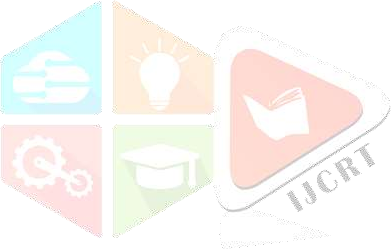


DIABETIC RETINOPATHY DETECTION USING DEEP LEARNING TECHNIQUES

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***Abstract*— *Diabetic retinopathy is referred as diabetic eye disease. It causes damage to the retina of the light sensitive tissues at the rear portion of the eye. It mainly affects the working age population in the developing country. Right now, recognizing DR is a tedious and manual interaction that requires a prepared clinician to analyze and assess advanced shading fundus photos of the retina. The rate of diabetes is more in local populations and the detection of diabetic retinopathy is needed but there is a shortage of equipment because there are expensive. With persistent advancement of deep learning models we hope to increase the accuracy of the technique and extend it to glaucoma diagnostics. In Early days convolutional neural network were used it takes more time and gives the low accuracy rate. In this paper Regional convolutional neural network and resnet were used to increase the accuracy rate and reduce the time consumption. Convolutional neural network takes image as an input and process it in different ways and assigns important to that images and produces the output by the images. In convolutional neural network there are many layers mainly input layer, hidden layer and output layer. If this technique is implemented. Diabetic retinopathy can be detected at the early stage and we can reduce the number of blindness and increase the accuracy rate and time consumption.***

***Keyword - Diabetic retinopathy, Fundus photography, Deep learning and Data set***

* 1. **NTRODUCTION**

Diabetic retinopathy ( DR) is a common complication of diabetes associated with retinal vascular damage caused by long standing diabetes. Furthermore, the diagnosis of DR mostly depends on the observation and evaluation to fundus photographs of which procedure can be time - consuming even for experienced experts. Therefore computer aided automated diagnosis approaches have great potential in clinical to accurately detect DR in a short time which can further help to improve the screening rate of DR and reduce the number of blindness. For a deep learning model, the most important parts that should be focused on are data set, network architecture and training method. Before being used to train our model, fundus images data set obtained from public resources is pre - processed and augmented. The model accepts two fundus images corresponding to the left eye and right eye as inputs and then transmits them into the Siamese like blocks. The information from two eyes is gathered into the fully connected layer and ﬁnally the model will output the diagnosis result of each eye respectively.

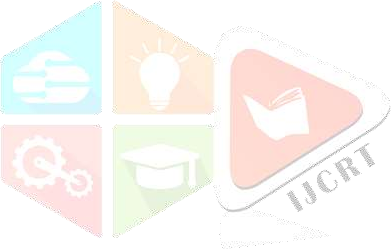
## EXISTING SYSTEM

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Besides a binocular model for the ﬁve class DR detection task is also trained and evaluated to further prove the effectiveness of the binocular design. The result shows that, on a 10 % validation set, the binocular model achieves a kappa score of 0 . 829 which is higher than that of existing non ensemble model. Finally the comparison between confusion matrices obtained through models wi th paired and unpaired inputs is performed and i t demonstrates that the binocular architecture does improve the classiﬁcation performance .

## PROPOSED SYSTEM

Result

For a deep learning model, the most important parts that should be focused on are data set, network architecture and training method. Before being used to train our model, fundus images data set obtained from public resources is pre -processed and augmented. The model accepts two fundus images corresponding to the left eye and right eye as inputs and then transmits them into the Siamese - like blocks. The information from two eyes is gathered into the fully-connected layer and ﬁnally the model will output the diagnosis result of each eye respectively.

## BLOCK DIAGRAM

Image Pre- Processing

Input fundus image

* C o l l e c t i n g t h e n o r m a l a n d a f f e c t e d e y e i m a g e s t h r o u g h O C T s c a n ( O p t i c a l

C o h e r e n c e T o m o g r a p a h y )

* T h i s m o d e l a c c e p t s t w o f u n d s i m a g e s

c o r r e s p o n d i n g t o t h e l e f t e y e a n d r i g h t e y e a s i n p u t s

* I n v o l v i n g t h e p r e p r o c e s s i n g s t e p we h a v e t o c o n v e r t t h e R G B i m a g e s t o

g r e y s c a l e a n d r e s i z e t h e i m a g e f r o m t h e c o l l e c t e d i m a g e .

* C o n v o l u t i o n a l N e u r a l

N e t wo r k ( C o n v N e t / C N N ) i s a D e e p

L e a r n i n g a l g o r i t h m wh i c h c a n t a k e i n a n i n p u t i m a g e , a s s i g n i m p o r t a n c e

( l e a r n a b l e we i g h t s a n d b i a s e s ) t o

v a r i o u s a s p e c t s / o b j e c t s i n t h e i m a g e a n d b e a b l e t o d i f f e r e n t i a t e o n e f r o m t h e o t h e r

## V.IMAGE PRE-PROCESSING:

D a t a s e t i s a p r i m a r y a n d s i g n i ﬁ c a n t p a r t t h a t n e e d s t o b e d e a l t wi t h f o r a d e e p l e a r n i n g a p p l i c a t i o n . T h e f u n d s p h o t o g r a p h s i n o u r d a t a s e t h a v e l a r g e v a r i a t i o n , s u c h a s d i s c r e p a n t b r i g h t n e s s o r r e s o l u t i o n , s i n c e m o s t o f t h e m a r e o b t a i n e d w i t h d i f f e r e n t e q u i p m e n t i n d i f f e r e n t e n v i r o n m e n t . B a s i c a l l y , t h e m o d e l a c c e p t s t wo f u n d s i m a g e s c o r r e s p o n d i n g t o t h e l e f t e y e a n d r i g h t e y e a s i n p u t s a n d t h e n t r a n s m i t s t h e m i n t o t h e S i a m e s e - l i k e b l o c k s .

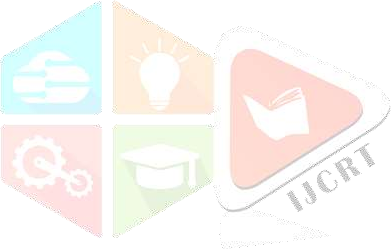
Feature Extraction

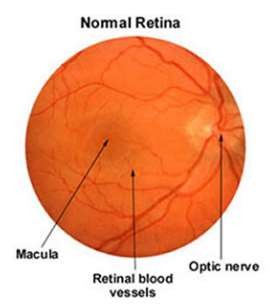
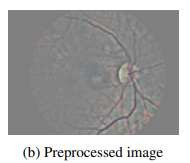
Convolution neural network

Right eye & Left eye score

## VII M ATCH IN G SCO RE:

T h e c o n f u s i o n m a t r i c e s o f p r e d i c t i o n r e s u l t s o f l e f t e y e , r i g h t e y e , a n d b o t h e y e s t o g e t h e r . T h e p r e d i c t i o n r e s u l t s o f t h e l e f t e y e a n d t h e r i g h t e y e h a v e v e r y s i m i l a r d i s t r i b u t i o n p a t t e r n s , i n d i c a t i n g t h a t t h e d a t a p a r t i t i o n m e t h o d p r e s e r v e s t h e o r i g i n a l i m a g e c a t e g o r i e s d i s t r i b u t i o n o f l e f t e y e s a n d r i g h t e y e s .

**VIII.DIAGRAM**



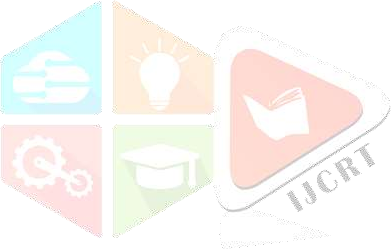
# A normal human retina

## VI CONVOLUTION NEURAL NETWORK ALGORITHM:

T r a n s f e r l e a r n i n g me t h o d i s a wi d e l y u s e d t r a i n i n g me t h o d o f c o n v o l u t i o n n e u r a l n e t wo r k . B y l o a d i n g t h e we i g h t s o f I n c e p t io n b l o c k s p r e - t r a i n e d o n I ma g e N e t d a t a s e t , t h e mo d e l wi l l h a s a b e t t e r we i g h t s i n i t i a l i z a t i o n b e fo r e s t a r t i n g t h e g r a d i e n t o p t i mi z a t i o n . M o r eo v e r , c o n s i d e r i n g t h e h u g e d i f f e r e n c e b e t we e n t h e fu n d u s i ma g e s d a t a s e t a n d I ma g e N e t d a t a s e t , n o n e o f l a ye r s i n w e i g h t - s h a r i n g I n c e p t i o n b l o c k s a r e f r o ze n .

# Retina which is affected by Diabetic retinopathy

## CONCLUSION

I n t h i s p a p e r w e a n a l y s i s t h e l i m i t a t i o n s o f d e t e c t i o n o f e a r l y s t a g e s o f d i a b e t i c r e t i n o p a t h y a n d a c c u r a c y a n d t i m e c o n s u m p t i o n . C o n s e q u e n t l y w e p r o p o s e r e g i o n a l c o n v o l u t i o n a l n e u r a l n e t w o r k , r e s n e t w i t h f l a s k w e b a p p l i c a t i o n f o r d i a b e t i c r e t i n o p a t h y d e t e c t i o n . D e e p l e a r n i n g m o d e l a r e i n t r o d u c e d w i t h t h e m o t i v a t i o n o f a c h i e v i n g a c c u r a c y r a t e . F u r t h e r mo r e f l a s k we b a p p l i c a t i o n i s u s e d i n t h i s p a p e r i t i s h e l p fu l i n d e t e c t i n g t h e e a r l y s t a g e s o f d i ab e t i c r e t i n o p a t h y. I n a d d i t io n t h e p r o p o s ed me t h o d c a n g a i n a c c u r a c y r a n g e s b e t we e n 9 2 . 5 to 9 6 % . O u r me t h o d c a n g a i n e a r l y c o n s i s t e n t a c c u r a c y r a t e a n d i mp ro v e me n t s i n e a r l y d e t e c t io n . I n d e e p l ea r n i n g mo d e l we t r a i n o u r i ma g e s u s i n g c o n v o l u t i o n a l n e u r a l n e t wo r k a l g o r i t h m.

## REFERENCES

1. A Brief Review of the Detection of Diabetic Retinopathy in Human Eyes Using Pre-Processing & Segmentation Techniques Yogesh Kumaran, Chandrashekar M. Patil International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-4S2, December 2018
2. ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION Diederik P. Kingma\* University of Amsterdam, OpenAI [dpkingma@openai.com](mailto:dpkingma@openai.com) Jimmy Lei Ba∗ University of Toronto [jimmy@psi.utoronto.ca](mailto:jimmy@psi.utoronto.ca) Published as a conference paper at ICLR 2015
3. Batch Normalization: Accelerating Deep Network Training b y Reducing Internal Covariate Shift Sergey Ioffe Google Inc., [sioffe@google.com](mailto:sioffe@google.com) Christian Szegedy Google Inc., [szegedy@google.com](mailto:szegedy@google.com) <http://arxiv.org/abs/1502.03167v3>
4. Convolutional Neural Networks for Diabetic Retinopathy Harry Pratta,∗ , Frans Coenenb , Deborah M Broadbentc , Simon P Hardinga,c, Yalin Zhenga,c International Conference On Medical Imaging

Understanding and Analysis 2016, MIUA 2016, 6-8 July 2016, Loughborough, UK

1. Diabetic Retinopathy detection through integration of Deep Learning classification framework Alexander Rakhlin e-mail: [rakhlin@gmx.net](mailto:rakhlin@gmx.net) February 2017
2. Diabetic Retinopathy Detection Using Eye Images Mohit Singh Solanki 12419 [mohitss@iitk.ac.in](mailto:mohitss@iitk.ac.in) Supervisor: Dr. Amitabha Mukherjee April 18, 2015
3. Indian Diabetic Retinopathy Image Dataset (IDRiD): A Database for Diabetic Retinopathy Screening Research Prasanna Porwal 1,\* ID , Samiksha Pachade Received: 5 June 2018; Accepted: 6 July 2018; Published: 10 July 2018
4. Prevalence and causes of vision loss in high-income countries and in Eastern and Central Europe in 2015: magnitude, temporal trends and projections Br J Ophthalmol: first published as 10.1136/bjophthalmol-2017-311258 on 15 March 2018.