IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Diabetic Retinopathy Detection Using A Hybrid Model Approach in Deep Learning (ResNet50 + CapsNet)

Ritika Sharma
Department of Computer Science And Technology
Usha Mittal Institute of Technology, Mumbai

Pooja Vichare
Department of Computer Science And Technology
Usha Mittal Institute of Technology, Mumbai

Rachana Dhannawat
Department of Computer Science And Technology
Usha Mittal Institute of Technology, Mumbai

***Abstract*—Diabetic retinopathy (DR), an eye disease, is taken into account amongst the worldwide diseases of blindness, commonly afflicting diabetic patients. The most common cause of this disease is the complication of polygenic disease within the retinal blood vessels. To avoid complete sightlessness prompt detection, treatment should be done in the early stages. Back in time physical tests, like physical examination of dilation of pupils, optical consistency picturing, were employed to find diabetic retinopathy. However, it's expensive in terms of time and includes high chances of human error. Given these implications, the goal of this paper is to detect the presence of diabetic retinopathy in the human eye using a hybrid deep learning mode. The proposed method improves the performance of a pretrained Convolutional neural network by utilising the dynamic routing algorithm from the capsule network approach (CNN).The idea is to build a hybrid deep learning model,a combination of pretrained RESNET-50 and dynamic routing algorithm to yield statistically significant performance in detecting DR stages. The projected system will assist ophthalmologists to take a preliminary call, it permits a DR classification considering traditional eyes, mild DR, Moderate DR, Severe DR, and Proliferative DR. After the successful implementation of the model training over ATOS dataset accuracy of 79% accuracy and at the 25th epoch, 27.54% loss was achieved which is significantly lower than [19],which obtained 64.72% loss value at 25th epoch.As a result, we've successfully built a hybrid model that predicts the DR stage with a lower proportion of data loss.**

***Index Terms*—DR - Diabetic retinopathy,Dynamic routing algorithm ,CNN- Convolutional neural network,RESNET-50, Mild DR, Moderate DR, Severe DR, and Proliferative DR.**

I. Introduction

When a disease is detected early, it is easier to treat. Diabetes is a condition in which a deficiency of insulin causes an increase in blood glucose levels [1]. 425 million adults are affected globally [2]. DR is a diabetic condition that causes the retina's blood vessels to enlarge and leak fluids and blood [3]. If DR grows to an advanced stage, it might result in vision loss. DR is responsible for 2.6 percent of blindness worldwide. For diabetes patients who have had the condition for a long time, the chances of developing DR increases. Regular retinal screening is necessary for diabetic people to diagnose and treat DR early enough to prevent blindness [4].

Detecting DR is often difficult because the method involves manual analysis by reviewers and it is time-consuming process that may result in late treatment. Furthermore, it necessitates extensive experience and valuable equipment, both of which are lacking in less less privileged areas. The automatic categorization of DR can help to resolve these issues.

In recent years,CNN architectures of deep learning are far more competitive than traditional image analysis.However, CNN architectures make use of pooling layers to achieve translational invariance, but it results in information loss such as position, size, rotation, and scale. According to research, the Capsule network can assist overcome some of these problems[7].The capsule network's neurons can encode geographic information as well as the likelihood of an object being present. Capsule networks have this quality, which makes them particularly promising for medical picture analysis.Furthermore, capsule networks (CapsNet) have recently received considerable attention in the field of medical technology as a possible replacement for CNN.However, CapsNet was employed in DR categorization in a few experiments. Using retinal fundus pictures, this research develops a deep learning model for Diabetic Retinopathy categorization. The objective of the paper is the creation of a hybrid deep learning model for retinal image categorization that combines RESNET-50 with the capsule network (one non-DR and four DR classes).

II. Literature Survey

Several strategies for DR classification have been proposed by researchers. Exudates detection in fundus images was proposed[8]. The approach of [9] utilising pretrained networks yielded the accuracy of 80.40%. [12] employed a CNN approach for categorisation of DR phases, achieving 95% specificity, 75% accuracy, and 30% sensitivity.[10] proposed a smartphone application with a 73.3% accuracy for detection of DR. [16] presented a 48.2% accurate transfer learning model that supported Inception-V3 for DR detection on the EyePACS database.To categorise DR,[14] employed pretrained models such as AlexNet, VGG16, and Inception-v3. AlexNet, VGG16, and Inception-V3 had average cross-validation accuracy of 37.43%, 60.04%, and 73.27%, respectively. In [18], a new pixel-wise score propagation model for DR classification was developed. For DR image categorization,[15] suggested a Synergic Deep Learning model.All of these solutions had the same goal: to employ an off-the-shelf solution instead of entering into the network's core, which resulted in lower accuracy. CapsNet, a medical technology counterpart to CNN, has recently received a lot of attention. For hyperspectral image classification,[13] implemented a strategy for combining CNN with existing capsule networks as 1D and 3D capsule networks.However, no attempt has been made to investigate the use of CapsNet in DR classification In this research paper,For DR classification, we developed an automated deep learning model. The following is the main contribution of the paper: developing a hybrid deep learning model that integrated RESNET -50 and the capsule network for the classification of retinal images into five classes.

III. Proposed Methodology

A. Network architecture

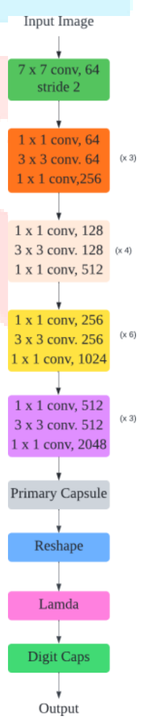

Fig. 1. Network Architecture

IV. Implementation

A. DATA COLLECTION AND EXPORATION

We used APTOS (Asia Pacific Tele-Ophthalmology Society) dataset containing fundus images. This collection has 6847 fundus photographs in total. Model testing uses 4103 photos (stored in Test.csv with picture ID and diagnosis label) while model training uses 2745 images (stored in Train.csv with image ID and diagnosis label).

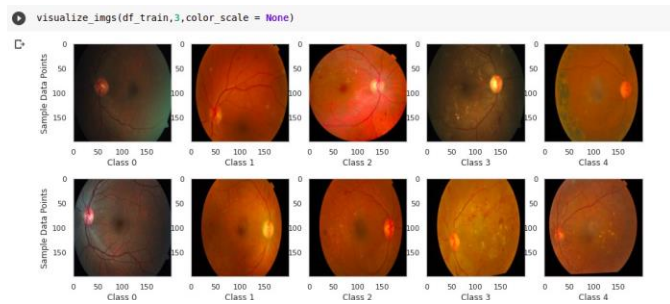

Fig. 2. Dataset

Dataset conatins 4102 train images and 2745 test images

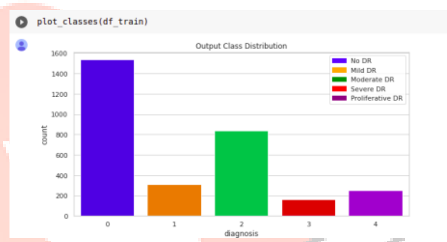

Fig. 3. Class distribution

The above graph shows labels on the x-axis denote the stages of DR, and the height of the histogram denotes the number of images present in that stage.

B. DATA AGUMENTATION

To boost the model's performance and generalisation capacity, image data augmentation is utilised to expand the amount of the training dataset. The ImageDataGenerator class in the Keras deep learning toolkit supports image data augmentation.It aids image data augmentation by shifting, flipping,rescaling, brightening, and splitting the data.

RGB to Grayscale:

Images are available in a variety of lighting situations, some of which are quite dark and difficult to visualise. As a result, the image is converted to grayscale.

C. Model (RESNET 50 + CAPSNET)

We used a transfer learning strategy due to the large amount of data available in publically available datasets. The first base model,we used the 50 layers deep Resnet50 architecture because of its proven effectiveness and ease of implementation. On the ImageNet dataset, this network was pre-trained. To

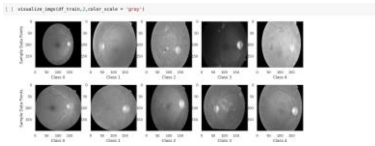

Fig. 4. RGB to Gray Scale

achive the hybrid model, last layers of RESNET50 model i.e. pooling layers are replaced by the primary caps,digicaps and capsule layers of casule network.Then, in order to achieve the best result, we trained our model using various parameter values. Finally, batch size(10), kernel size(1) and relu, activation function, and training the model across 25 epochs are some of the most important parameters and factors that best fit our model.

```
base_model = ResNet50(n_class=10,
  num_routing=3,input_shape=(28, 28, 1))

base_model.summary()

Model: "ResNet50"
 Layer (type)                   Output Shape          Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 28, 28, 1)]   0           []

 zero_padding2d (ZeroPadding2D)  (None, 34, 34, 1)    0           ['input_1[0][0]']

 conv1 (Conv2D)                 (None, 14, 14, 64)    3200        ['zero_padding2d[0][0]']

 bn_conv1 (BatchNormalization)  (None, 14, 14, 64)    256         ['conv1[0][0]']

 activation (Activation)        (None, 14, 14, 64)    0           ['bn_conv1[0][0]']

 max_pooling2d (MaxPooling2D)   (None, 6, 6, 64)      0           ['activation[0][0]']

 res2a_branch2a (Conv2D)        (None, 6, 6, 64)      4160        ['max_pooling2d[0][0]']

 bn2a_branch2a (BatchNormalizat  (None, 6, 6, 64)     256         ['res2a_branch2a[0][0]']
 ion)

 activation_1 (Activation)      (None, 6, 6, 64)      0           ['bn2a_branch2a[0][0]']

 conv2 (Conv2D)                 (None, 1, 1, 256)     524544      ['activation_48[0][0]']

 conv2d (Conv2D)                (None, 1, 1, 256)     65792       ['conv2[0][0]']

 reshape (Reshape)              (None, 1, 256)        0           ['conv2d[0][0]']

 lambda (Lambda)                (None, 1, 256)        0           ['reshape[0][0]']

 digitcaps (CapsuleLayer)       (None, 1, 256)        40970       ['lambda[0][0]']

==================================================================================================
Total params: 24,212,746
Trainable params: 24,159,626
Non-trainable params: 53,120
```

Fig. 5. Architecture

V. Result

The ResNet50 + CapsNet model detects and classifies Diabetic Retinopathy at various stages with an accuracy of 79% and a loss of around 27.54%. If the necessary improvements are performed, hybrid is capable of identifying and classifying different phases of DR with more accuracy.

```
accuracy_score = base_model.evaluate(validation_generator)
print(accuracy_score)
print("Accuracy: {:.4f}%".format(accuracy_score[1] * 100))
print("Train score = ", accuracy_score)
print("Validation score = ",validation_score)

print("Loss: ",loss_percentage)

Train score =  0.825
Validation score =  0.791
Loss:  0.21
```

Fig. 6. Accuracy

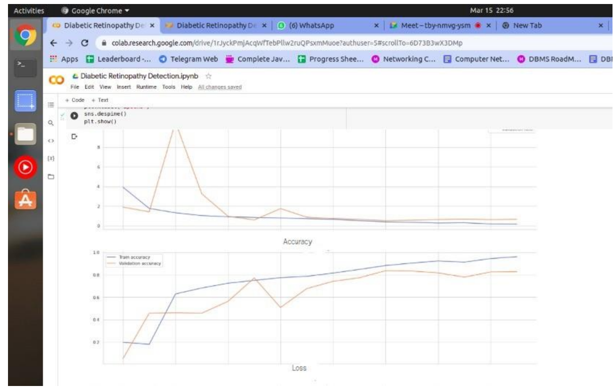

Fig. 7. Graphical representation of training and validation accuracy

Figure 7 shows the accuracy and loss plotted over epochs for the training and validation datasets.. The accuracy plot shows that the model can be trained more because the pattern for accuracy on both traing and validation datasets is still going to rise over the last few epochs. The loss plot shows that the model performs similarly on the train and validation datasets. If the parallel plots begin to deviate consistently, it may be time to stop training at a previous epoch.

```
# Submission file ouput
print("Submission File: \n---------------\n")
print(my_submission.head()) # Displaying first five predicted output
```

	id_code	diagnosis
0	0005cfc8afb6	2
1	003f0afdcd15	3
2	006efc72b638	3
3	00836aaacf06	2
4	009245722fa4	3
5	009c019a7309	2
6	010d915e229a	3
7	0111b949947e	1
8	01499815e469	3
9	0167076e7089	0

Fig. 8. Test Result

VI. Conclusion Future Scope

The research,we provided a model that can predict the DR stage. The benefits of hybrid model training include minimal information loss and the ability to categorise thousands of photos per minute.The proposed method can be utilised to screen for diabetes in the medical area. This test is highly simple, efficient, and non-invasive when compared to the standard approach. This system will be extremely cost-effective and inexpensive once it is in place. As a result, it could be included in future preventative checkups. Early treatment can help control the condition and possibly help some individuals achieve remission.

REFERENCES

[1] Taylor, R., & Batey, D. (2012). Handbook of retinal screening in diabetes: Diagnosis and management (Roy Taylor & D. Batey, Eds.; 2nd ed.). John Wiley & Sons. https://books.google.at/books?id=836CqvTVKwkC

[2] What is diabetes. (n.d.). Idf.Org. Retrieved April 8, 2022, from https://www.idf.org/aboutdiabetes/what-is-diabetes.html

[3] Gregori, N. Z. (2021, September 14). Diabetic retinopathy: Causes, symptoms, treatment. American Academy of Ophthalmology. https://www.aao.org/eye-health/diseases/what-is-diabetic-retinopathy

[4] Chakrabarti, R., Harper, C. A., & Keeffe, J. E. (2012). Diabetic retinopathy management guidelines. Expert Review of Ophthalmology, 7(5), 417–439. https://doi.org/10.1586/eop.12.52

[5] Grading diabetic retinopathy from stereoscopic color fundus photographs—an extension of the modified Airlie house classification. (1991). Ophthalmology, 98(5), 786–806. https://doi.org/10.1016/s0161-6420(13)38012-9

[6] Scanlon, P. H., Sallam, A., & van Wijngaarden, P. (2017). A practical manual of diabetic retinopathy management (Peter H. Scanlon, A. Sallam, & P. Van Wijngaarden, Eds.; 2nd ed.). John Wiley & Sons.

[7] Huang, L. (n.d.). Exploring dynamic routing as A pooling layer. Thecvf.Com. Retrieved April 8, 2022

[8] Javeria, A., Muhammad, S. Y. M., Hussam, A., & Steven, L. F. (2017). A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions. J. Comput. Sci, 19, 153–164.

[9] Jain, A., Jalui, A., Jasani, J., Lahoti, Y., & Karani, R. (2019). Deep learning for detection and severity classification of diabetic retinopathy. 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT).

[10] Suriyal, S., Druzgalski, C., & Gautam, K. (2018). Mobile assisted diabetic retinopathy detection using deep neural network. 2018 Global Medical Engineering Physics Exchanges/Pan American Health Care Exchanges (GMEPE/PAHCE).

[11] Harun, N. H., Yusof, Y., Hassan, F., & Embong, Z. (2019). Classification of fundus images for diabetic retinopathy using artificial neural network. 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT).

[12] Jain, A., Jalui, A., Jasani, J., Lahoti, Y., & Karani, R. (2019). Deep learning for detection and severity classification of diabetic retinopathy. 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT).

[13] Zhu, K., Chen, Y., Ghamisi, P., Jia, X., & Benediktsson, J. A. (2019). Deep convolutional capsule network for hyperspectral image spectral and spectral-spatial classification. Remote Sensing, 11(3), 223. https://doi.org/10.3390/rs11030223

[14] Wang, X., Lu, Y., Wang, Y., & Chen, W. (2018). Diabetic retinopathy stage classification using convolutional neural networks. In 2018 IEEE International Conference on Information Reuse and Integration (IRI).

[15] Shankar, K., Sait, A. R. W., Gupta, D., Lakshmanaprabu, S. K., Khanna, A., & Pandey, H. M. (2020). Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognition Letters, 133, 210–216. https://doi.org/10.1016/j.patrec.2020.02.026

[16] Masood, S., Luthra, T., Sundriyal, H., & Ahmed, M. (2017). Identification of diabetic retinopathy in eye images using transfer learning. 2017 International Conference on Computing, Communication and Automation (ICCCA).

[17] Understanding Capsule network architecture. (n.d.). Intel. Retrieved April 12, 2022, from https://www.intel.com/content/www/us/en/developer/articles/technical/understanding-capsule-network-architecture.html

[18] de la Torre, J., Valls, A., & Puig, D. (2020). A deep learning interpretable classifier for diabetic retinopathy disease grading. Neurocomputing, 396, 465–476. https://doi.org/10.1016/j.neucom.2018.07.102

[19] (N.d.). Ejmcm.Com. Retrieved May 20, 2022, from https://ejmcm.com/ahttps://ejmcm.com/article_5388_9491001389826ef33eab4d8d77ae9a98.pdfrticle_5388_9491001389826ef33eab4d8d77ae9a98.pdf