Diabetic Retinopathy Detection Using Convolutional Neural Network and Residual Blocks

A Project Report

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Abstract

Diabetic Retinopathy (DR) is a disease that occurs in the eyes of long-term diabetics in a patient. It also affects the retina which causes eye blindness. So, we have to detect diabetic retinopathy early to decrease the risk of blindness. Deep learning models are proposed to detect the blood abnormalities (micro-aneurysms, hemorrhages, and hard and soft exudates) that exist in the retina images. To address this, we have proposed an automated detection of DR severity using a convolution neural network (CNN) and residual blocks. Deep learning model performs well when they have trained on large datasets. So, we have used general data augmentation for increasing the dataset size and to avoid data imbalance problem, and we have also used pre-processing techniques to enhance the image quality like removing noise, improving image contrast, etc. From extensive experimental results on publicly available database our proposed model has fair accuracy compared to other models. Thus, our proposed model shows better efficiency for real-time diagnosis.

Keywords: Diabetic retinopathy, Deep learning, Convolutional neural network, Residual network

1 Introduction

Diabetic Retinopathy is the major cause of blindness if it is not predicted or detected in the early stages. As per records, there are 415 million diabetic patients worldwide. It may also affect many organs like the heart, kidneys, eyes, etc. To prevent this diabetic retinopathy we should be screened every year. Diabetic Retinopathy is divided into 2 stages: Non-proliferative DR and Proliferative DR. this proliferative DR has 4 classes: Mild Non-Proliferative Diabetic Retinopathy (mild NPDR), Moderate Non-Proliferative Diabetic Retinopathy (moderate NPDR), and Severe Non-Proliferative Diabetic Retinopathy (severe NPDR), and proliferative Diabetic Retinopathy (PDR) as shown in Fig.1.

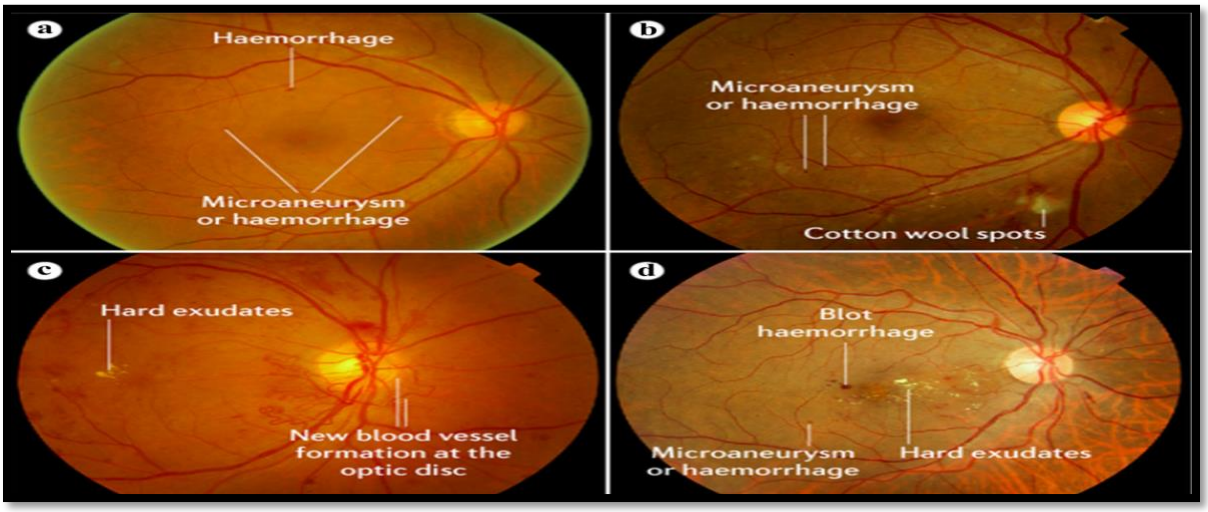

Fig.1: Stages of DR: a) mild DR, b) moderate DR, c) severe DR, d) PDR

The ophthalmologists or trained clinicians evaluating and examining the retina images is a time taking and cost-consuming process. The manual detection of the disease seems to be result in an error. So, deep learning has been used widely in medical application which will speed up the detection and classification process and also improves the accuracy of detection.

In this literature, to implement automated detection of DR severity we have used some methods for improvement over other methods. 1) Pre-processing is used for removing the noises present in the image and improves the image quality. We have used 3 pre-processing techniques (a) Median subtraction, it uses median filter for removing noise. (b) Gamma correction is generally used for non-linear methods on the pixels of image input and remodels the saturation of the image. In this the gamma value builds the relation between the pixel value and actual brightness of an image. (c) Adaptive histogram equalization is used to improve the contrast of image with respect to several histograms. 2) Data augmentation is used for balancing the imbalanced dataset by increasing the other class images. 3) At last, we have used our proposed model Convolutional neural network with Residual blocks which is also known as RenNet-18. Generally, when we are using CNN we have over fitting issues so we are using residual blocks where it uses the skip connection to avoid the over fitting.

1.1 Contribution

- Preprocessing and Data Augmentation techniques are used to remove noises present in images and class imbalance problems.
- We have proposed a model for automatic detection of the DR stage using a convolutional neural network (CNN) and Residual Blocks.
- Our proposed model has experimented on the ‘Diabetic Retinopathy 2015 Data Colored Resized’ dataset [19] and checks the performance measures (accuracy, precision, recall, F1 score) which are used to find the efficiency of the model.

2 Related Works

Deep Neural Networks, especially Convolution Neural Networks (CNN) have shown better efficiency for the classification of images. [1] Akhilesh Kumar gangwar suggested the Inception-ResNet-v2 pre-trained model and custom blocks of CNN, with 82.18% accuracy. [2] Qiang Wu suggested a multi-level iterative method of CNN and enhanced learning, with 91.79% accuracy. [3] Ronnie D. Caytiles, Suvajit Dutta, Syed Muzamil Basha, Bonthala CS Manideep, and N. Ch. S. N. Iyengar were suggested CNN on the processed VGG16 model, with 78.3% accuracy. [4] Borys Tymchenko, Philip Marchenko, and Dmitry Spodarets suggested CNN and a multistage approach to transfer learning and achieve 0.92 quadratic weighted kappa’s (QWK). [5] Darvin Yi, Carson Lam, Tony Lindsey, and Margaret Guo suggested CNN and transfer learning on pre-trained (GoogLeNet, AlexNet), with 74.5% accuracy. [6] Qaisar Abbas suggested deep visual features, with 0.924 AUC. [7] Deep Sidhpura, Darshit Doshi, Dr. Prachi Gharpure, and Aniket SheQoy were suggested Deep CNN, with 0.3996 of quadratic weighted kappa (QWK). [8] Fiaz Gul Khan and Sangheon Pack suggested the VGG-NiN model, with a 59.6 F1 score. [9] Supriya Mishra, Seema Hanchate, and Zia Saquib suggested DenseNet, with 0.9611 accuracies. [10] Gazala Mushtaq and Farheen Siddiqui suggested Convolutional Network DenseNet-169, with 78% accuracy. [11] Quang H. Nguyen, Ramasamy Muthuraman, Laxman Singh, Gopa Sen, Anh Cuong Tran, Binh P. Nguyen, and Matthew Chua were suggested pre-trained models (VGG-16 and VGG-19), with 82% accuracy. [12] Gen-Min Lin, Jiann-Torng Chen, Ke-Hung Chien, Ming-Cheng Tai, Shu-I Pao, and Hong-Zin Lin were suggested Bi-channel Convolutional Neural Network, with 87.83% accuracy. [13] Shahabuddin Shamshirband suggested five Deep CNN (Resnet50, Inceptionv3, Xception, Dense121, Dense169), with 80.8% accuracy. [14] Muhammad Hussain suggested designing CNN, two stages of transfer learning and three state art models (VGG19, ResNet152, and dual-path network), with 98.8%accuracy. [15] Alpana Rajan, Anil Rawat, Amit Paraye, Gaurav Saxena, and Dhirendra Kumar Verma were suggested InceptionResNetV2, with 0.92 AUC. [16] Shaohua Wana, Yan Lianga, and Yin Zhang suggested CNN coupled with transfer learning and hyper-parameter tuning, with 95.68% accuracy. [17]

Weihong Yu and Youxin Chen were suggested Inception-v3 enhanced by lesion-Net, with 0.943 AUC. [18] Zilin Zhang suggested efficient net-B3, with 0.935 quadratic weighted kappa's (QWK).

All the above existing deep learning models achieve improvement over one another. However, these deep learning models require a large amount of training data and time. CNN with Residual blocks is achieving fair accuracy than other models. So, we are using this model to find the severity stage of DR.

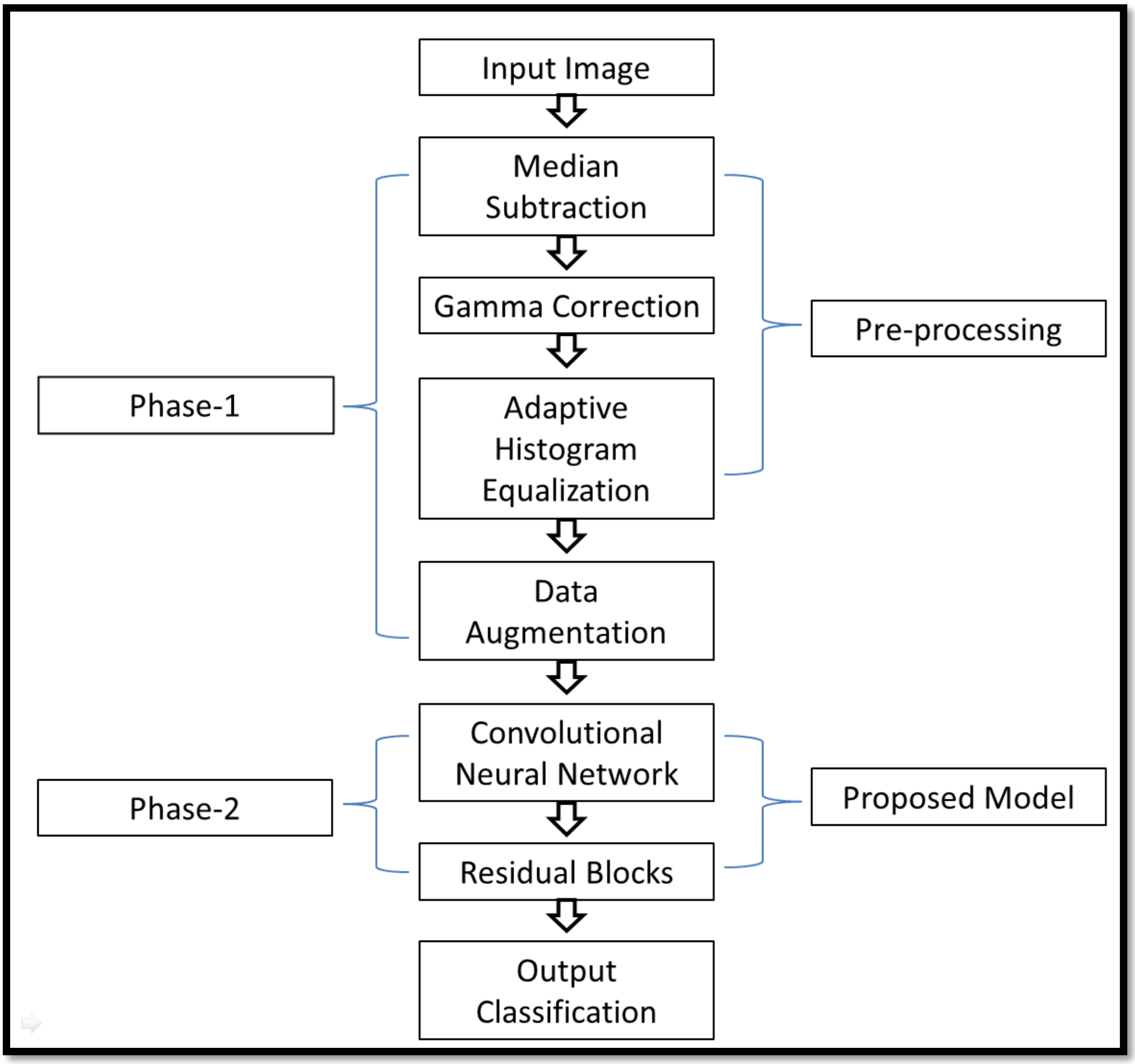

Fig.2: General Structure of Proposed Model

3 Proposed Work

Pre-processing and Augmentation, convolutional neural network (CNN) and Residual Blocks are the 2 phases involved in our proposed model as shown in Fig.2.

3.1 Pre-processing and Augmentation

In phase-1 we have 2 layers: (1) Pre-processing, in this we apply circle crop, median subtraction, gamma correction, and adaptive histogram equalization for improving the image quality. (2) General data augmentation, this method (rescale, brightness, zoom, shear, rotation, and flipping) is used to overcome the data imbalance.

3.1.1 Pre-processing

Usually, all the medical images are very difficult to analyze and complicated. So, the pre-processing technique is very important to improve the features of the image for classification, and we have to ensure that all the images are in uniform size. These methods are useful for removing the noise. From Fig.3 we can see the images from all classes in the dataset.

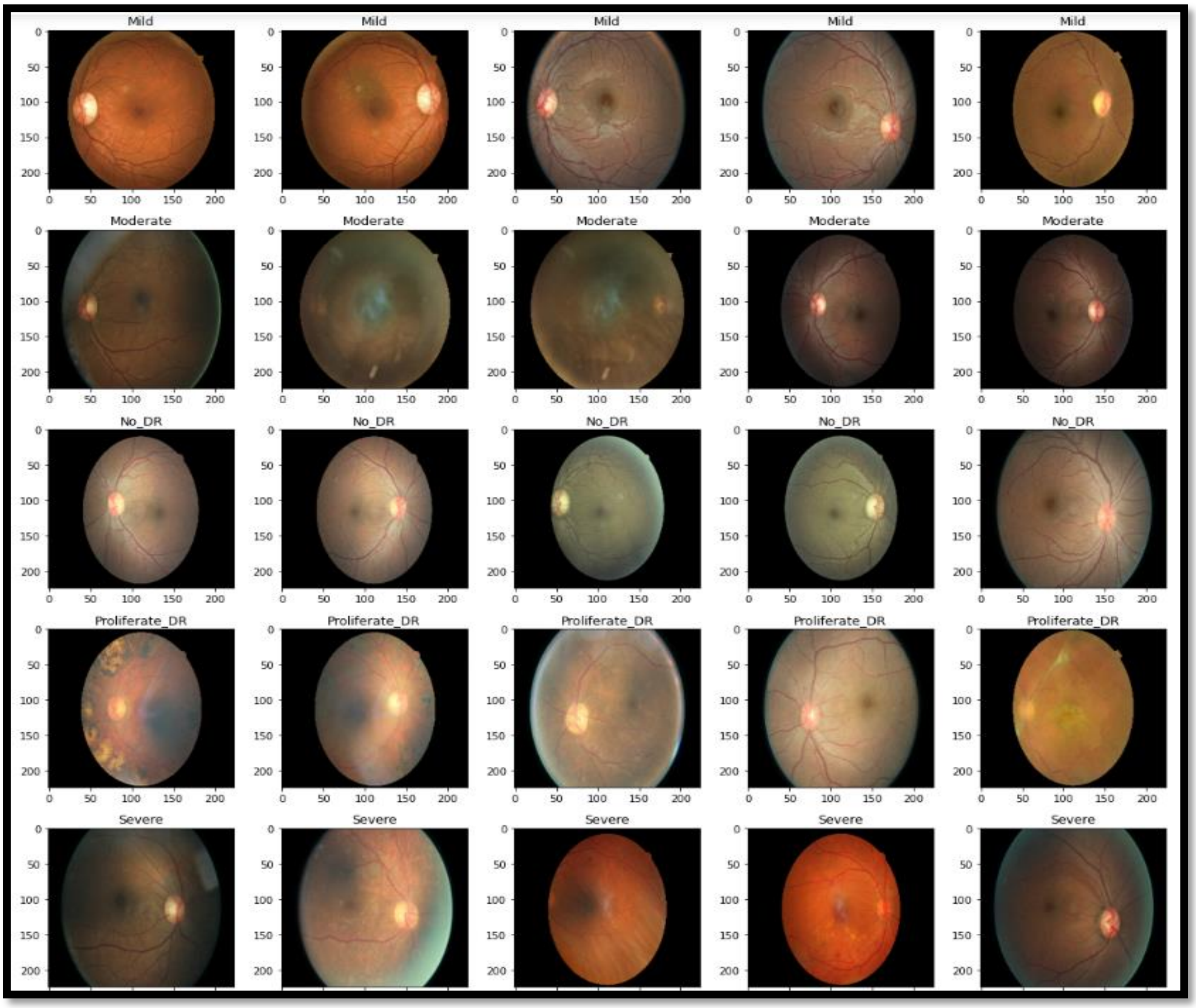

Fig.3: Images of different classes before pre-processing.

From Fig.3 we can find that the images are varied clearly from one another. So we required the pre-processing method. We have totally used 4 types of pre-processing methods, they are: (1) Circle-crop, it is used to remove the unwanted background noise of the image and made all the images into uniform size 256*256. (2) Median Subtraction, it uses median filter for removing noise where median filter prevents the edges and it is faster than other filters. (3) Gamma Correction, it is generally used for non-linear methods on the pixels of input image and remodels the saturation of the image. In this the gamma value builds the relation between the pixel value and actual brightness value of an image. (4) Adaptive histogram equalization is used to enhance the contrast of image with respect to several histograms. From Fig.4 we can see the images after the pre-processing layer. After pre-processing we can see that the images have no noises and in uniform size.

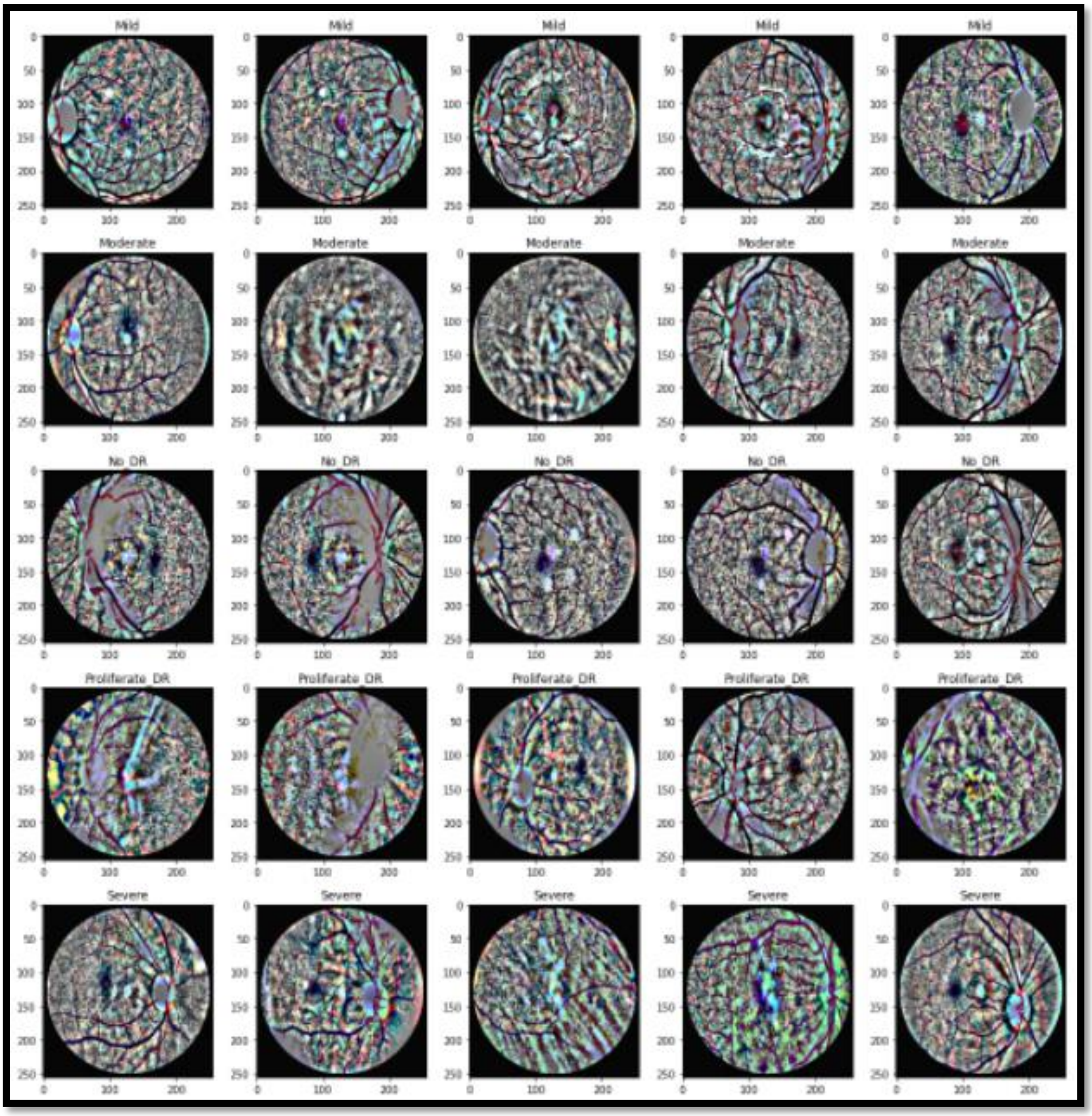

Fig.4: images of different classes after pre-processing

3.1.2 Augmentation

Although, if the images are pre-processed and ready for the process, there may exist one main challenge which is data imbalance. From Tabel.1 we can find that all the stages have a different number of images with a large margin, this may lead to over-fitting while training. So, augmentation helps us to solve this problem. The collection of medical images is a very difficult task. So, Augmentation will help us to increase the number of images that are very similar to the original images without manual collection of the new data. We used general data augmentation including rescaling, brightness, zoom, shear, rotation, and flipping.

Stages of DR	No DR	Mild	Moderate	Severe	Proliferative
Total images	25,810	2,443	5,292	873	708

Table.1: Total number of images in each class from the dataset

3.2 Deep Learning Model

Here, we have used a convolutional neural network (CNN) and imported multiple residual blocks into the CNN as shown in Fig.5.1 and this model is also called as ResNet-18. In this model we have 8 main layers. (1) Zero-Padding is used to adding zeros symmetrically to the input matrix, so that we can use all the pixels equally. (2) Convolutional Layer uses filters and parameters which are useful to learn through training and it also decrease the size of the input matrix. (3) Batch Normalization is a normalization technique done between the layers of neural network along mini-batches instead of full data. It will speed up the training and uses higher learning rates. And ReLU is used to prevent the exponential growth to operate the neural network. (4) Max pooling down-samples the input along its spatial dimensions by taking maximum value over input window for each channel of the input. (5) Residual block (Res-Block) is useful to prevent from vanishing gradient problem using skip connection or short path. (6) Average pooling down-samples the input along its spatial dimensions by taking average value over input window for each channel of the input. (7) Flatten Layer is used to convert all the 2D-Dimensional arrays from pooling layer into a single linear vector and the flattened vector is fed as input to fully connected layer. (8) Dense layer receives all the neurons of previous layer and classify the images using the softmax activation function.

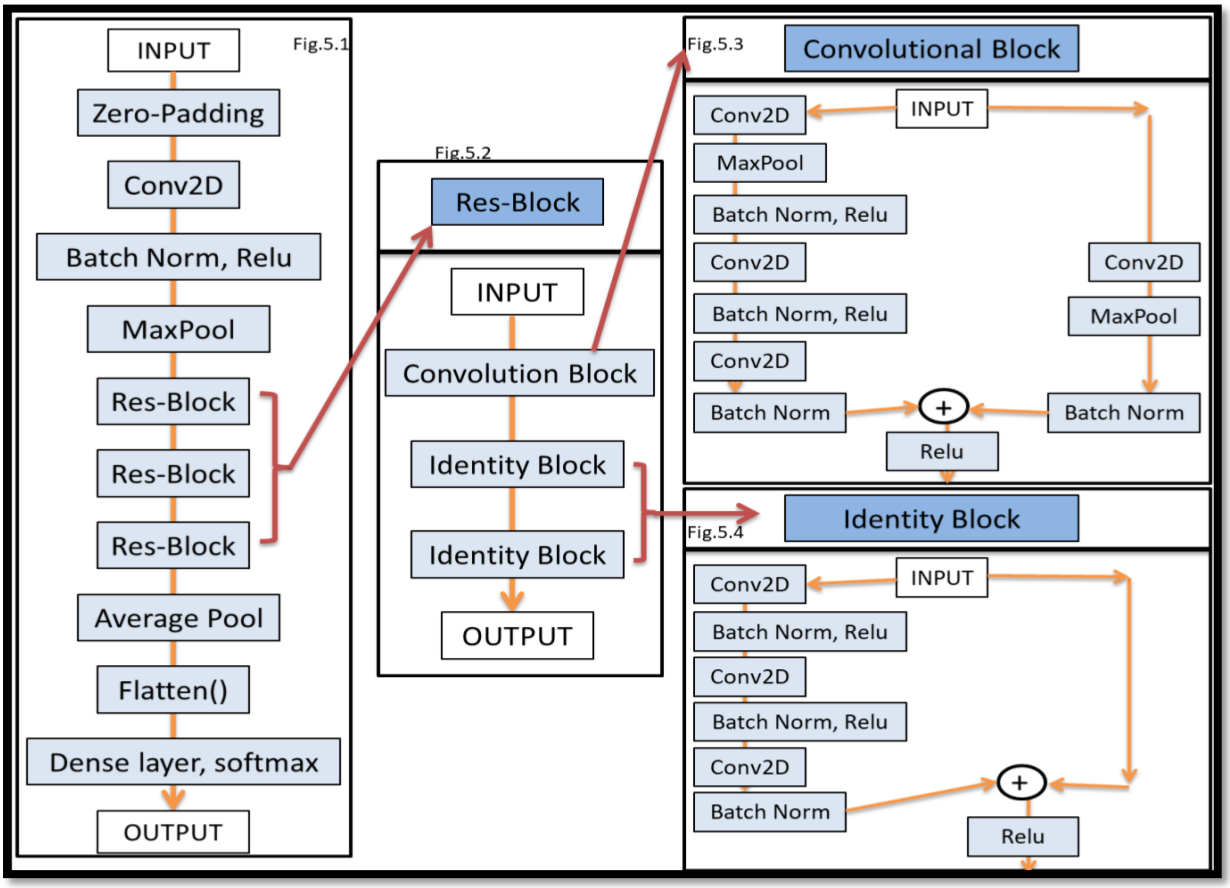

Fig.5: proposed architecture.

In Fig.5.1 we have Res-Block which has one Convolutional block and two identical blocks as shown in Fig.5.2. In Convolutional block we have 2 paths, in main path we have 7 layers and in short path (skip connection) we have only 3 layers as shown in Fig.5.3. And in Identity block also we have 2 paths, in main path we have 6 layers and in short path (skip connections) don't have any layer it directly send the input to output.

4. Details of Implementation and Results

Details of implementation contain the dataset details and testing environment, and Results contain Metrics that are used to access the performance of our proposed model.

4.1 Details of Implementation

4.1.1 Description of Dataset [19]

Our proposed model has experimented on the 'Diabetic Retinopathy 2015 Data Colored Resized' dataset to check the performance. This dataset contains 25810 no DR images, 2443 mild DR images, 5292 moderate DR images, 873 severe DR images, and 708 proliferative DR images. A total of 35,126 retina fundus images are there in the dataset. The distribution of images in all classes is imbalanced. So, we are increasing the images in all the classes as explained in Sect.3.1.2.

4.1.2 Test Environment

The results or outcomes of our proposed model are examined and trained on NVIDIA GEFORCE (graphic processing unit) with deep learning libraries, tensor flow, and Keras were used.

4.2 Results

4.2.1 Performance Measures

There are many performance measurements in deep learning methods to calculate their performances. The most commonly used measurements are Accuracy, Precision, Recall, and F1-score. Let us consider 4 kinds of image classification:

- False-negative (FN) → classified images that don't have DR but have DR.
- False-positive (FP) → classified images that they don't have DR correctly.
- True negative (TN) → classified images that have DR even though they are fine.
- True positive (TP) → classified images that they have DR correctly.

AUC is a graph created by plotting sensitivity against specificity, Accuracy = TN + TP / (FN + FP + TN + TP), Precision (P) = TP / (FP + TP), Recall (R) = TP / (TP + FN), F1-score = 2 * R * P / (R + P).

4.2.2 Results

Various parameter results on our proposed model like precision, recall, and F1-score are shown in Table.2. From the confusion matrix Fig.5 we can find the accuracies for class 0, class 1, class 2, class 3, class 4 are 89%, 0%, 39%, 52%, and 31% respectively.

-	Precision	Recall	F1-score	Support
No DR	0.80	0.99	0.89	3886
Mild DR	0.00	0.00	0.00	375
Moderate DR	0.60	0.28	0.39	769
Proliferative DR	0.70	0.41	0.52	93
Severe DR	0.61	0.21	0.31	146
Weighted average	0.71	0.78	0.73	5269

Table.2: various parameter observations.

Conclusion

The proposed model was tested on the ‘Diabetic Retinopathy 2015 Data Colored Resized’ dataset to check the accuracy of detection. Then, we generated synthetic images using the data augmentation technique. The experimental results of the ‘Diabetic Retinopathy 2015 Data Colored Resized’ dataset show a fair accuracy of our proposed model when compared to other models.

In the future, we will improve this work by using different auto-encoder, networks, and data augmentation techniques. And also we will test this tool in real clinical practice conditions.

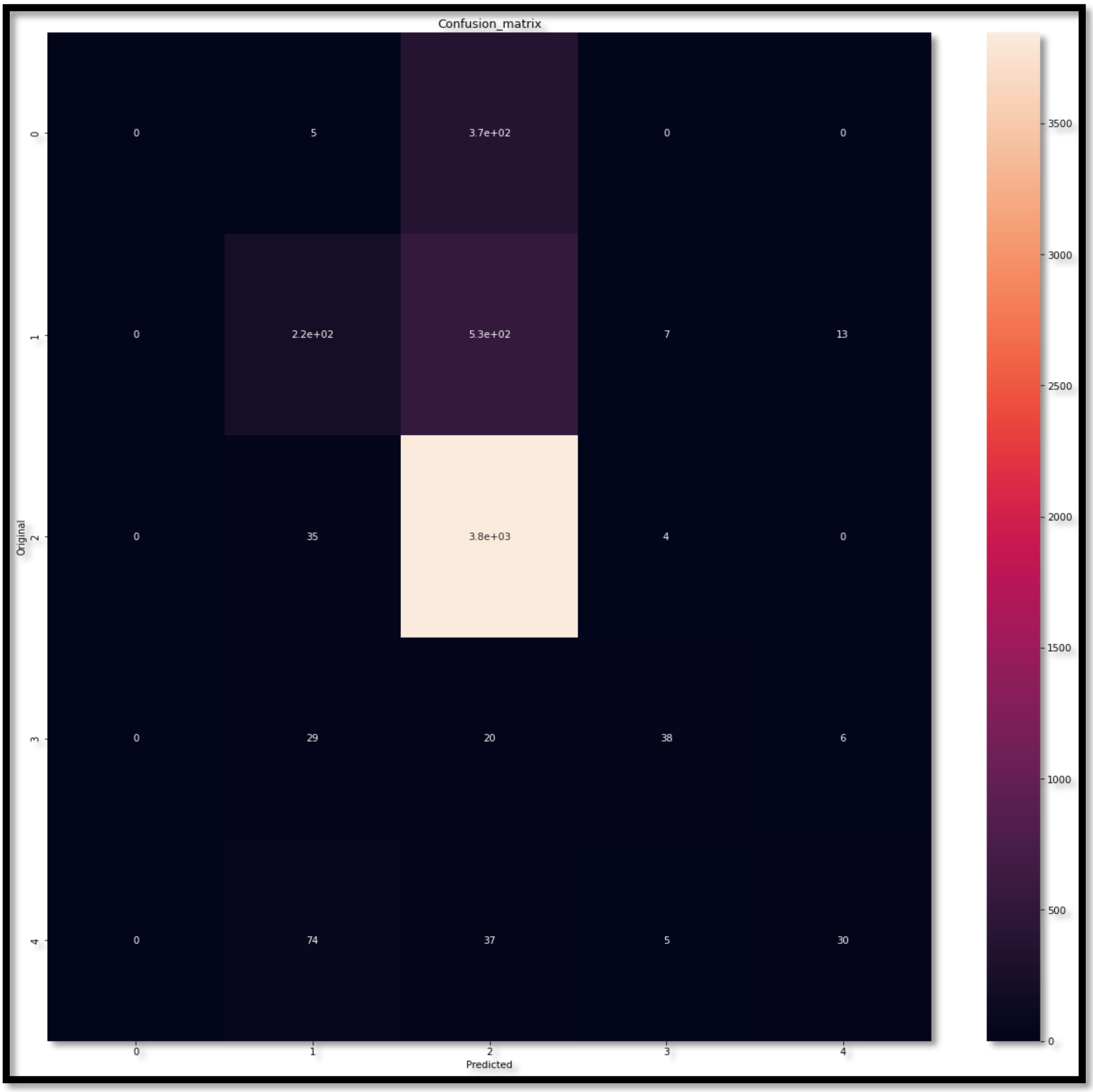

Fig.6: Confusion matrix

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