International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org || PP. 194-201

Detection of Diabetic Macular Edema using Retinal Fundus Images

Nischitha M Ragi[1], Yash Jaiswal[2], Vachana V[3], Richa Bharti[4], Dr. Dayananda P[5]

[1]*Department of Information Science of engineering, J.S.S. Academy of Technical Education, Bengaluru, India*
[2]*Department of Information Science of engineering, J.S.S. Academy of Technical Education, Bengaluru, India*
[3]*Department of Information Science of engineering, J.S.S. Academy of Technical Education, Bengaluru, India*
[4]*Department of Information Science of engineering, J.S.S. Academy of Technical Education, Bengaluru, India*
[5]*Department of Information Science of engineering, J.S.S. Academy of Technical Education, Bengaluru, India*

Abstract: *Machine learning (ML) is the process of teaching algorithms from experience and data, so they can learn and develop on their own. This field is known as artificial intelligence. In machine learning, a model is built from samples of data, also known as training data, from which it can make predictions or choose without being explicitly trained. A wide range of applications, including medicine, email filtering, speech recognition, and computer vision, rely on machine-learning algorithms because they are difficult or impossible to develop through traditional methodsAI textbooks define the world as consisting of "intelligent agents," including machines, animals, and humans. The natural intelligence of animals, including humans, cannot be replicated by machines. Macular edema is a result of abnormal leakage and accumulation of fluid in the macula from damaged blood vessels in the surrounding retina. Popularly, "artificial intelligence" refers to machines that mimic human cognitive functions, such as learning and problem-solving. Diabetics can develop diabetic retinopathy, which can cause macular edema. A number of diseases can affect your optic nerve, includingglaucoma. When fluid accumulates around the front of your eye, it becomes puffy. That fluid puts your eye under increased pressure, causing damage to the nervus opticus.*
Keywords – *DME, CNN, Deep Learning, Image Processing, Neural Networks*

I. Introduction

About 30 million Americans have glucoma (Diabetes macular edema), and another 86 million have diabetes macular edema. Medical costs and lost wages U.S. health care systems spend more than $245 billion annually onmedical bills and the wage loss associated with it. There are 79 million people living with diabetes outside the United States, approximately 8.3% of the global population. The number of adults at risk of developing macular edema is also increasing. By 2035, there will be 592 million people with macular edema associated with diabetes,an increase of 55 percent over the previous 22 years. As many as 33% of Americans are predicted to have diabeticmacular edema by 2050, according to the CDC. Diabetes patients with macular edema are at risk for both macrovascular and microvascular disorders, such as high blood pressure, heart disease, and stroke. The purpose of our proposal is to reduce the number of processes carried out by an individual by developing an automated detection method that uses clahe and median filters during image pre-processing and watershed segmentation during image segmentation.

II. Literarure Survey

Detection of DME involves the identification of lesion and exudates in the retinal fundus images of a human. This clinically a tough job, The below referenced research papers consist some of the groundbreaking work provided with the support of artificial intelligence in the identification.

Diabetic Retinopathy Detection via Deep Convolutional Networks for Discriminative Localization and Visual Explanation: Zhiguangwang,Jianbo Yang (2019)

In order to achieve the proposed method's visual interpretability, a regression activation map (RAM) was included after the global average in the pooling layer of convolutional networks (CNN). In an experiment done on a large retinal image dataset, the proposed CNN model may succeed in detecting DR with high accuracyCNN has had exceptional success in the field of computer vision. Using the Kaggle website, colourretina images were downloaded for each individual, one for the left eye and one for the right eye. Diabetic retinopathy labels provided by clinicians who rated the disease's presence.

Comparative study in early detection of symptomatic diabetic macular edema:-Nilesh shrimali, Somesh Aggarwal

A compounding factor in developing countries is the fact that patients present to hospitals with advanced disease, and consequently suffer from future complications of chronic macular edema. In addition to suggesting OCT for symptomatic patients, it also promotes the judicious and efficient use of OCT in developing countries like India, where cost is usually a priority. The Amster grid might prove inexpensive, simple, and reliable for detecting metamorphopsia and thus detecting diabetic macular edema early. The Macular computerized psychophysical test(MCPT) has been shown to be superior to the Amster grid in detecting AMD related lesions, and is being investigated to see if it can provide early detection of CNV at home.

A computerize tool for detection of Diabetic Maculae Edema Grading supported multilayer deep learning and transfer learning : BY Qaisar Abbas

As diabetic retinopathy is a common disease, it eventually results in loss of vision. DME can be a time consuming task for clinical experts. To acknowledge the severity of DME, several computerized diagnostic systems were developed in the past. An automatic feature learning scheme has been developed in paper to grade the severity of DME and other eye-related diseases. Researchers have proposed using a pre-trained CNN model to detect disease.

Therefore, a novel feature-based model was proposed to support DCNN to diagnose DME-related diseases. A mobile application will soon be developed to assist clinical experts in determining the severity level of DME disease.

A Novel ML Algorithms to automatically predict visual outcomes in intravitreal-Treated patient with diabetic macular edema :- shao-chunchen

Based on the author's findings, they discovered that baseline OCT parameters did not have any effect on visual outcomes. ML algorithms have been used to detect diseases such as cancer and PTSD. Author's model was built only using baseline OCT measurements, so there is likely to be a discrepancy. An algorithm can be constructed based solely on baseline clinical characteristics of patients for predicting final aucity in intravitreal after 5,278 and 104 weeks using ANNs with strong correlation coefficients. Around 5-9 etors letters or 1-2 lines of vision were available in the SEM. As a tool to help with expectation and explanation, the expalined models could be helpful in clinics. The application of ML to DME cases and outcomes could benefit patients with the disorder.

Convolutional Neural Network For Diabetic Retinopathy : Harry Prat , Frans Coenen (2016)

The paper introduced with the technique of Initializing the network with Gaussian initialization which reduced initial training time. Kaggle provided a dataset to optimize and train on consisting of over 80,000 images with approximately 6 million pixels per image, and the loss function used was the widely used categorical cross-entropy function. Using a high-end GPU and sizing the image to train on the entire public library of work, Author's were able to learn using the GPU.

Hyperparameter Tuning deep-learning for diabetic Retinopathy Fundus Image Classification : K.shankar,Yizhuo Zhang (2020)

An additional hyperparameter is presented to settle in a particular technique for a specific scenario. Adding more hyperparameters enhances the performance of the applied technique. A simple model of inception is used in training varying portions are segmented as multiple subnetworks , therefor amount of filters can be altered easily from the inception method. To reduce the number of unnecessary operations, Inception V4 has been proposed.

Automatic detection and monitoring of diabetic retinopathy using efficient CNN and adaptive histogram : Asramomeni pour, Hadiseyedarabi (2020)

An efficient net design and a valuable pre-processing technique called CLAHE are used to create a novel DR model. In the CLAHE Method, the image is divided into tiles without overlap, and the histogram is trimmed over a threshold. The use of skilled ophthalmologists is crucial for DR. This procedure involves visually examining the retina for symptoms.

III. Proposed Model

In the proposed model represents the abstract overview of the overall architecture of the system. Referencing thedifferent research paper landed to the conclusion that for the classification of image related data, Convulational neural networks are best-suited. There are some disadvantages which arises due to the quality of images used fortraining the CNN model, this can be removed by using the image pre-processing techniques. The MESSIDOR-2 data set in Kaggle have images already pre-processed and augumented to increase the variation hence help in training the model. Now for our approach, A custom CNN was used, this CNN is a sequential architecture with 5 stacks of convulatioanal layer and an additional stack of fully connected dense layer. These layer are stacked one over another to form a full-fledged Convulational Neural Network. It took nearly 3-4 hour to train on the dataset.

Compare to state-of-the are CNN architecture like VGG16 and mobileNet, our model showed and overall accuracyof 71%, where as VGG16 showed an accuracy of 97% and mobileNet showed an accuracy of 89%

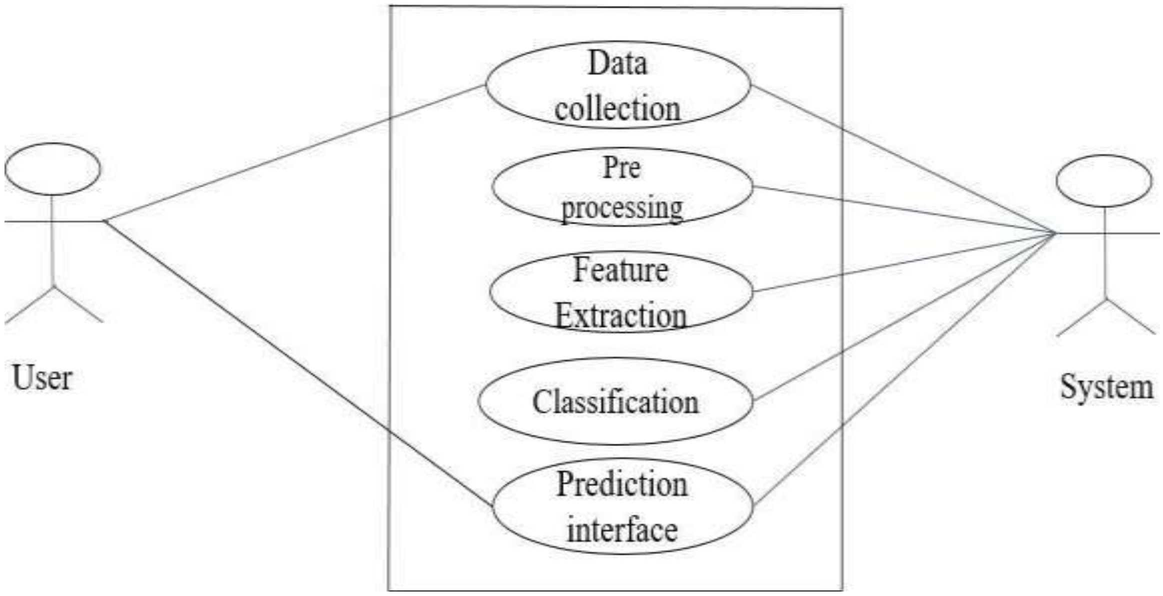

Figure 1

This project's pre-processing flow will be represented in flowchart Fig 2, For different Neural Network architecture to work and train faster, the pre-processing step is required, MobileNet architecture which is said to be lightweight and much faster than VGG16 uses image which has to be re-sized by 244x224x3, whereas VGG16 being 533megabytes of size is capable of providing much better results with a trade-off with training speed, time and resource intensive. For the custom sequence architecture of the project, the image size has been reduced to 50x50x3 and the RGB colored has been changed to gray-scale of area of interest.

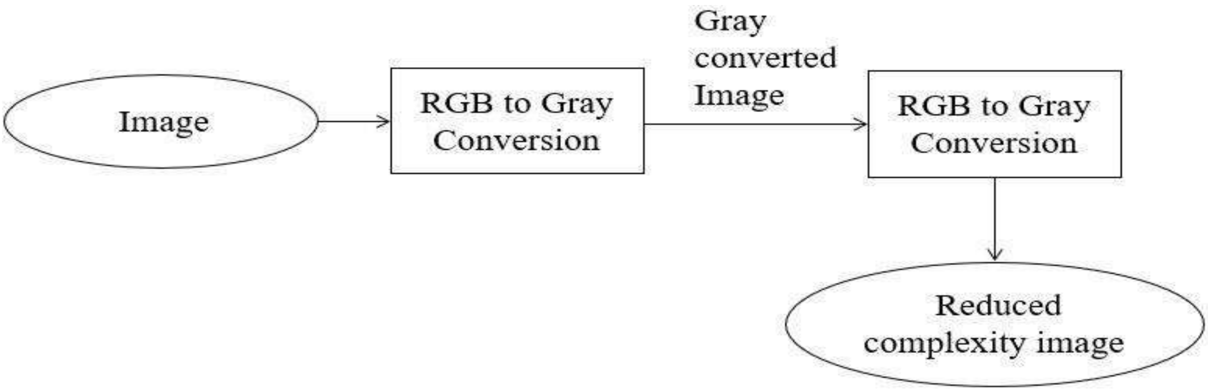

Figure 2 Pre-processing stage

The project's feature selection part is illustrated in Fig 3, Focusing and finding the region of interest saves a lot of time in computation of results.

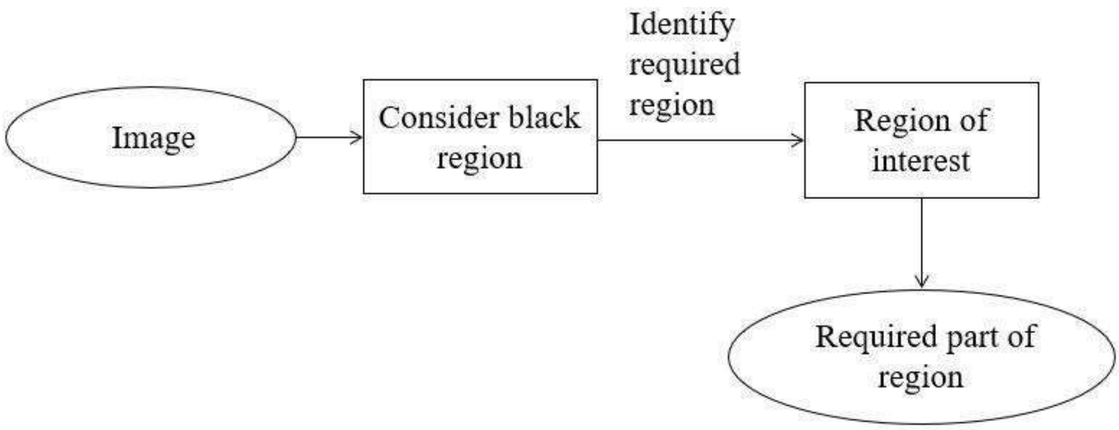

Figure 3 Feature Selection

Fig 4, shows the feature extraction process and feeding the region of interest part of the image to the CNN for the prediction. Here, Rectified Linear unit also known as ReLU is used as activation function, MaxPOOL2D isused for pooling layer with dropout of 0.8. After which the tensor is flattend to single dimension vector containing the maximum value from the tensors.

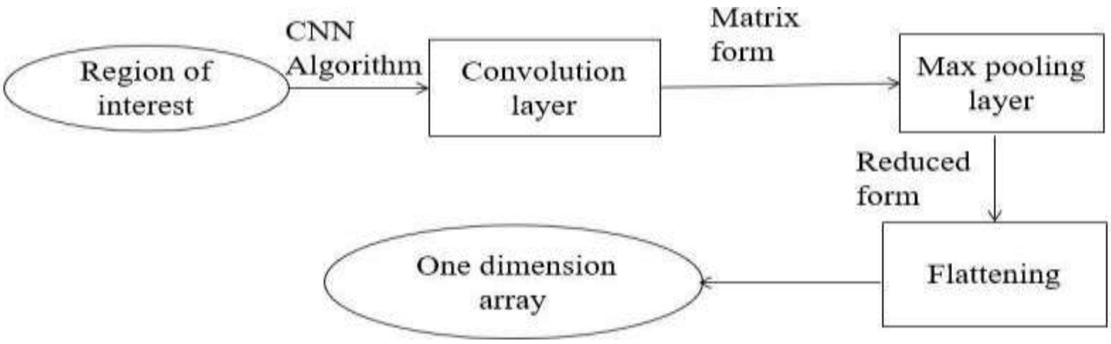

Figure 4 feature extraction process

Fig 5, Represents the classification and detection process. Here for the fully-connected layer softmax function is used since the classification is not binary but categorical. Also for optimizer function adam optimizer is used.

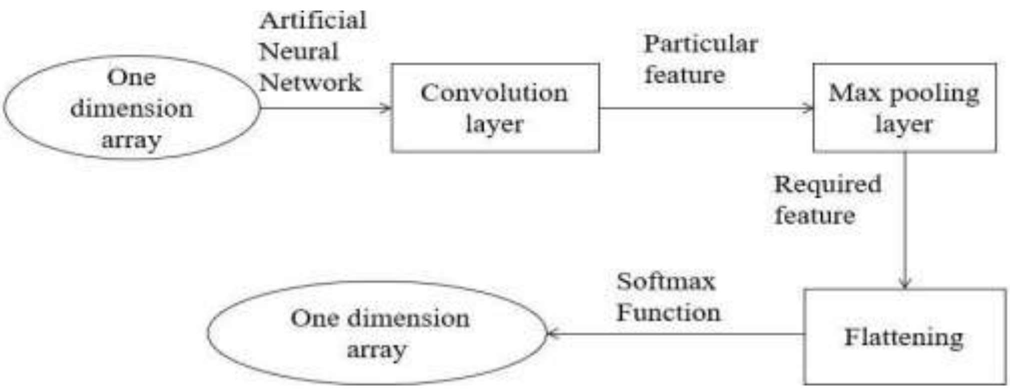

Figure 5 classification and detection

IV. Figures And Tables

The given figure 6 below illustrate the structure of retina, The macular region there consist of area susceptible to DME,

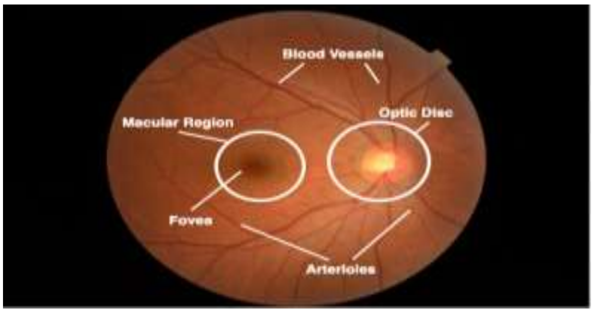

Figure 6 Structure of Retina

The figure 7 shows a retinal fundus image with exudates collected over the macular region, It cases may range from mild to severe depending on the amount of exudates lesions collected.

Figure 7 DME affected eye

MobileNet CNN Architecture shown in table 1

Table 1 MobileNET Architecture

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

The architecture of VGG16 Neural Network is shown in table 2

Table 2 VGG16 Architecture

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Architecture of sequential CNN is shown in table 3

Table 3 Sequential CNN

Type/Stride	**Filter SHAPE**	**Activation Function**
Conv2D/3	3x3x3x32	**ReLU**
Conv2D/3	3x3x3x64	**ReLU**
Conv2D/3	3x3x3x128	**ReLU**
Conv2D/3	3x3x3x32	**ReLU**
Conv2D/3	3x3x3x64	**ReLU**
Fully Connected	1024	**ReLU**
Fully Connected	5	**Softmax**

V. Results

The below pictures illustrate the predicted output from the CNN, The dataset was provided from MESSIDOR-2 Kaggle database. The images were already augumented and the pre-processing required was the conversion of images from RGB channel to gray-scale and re-sizing of the image.

Figure 8 Severe

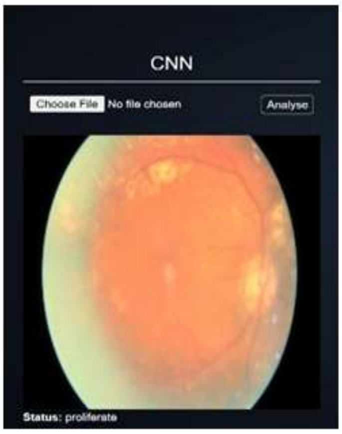

Figure 9 Proliferate

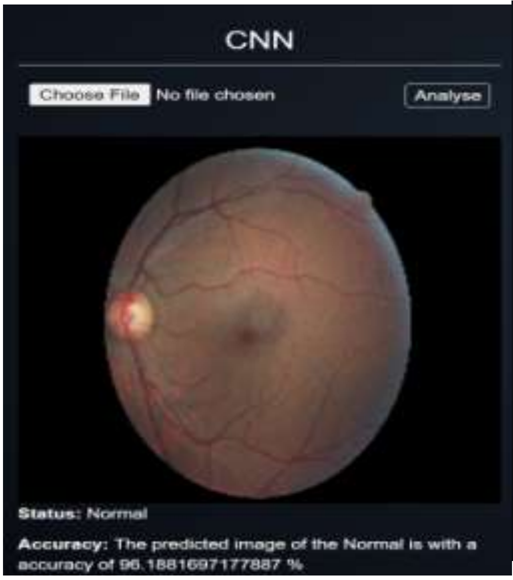

Figure 10 Normal Figure 11 Moderate

Figure 12 Mild

VI. Conclusion

Proposed work provides an automated tool for early diagnosis of diabetic macular edema
The method is straightforward, robust and computationally less complex and improved success rate for feature,and lesion detection are achieved as compared with state-of-the-art-methods. This project takes input as fundus image and processes it to detect diabetic retinopathy . Early detection Diabetic Macular Edema will be very beneficial for the patient, as he/she can then proceed with the treatment and can avoid permanent vision loss. The future scope of this project is that it can be integrated with powerful GPUs using cloud service provider infrastructure to decrease the training time of model as well as combination of several CNN algorithm can be used to achieve ensemble machine learning model to provide results with more precision and more accuracy. Proposed work provides an automated tool for early diagnosis of diabetic macular edema. The method is straightforward, robust and computationally less complex and improved success rates for feature, and lesion detections are achieved as compared with state-of-the-art methods. This project takes input as fundus image and processes it to detect diabetic retinopathy. · Project can run on any Python(Anaconda) installed- platform and can manage well with stack of fundus images, given one at a time. · The result stage will diagnose the type of damage caused to retina

References

Journal Papers:

[1]. K. D. Bowers, A. Juels, and A. Oprea. Hail: a high-availability and integrity layer for cloud storage. In Proceedings of the 16th ACMconference on Computer and communications security, pages 187– 198,2009.

[2]. D. Burihabwa, R. Pontes, P. Felber, F. Maia, H. Mercier, R. Oliveira, J. Paulo, and V. Schiavoni. On the cost of safe storage for public clouds: an experimental evaluation. In Proceedings of the 35th IEEE Symposium on Reliable Distributed Systems, pages 157–166, 2016.

[3].]J. Y. Chung, C. Joe-Wong, S. Ha, J. W, and M. Chiang. CYRUS: Towards clientdefined cloud storage.In Proceedings of the10th ACM European Conference on Computer Systems, EuroSys'15,2015.

Proceedings Papers:

[4]. Top Cyber Threats for 2016; integrity attack on financial sector likely.http://www.carriermanagement.com/news/2015/11/30/148345.htm.

[5]. W. Ashford. Info security Europe 2010: Data integrity attacks to become more common, say experts. http://www.computerweekly.com/news/1280092630/Infosecurity-Europe-2010- Dataintegrity-attacks- tobecome-more-common-say-experts.

[6]. G. Ateniese, S. Kamara, and J. Katz. Proofs of storage from homomorphic identification protocols. In International Conference on the Theory and Application of Cryptology and Information Security, pages319–333, 2009.

[7].]P. S. Barreto and M. Naehrig. Pairing-friendly elliptic curves of prime order. In International Workshop on Selected Areas in Cryptography, pages 319–331, 2005.