Diabetic Retinopathy Detection
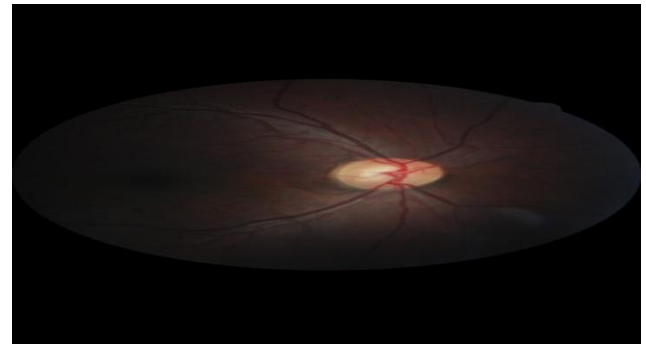
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Abstract - Diabetic Retinopathy (DR) is the leading cause of blindness in the working-age population of the developed world and is estimated to affect over 93 million people. Detecting DR is a time consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. In this paper, we have proposed three different methods for classifying DR Images. The first method uses Convolutional Neural Network We have divided our model into different stages ,we have first of all segregated of all the images from our dataset into two types one is the images which have daibatic retinopathy and other which doesn't have diabetic retionopathy, we then also segregated images with high resolution and other with low resolution .Then we started preprocessing the images , we used canny edge detection to dig out useful data and reduce the quantity of data to be processed. And then we used hough transform circle to mark it, before doing all these steps we converted all these files into grayscale, then we trained our system using convolutional nueral network algorithm and using that output we fed our system with testing datset and got our accuracy

1. INTRODUCTION

Diabetic retinopathy can be diagnosed into 5 stages: mild, moderate, severe, proliferative or no disease. The various signs and markers of diabetic retinopathy include microaneurysms, leaking blood vessels, retinal swellings, growth of abnormal new blood vessels and damaged nerve tissues. DR detection is challenging because by the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment. Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is effective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed.

The need for a comprehensive and automated method of DR screening has long been recognized, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. The current research in diagnosing diabetic retinopathy has been based on explicit extraction of features like microaneurysms and lesions through which the classification is performed. There has also been research in using machine learning techniques to classify the image as normal or diseased.

2. PROPOSED SYSTEM

Convolutional Network for Diabetic Retinopathy

They are comprised of neurons that have learn-capable loads and inclinations. Every neuron gets a few data sources, plays out a speck item and alternatively tails it with a nonlinearity. The entire system despite everything communicates a solitary differentiable score work: from the crude picture pixels toward one side to class scores at the other. And they have a misfortune functionon the last (completely associated) layer
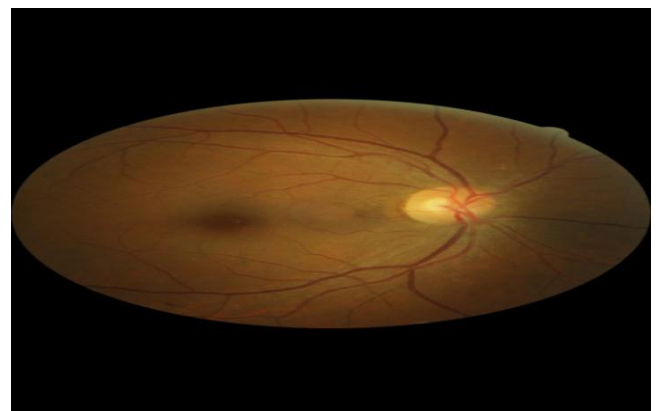
In this engineering at first we utilize a portion of (7*7) in light of the fact that it will separate straightforward highlights from the picture and we use step of 2 for first convolutional layer. Expectedly this is smarter to utilize little bit size with the goal that it can separate more data from the picture. Be that as it may, beginning convolutional layer remove straightforward highlights from the picture so we use part of size (7*7) with a step of 2. For rest of system for convolutional layer we use part size of (3*3) with a step of one so we can remove more data and then some complex highlights of the picture. For pooling we use max pooling of bit size of (3*3) with a step of 2 so we can lessen the size of the yield of past layer so that we can diminish the quantity of boundaries by extricating significant data by utilizing most extreme incentive around a pixel. To control the overfitting we utilize various methods like cluster normalization[6], dropout[7] and so on we introduce the portions as default which is utilizing glorot uniform technique. The portions introduction isn't significant on the grounds that we utilize the bunch standardization between Conv2D layer and enactment layer since preparing Deep Neural Networks is confounded by the way that the appropriation of each layer's sources of info changes during preparing, as the boundaries of the past layers change. This eases back down the preparation by requiring lower learning rates and cautious boundary introduction, what's more, makes it famously difficult to prepare models with immersing nonlinearities. We allude to this marvel as inward co-variate move, and address the issue by normalizing layer inputs. At first we utilize less number of pieces since beginning layers will separate basic highlights, so by expanding profundity of system we increment the quantity of portions. So the layers which are toward the finish of the system will extricate increasingly complex highlights. What's more, finally we use three completely associated layers. We use initiation work as LeakyReLU[8] in light of the fact that ReLU is dynamic during back-spread just when the units are certain and zero in any case. This prompts two issues

1. Dead Neurons

2. Bias Shift

Dead Nuerons

If the units are not activated initially, then they are always in the off-state as zero gradients flow through them (Dead Neurons). This can be solved by enforcing a small negative gradient flow through the network (Leaky ReLU)

Bias Shift

From ReLU, there is a positive bias in the network for subsequent layers, as the mean activation is larger than zero. Though they are less computationally expensive compared to sigmoid and tanh because of simpler computations, the positive mean shift in the next layers slows down learning. This is corrected by either using batch normalization or

using activations functions like ELU, SeLU or parametric exponential unit to shift mean towards zero and reduce bias in the activations.
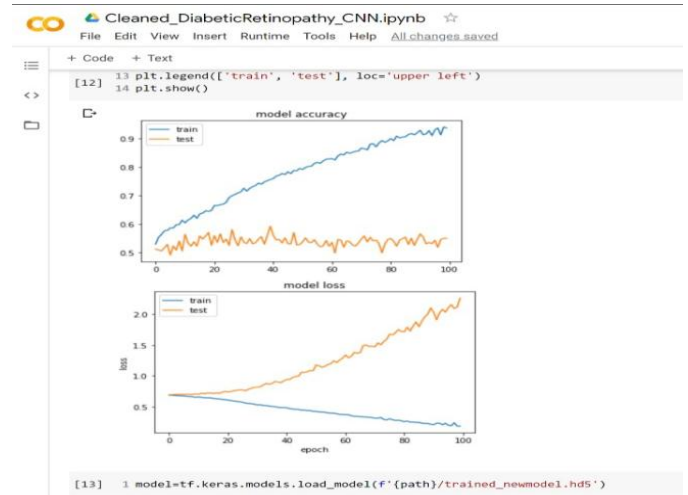
Convolutional Layer CONV layer will compute the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume

Activation Layer LeakyReLU layer will apply an elementwise activation function. This leaves the size of the volume unchanged. LeakyReLU allow a small, non-zero gradient when the unit is not active.

Batch Normalization Layer Normalize the activations of the previous layer at each batch, i.e. applies a transformation that maintains the mean activation close to 0 and the activation standard deviation close To 1

Max Pooling Layer POOL layer will perform a down-sampling operation along the spatial dimensions (width, height).

Fully Connected Layer FC layer will compute the class scores, resulting in volume of size [1x1x5], where each of the 5 numbers corresponds to a class score. Each neuron in this layer will be connected to all the numbers in the previous layer.
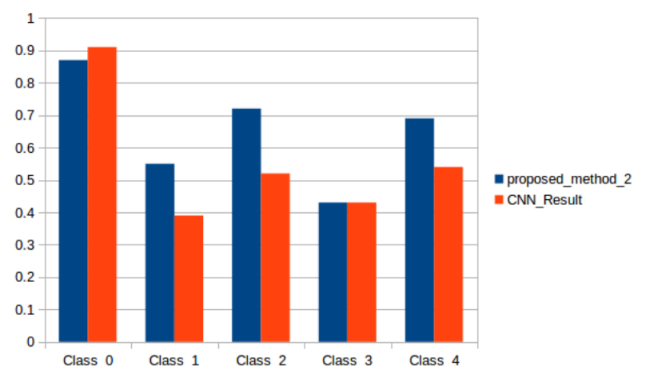

FIGURE 4.1: f1-score Comparison1

3. CONCLUSION

Techniques like Automated detection and screening gives a opportunity to prevent a big proportion of vision loss in our population. CNNs promise to power the large amounts of images that have been used for physician interpreted screening and learn from raw pixels. Using transfer learning we are getting better results, except class0, f1-score for all the classes is greater than or equal to their f1-score.CNN algorithm has proven to be a very successful algorithm for image classification in diabetic retinopathy detection

REFERENCES

[1] R. Ghosh, K. Ghosh, and S. Maitra. Automatic detection and classification of diabetic retinopathy stages using cnn. In 2017 4th International Conference on Signal Processing and Integrated Networks (SPIN), pages 550–554, Feb 2017. doi: 10.1109/SPIN.2017.8050011

[2] Rajendra Acharya U, Chua Kuang Chua, E. Y. Ng, Wenwei Yu, and Caroline Chee. Application of higher order spectra for the identification of diabetes retinopathy stages. J. Med. Syst., 32(6):481–488, December 2008. ISSN 0148-5598. doi: 10.1007/ s10916-008-9154-8. URL http://dx.doi.org/10.1007/s10916-008-9154-8.

[3] Karel Zuiderveld. Graphics gems iv. chapter Contrast Limited Adaptive Histogram Equalization, pages 474–485. Academic Press Professional, Inc., San Diego, CA, USA, 1994. ISBN 0-12-336155-9. URL http://dl.acm.org/citation.cfm?id= 180895.180940.

[4] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324, Nov 1998. ISSN 0018-9219. doi: 10.1109/5.726791

. [5] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37, ICML'15, pages 448–456. JMLR.org, 2015. URL http://dl.acm.org/citation. cfm?id=3045118.3045167