the weights. Resnet introduces skip connections which adds the actual input to the output of the convolution layer otherwise with the normal networks sometimes there isn't a value with which further processing cannot happen. But, Resnet solves this problem.

Fundus images of the eye are collected, where every image is being assigned to unique id-code which is similar to naming a image and are pre-processed. It includes resizing all the images to the same size(728 x 728) and then converting 3 layered images BGR- Blue Green Red to single layer, grayscale images. A grayscale image only consists of the shades of grey which helps in the proper detection of the outpouchings in the retina. The main reason of gray scaling is that it is used for extracting descriptors instead of operating on the color images. Grayscale simplifies the algorithm and reduces the computational requirements by removing the areas around the pupil. Color cropping is used to change the color version in order to highlight the affected region. Gaussian blur function is used to blur the image which enables viewing the screen from translucent screen. It enhances the image structures at different scales. These pre-processed images are given as input to the Resnet50 which is 50 layers deep and uses backpropagation method to update the weights and detects the presence of RN.

2. Related Work

Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy[1] was described by A. Kwasigroch, B. Jarzembinski, and M. Grochowski performed with various architectures having different configurations like using different data augmentation, different objectives, transfer learning but they obtained best performance with the VGG-D architecture attaining 82% accuracy with the model. Automatic Diabetic Retinopathy detection and classification System [2] was proposed by Z.A Omar et al. The authors focused on early detection of Diabetic Retinapathy and classifying them into classes. The author proposed a DR detection algorithm and found accuracy of upto 98% and 100% in obtaining the presence of hemorrhages and exudates respectively from the datasets obtained from Hospital Serdang, Malaysia for training and testing was done from datasets in DIARETDB1 database.

Zhengyang Zhou and Hefei described a system Attention based Stack ResNet for Citywide Traffic Accident Prediction [3] with the data that was obtained Traffic data in the New York city in 2017 using Resnet50 algorithm to model the urban data which contained cross-domain data which contained temporal and spatial dependency. Modulation Pattern Recognition based on Resnet50 Neural Network[4] was described by Xiao Tian and Chao Chen achieving an accuracy of 85% with the noise ratio 2db. The authors used various deep learning algorithms like Inception, Xception, VGG19, VGG16, Resnet50 and finally found the best performance with Resnet50 algorithm with good recognition on constellation modulation mode.

M. Jena, S. P. Mishra, and D. Mishra described a system called Detection of Diabetic Retinopathy Images using a Fully Convolutional Neural Network [5] where the authors have proposed a neural network with maxpooling layer, ReLu and six convolutional layers attaining the model to be 91.66%. Diabetic Retinopathy Detection using ensemble deep Learning and Individual Channel Training is a system of ensemble deep learning [6] was proposed by Harihanth K and Karthikeyan B which combineed the predictions that is obtained from various models like DenseNet169, DenseNet121, Inceptionv3, Xception, ResNet50 which reduces the variance, error in the result and the dataset is obtained from EyePACS in Kaggle and this system produced an accuracy of 81.85%.

Morphology-Based Exudates Detection from Color Fundus Images in Diabetic Retinopathy[7] was described by Morium Akter, Mohammad Shorif Uddin and Mahmudul Hasan Khan where histogram equalization was performed to the fundus images in order to enhance the contrast and then distance transformation is done which enhances the presence of the exudates with 99% accuracy.

Aparna. K. Pujitha, Gamalapati. S. Jahnavi, and J. Sivaswamy described a system called Detection of neovascularization in retinal images using semi-supervised learning [8] where detecting abnormality at patch level was 96.76% while with image level it was 91.85%. The authors have performed label fusion where the fusion happens with the labels from co training and information from the nearest neighbour present in the feature space. With the labels, weights and the similar feature that is being obtained, the computation of weights happens.

A Survey on Diabetic Retinopathy Disease Detection and Classification using Deep Learning Techniques [9] was described by Valarmathi S and VijayaBhanu R on the automated detection systems and found that these systems were cost efficient. Some concepts of CNN, Deep Learning were explored and the advantages and disadvantages of each automated system were described.

Food Recognition with ResNet-50 [10] was described by Zahisham et al., where a framework with ResNet 50 architecture was proposed and used a process called fine-tuning a pre-trained model which is one of the common approaches in building the architecture. The method produced an accuracy of 40.08%, 39.75% and 35.32% for ETHZ-Food 101 dataset, UECFOOD100 dataset and UECFOOD256 dataset respectively.

There are many methods and techniques available to find DR at an early stage and its types detecting its severity but there are only few methods available to detect the presence of RN. Laser photocoagulation and Intravitreal bevacizumab are safe and effective treatment of RN. Detecting the presence of RN and projecting to proper treatment will prevent the patients from blindness. The cause for blindness could be due to various reasons but if a patient has RN then predicting its presence and projecting them to proper treatment will help them. This system helps to determine the presence of RN in the image.

3. Proposed Work

The datasets are provided by APTOS – Asia Pacific Tele-Ophthalmology Society which constitutes retina images that were taken using Fundus Photography projecting under various imaging conditions like the images being underexposed, overexposed, out of focus and images containing artifacts that have been gathered from multiple clinics in India.

3.1 Image pre-processing

Image pre-processing in this paper includes:

Resizing: The images in the datasets are of varied sizes. To process them more effectively, resizing all the images to same size, i.e., having same length and breadth 728 x 728. Only the eyeball is needed and so all the areas surrounding the eyeballs are cropped enabling only the needed pixels.

Converting BGR to Grayscale images: The normal fundus images will have colour variation among them like some have lighter shade and some have darker shade of retina which enables more red colours. Due to which main nerve cells merge with the surrounding and the outbursts of the retina are not shown precisely. Applying grayscale to the images normalizes all the images with the shades of grey where the image ranges from having dark black to bright white and the outburst of the blood vessels- RN are shown in dark shades of grey as compared with the remaining parts which enhances the affected parts.

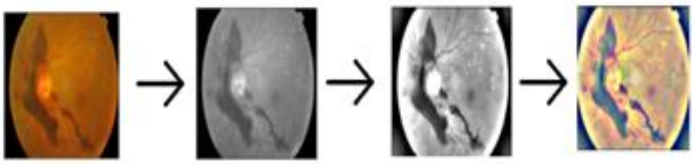

Figure 1. Image Pre-processing

Color cropping & Gaussian Blur for the images: After Gray scale conversion the nerve cells are not shown precisely and there are unwanted areas present i.e., the areas surrounding the eye ball which is represented in dark black color are not needed. Color cropping is performed for changing the color version of the images like grayscale to BGR and then converting to RGB which highlights the nerve cells and the outburst of retina clearly. Gaussian function is applied which helps in blurring of the image so that the nerve cells are enabled better than the before.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation, i.e., the variation with the set of values.

After enabling Gaussian blur, the unwanted parts around the eyeball are removed, thus focusing inside the eye and performing training will give more accurate results.

3.2 Residual Network with 50 Layers-Resnet50

Residual Network introduces residual/skip connections to overcome the problem of vanishing gradient. Here, the convolutional layers are being stacked as traditional layers and the input is added to the loss function directly which has been calculated for each layer. To increase the overall accuracy, the network has to learn from the difference between the input, X and the output, Y which is Y=X.

$$Y = F(X) + X \tag{2}$$

In the normal traditional networks are trained on the basis of Y whereas in Resnet, the algorithm is trained on the basis of the loss function, F(X).

Resnet50 enables faster learning with the concept of batch normalization which enables the data flow to happen between the intermediate layers of the network.

It constitutes two types of blocks:

- Identity Block- Where the blocks are arranged in a way which makes input of the network and its output are same.
- Convolutional Block- Convolutional layer is added in a shortcut path so that the input can be added to the output. There are two ways for matching the output size, they are: (i) (i)Performing 1*1 convolutions, i.e., assigning the filter size as one.

Padding the input volume- where layers having zero are being added to the input image and this prevents shrinking of the image size.

$$\text{Output of the layer} \quad = \frac{n+2p-f}{s} + 1 \ \frac{n+2p-f}{s} + 1 \tag{3}$$

Where, n is the image size, p is padding, f is the filter size and s is the stride. Stride with value 2 is given to reduce the size instead of using max pool or average pool. The output of the first layer is given as input to the other layer.

Table 1. Training Images

Class	Number of Images
Healthy Eye Images	250
DR	480
RN	2932

There are 3662 training images with all the 3 classes and the model is trained with 1992 images which constitutes of images belonging to various classes like images having RN, DR and healthy eye images.

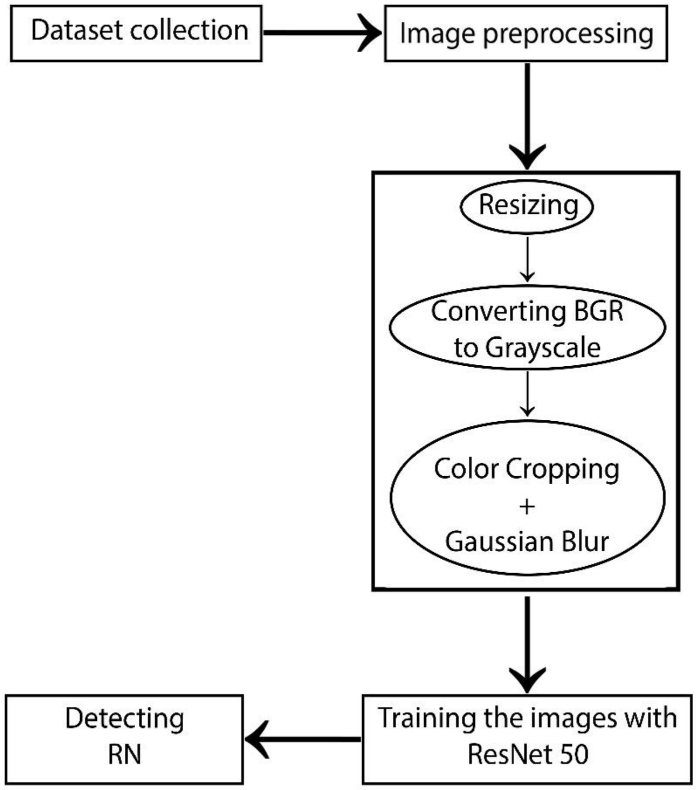

Figure 2. Architecture Diagram

The features are represented by the method of Transfer Learning from ImageNet, which is a pretrained model consisting 1000 classes where this trained model has weights calculated and these weights are used in our system instead of training them from beginning, it reduces the error rate and the time taken to train the model. The model is trained with the learning rate of $1e^{-4}$ which is an important parameter to control the model to change with the estimated error for every weight that is being assigned. The learning rate as $1e^{-4}$ moderately trains the network each time when the weights are being assigned.

A 2Dimensional convolutional layer called Conv2D are being used to obtain high accuracy in the determining the presence of RN. In order to make the network learn and perform better, the concept of Batch Normalization, BN- which normalizes the layers by re-centring and rescaling is used leading to stabilizing the network.

The activation function for best performance that is being used here is ReLu-Rectified Linear Unit which is being considered as one of the existing best activation functions which is being used after the extraction of feature maps. The performance of element wise operations, sets all the negative pixels to zero and introduction to non-linearity to the network is done by ReLu.

There consists of 5 sets of Convolutional layers producing 50 layers. Generating feature maps for every classification, the Global Average Pooling operation is being used. To reduce the problem of overfitting and preventing the networks from mugging up, dropout function of 0.5 which regularizes the network 50% is used and Early Stopping is also being used to face this problem of overfitting.

A deeply connected layer, Dense layer is a layer which includes deeply connected neurons that are being connected to all of its preceding layers and finally the output is obtained as 0- Healthy eye images, 1- DR, 2- RN. The loss function that is being used here is Categorical cross entropy which is used by the model in order to decide the presence of RN in an image among the existing classifications.

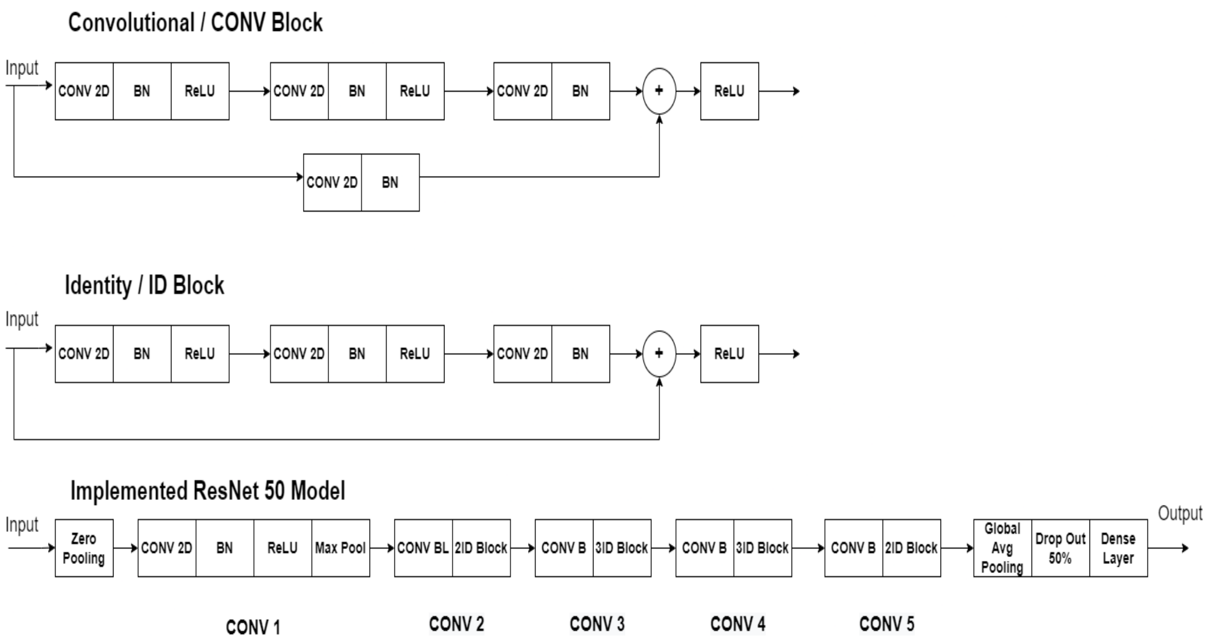

Figure 3. Block Diagram of ResNet 50

4. Results and Discussion

ResNet 50 with advantages like the capability to learn from residual representations rather than learning from signal representation and with the concept of skip connections, it enables the model to be trained properly without facing any vanishing gradient/weight problems that need to be updated during backpropagation method which has led the training and testing of the images with the model efficiently.

The output contains 4 columns: serial number, id_code - the name of the image, diagnosis- number depicting the stage like 0-No DR i.e., the healthy eye images without any disease, 1-DR images that are affected by diabetic retinopathy, 2-RN images having retinal neovascularization which are the images with outburst of blood vessels and Status- the name of the stage.

	id_code	diagnosis	Status
0	0005cfc8afb6	2	RN
1	003f0afdcd15	2	RN
2	006efc72b638	2	RN
3	00836aaacf06	2	RN
4	009245722fa4	2	RN
5	009c019a7309	2	RN
6	010d915e229a	2	RN
7	0111b949947e	0	No
8	01499815e469	2	RN
9	0167076e7089	0	No
10	01c31b10ab99	1	DR

Figure 4. Output

Average Precision value, AP is used to determine the accuracy of the model – Accuracy= (TP+TN)/N. Precision= TP/(TP+FP), Recall= TP/(TP+FN) where, TP-True Positives, TN-True Negatives, FP-False Positives, FN-False Negatives and F1 Score= 2*{(Precision*Recall) / (Precision+ Recall)}. The obtained values are Precision- 73%, Recall- 54% and F1 Score- 62%. Our model has produced 88.97% accuracy in predicting the presence of RN where the model is trained with 3662 images containing different classes and tested with 1992 images. The model is trained with Resnet 50 with 10 epochs for achieving this accuracy in a fully connected neural network.

Table 2. Performance Evaluation

Accuracy	**Precision**	**Recall**	**F1 Score**
88.97%	73%	54%	62%

Table 3. Comparison with other models

Model used	**Accuracy**
Resnet 50	**88.97%**
VGG-D Architecture [1]	82%
Modulation Pattern [4]	85%

5. Conclusion and Future Work

The proposed model is trained to predict the presence of Retinal Neovascularization (RN) in the patients having high blood sugar levels and Diabetic Retinopathy. This model produces an accuracy of 88.97%. Thus, predicting its presence will help the patients from blindness.

Future enhancement can be performed with another efficient methods like YOLO algorithm and ResNet 152 which has 152 layers deep network that will help in predicting the presence of RN more accurately.

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