Detection of Glaucoma Disease By Using Retinal Eye Images

Dr. S Jeyabalan[1], Rohini.H[2], Navya L[3], N.Yathish[4], Lohith H.N[5]
[1] Professor, Dept of Computer Science
[2, 3, 4, 5]Dept of Computer Science
[1, 2, 3, 4, 5] RRCE, Bengaluru, India

Abstract- *Glaucoma is one of the severe visual diseases that lead to damage the eye irreversibly by affecting the optic nerve fibers and astrocytes. Consequently, the early detection of glaucoma plays a virtual role in the medical field. The literature presents various techniques for the early detection of glaucoma. Among the various techniques, retinal image-based detection plays a major role as it comes under noninvasive methods of detection. While detecting glaucoma disorder using retinal images, various medical features of the eyes, such as retinal nerve fiber layer, cup-to-disc ratio, apex point, optic disc, and optic nerve head, and image features, such as Haralick texture, higher-order spectra, and wavelet energy, are used. In this paper, a review and study were conducted for the different techniques of glaucoma detection using retinal fundus images. Accordingly, 45 research papers were reviewed and the analysis was provided based on the extracted features, classification accuracy, and the usage of different data sets, such as DIARETDB1 data set, MESSIDOR data set, IPN data set, ZEISS data set, local data set, and real data set. Finally, we present the various research issues and solutions that can be useful for the researchers to accomplish further research on glaucoma detection..*

I. INTRODUCTION

In all over the world, there are more than 66.8 million people who are blind due to Glaucoma, a multifactorial neurodegenerative disease that deteriorates vision over time. It takes a considerable amount of time to assess the potential risk of glaucoma disease in diagnosis as well as in treatment. Blood pressure in the eye increases due to intraocular pressure (IOP), and this leads to the break of the optic nerve axon due to its progression to dangerous levels. Therefore, the most important risk factor in the development of glaucoma is an increase in IOP. Blindness may result if this slows down vision loss. In addition to the intra ocular hypertension disease, glaucoma is also accompanied by optic nerve damage. The brain is unable to detect images because of the damaged optic nerve. An optic nerve degeneration is the complaint of the physiologist, which manifests in the optic nerve head and also in the visual area. Glaucomatous damage is irreversible, but being detected early as well as receiving the recommended treatment helps reduce the risk of vision loss. As a result of fluid pressure, glaucoma eyes have a smaller diameter than normal eyes. Fluid usually accumulates in the front part of the eye when this happens. Anormal eye has a pressure of 21 millimeters of mercury. We suffer damage to our optic nerves as the pressure in our eyes increases with fluid levels in our eyes. There is the potential for both eyes to lose vision as the disease progresses. With early detection and treatment, glaucoma can often be prevented from leading to blindness. It is rare to notice any symptoms during the early stages of glaucoma, since it progresses inside theeye.

In Glaucoma, the optic nerve is continuously damaged. Fluid usually accumulates in the front part of the eye when this happens. A normal eye has a pressure of 21 millimeters of mercury. We suffer damage to our optic nerves as the pressure in our eyes increases with fluid levels in our eyes. There is the potential for both eyes to lose vision as the disease progresses. With early detection and treatment, glaucoma can often be prevented from leading to blindness. It is rare to notice any symptoms during the early stages of glaucoma, since it progresses inside the eye. Gloucoma is the leading cause of blindness, contributing to approximately 5.2 million cases of total blindness worldwide and potentially affecting 80 million people within 10 years, according to the World Health Organization (WHO).Glaucomatous damage is determined primarily by the appearance of the optic cup. Glaucoma causes the cup to enlarge, extending to the disc area. Glaucoma is an eye disease that can cause blindness if not detected in the early stages. The optic cupto disc ratio measures the diameter of the optic cup portion compared to the diameter of the optic disc. Eye blindness is caused by it a second most common cause. In order to perform analyses of eye's internal structure, fundus cameras have been used. In order to perform analyses of eye's internal structure, fundus cameras have been used. There are a number of techniques used to detect glaucoma, including Topcon image net system, optical coherence tomography, and retinal nerve fiber layer analysis.

II. LITERATURE SURVEY

[1] Glaucoma is a serious irreversible cause of blindness that is most common in those over 40 years old. This disease is prevalent in Colombia, and is made worse because there are not enough ophthalmologists to serve the country's population. It is the most popular screening method for glaucoma detection due to its trade-off between portability, size, and cost. This paper presents a computational tool that can detect glaucoma automatically.[2] Globally, glaucoma is the second leading cause of blindness. Around the world, 66.8 million people suffer from glaucoma, with 6.7 million becoming blind from it. A structural change that arises in the internal eye is the only early indicator of glaucoma. The Cup to Disc Ratio (CDR) is a measure of glaucoma and can be used to categorize fundus images. [3] An optic nerve injury leads to the development of Glaucoma, an ocular disorder that causes vision loss. The optic cup is measured to diagnose glaucoma. As the optic cup and blood vessels interweave, segmenting the optic cup is quite tedious. For the segmentation of the optic cup, preprocessing and K-means clustering are applied, which is then further processed to determine the cup's dimension. The perimeter method of fractal analysis is used for the detection of glaucoma and is based on the fact that the fractal dimension is used for determining the dimension of irregular objects. Experimental results show that fractal algorithms accurately detect glaucoma.[4] The application of fractal analysis (FA) to the prediction of glaucoma progression is investigated. A pseudo-two-dimensional image of a retinal nerve fiber layer drawn from 1-D retinal nerve fiber data obtained from subjects with progressive or nonprogressive glaucoma may be converted using FA. Box-counting is used for obtaining our FA features as is a multifractional Brownian motion technique that combines characterization of texture and multiresolution. Multiclass classification based on Gaussian kernels uses both features.[5] There is no cure for glaucoma anyway. There have been many attempts to automate glaucoma detection using Color Fundus Images (CFI) and Optical Coherence Tomography (OCT) images by extracting structural features. A glaucoma assessment can be made by analysing the optic nerve head (ONH) in a CFI and the Retinal Layers (RL) in an OCT image. Despite this, current works are not as accurate as expected.[6] There is no cure for glaucoma anyway. There have been many attempts to automate glaucoma detection using Color Fundus Images (CFI) and Optical Coherence Tomography (OCT) images by extracting structural features. A glaucoma assessment can be made by analysing the optic nerve head (ONH) in a CFI and the Retinal Layers (RL) in an OCT image. Despite this, current works are not as accurate as expected.[7] Measuring causes the container zone to increase and causes side vision loss. In normal circumstances, highly trained clinicians examine fundus pictures in an arduous manner. With the goal of programming recognition of eyes influenced with glaucoma, we will utilize picture preparation separating and transforming techniques and actualize for example, on equipment using the DM3730 Texas Instruments (TI) chip (SOC) or utilizing the LabVIEW based NI interface framework.. [8] Measuring causes the container zone to increase and causes side vision loss. In normal circumstances, highly trained clinicians examine fundus pictures in an arduous manner. With the goal of programming recognition of eyesinfluenced with glaucoma, we will utilize picture preparation separating and transforming techniques and actualize for example, on equipment using the DM3730 Texas Instruments (TI) chip (SOC) or utilizing the LabVIEW based NI interface framework..

III. SYSTEM ARICHITECTURE AND DESCRIPTION

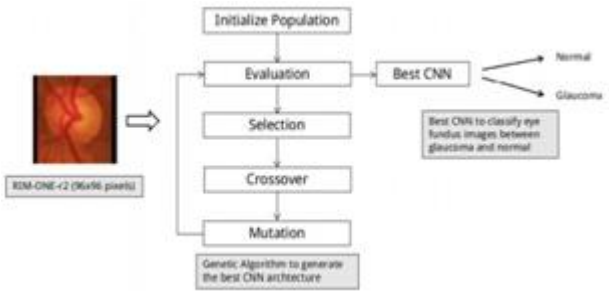

Figure 1. High level block diagram

CNN Model:The idea of using CNNs to detect disease in mulberry leaves requires that before diving into the notion of how CNNs function and function, one needs to have a grasp of how the human brain is able to recognize objects that differ from one another's attributes. In the brain, we have several layers of neurons, each layer holds information about the object and all the features are extracted by the neurons and stored in our memory. The next time we see that object, the brain.As it matches stored features to recognize an object, it can be mistaken for a simple "IF-THEN" function, and to some extent, that is true, but it also has another unique feature, Self- Learning, which can give it a tough fight against a human brain.To detect the diseases in leaves, images are processed with the Basic CNN..

IV. WORKING ANDMETHODOLOGY

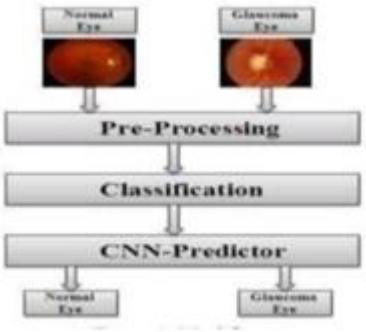

Figure 2:System Design

A. Data Classification: The data were obtained from a Kaggle dataset. Because it is a dataset of photographs from various sources, cameras, and resolutions, with variations in noise and lighting, its heterogeneity is high. A range of resolutions were used with these images in order to achieve ease of omparison. We have now completed some preprocessing steps We selected 500 images from the Kaggle dataset after these preprocessing steps. The system is trained using 70% of the 500 images while the remaining 30% is used for testing purpose. This table shows how the 500 images were decomposed

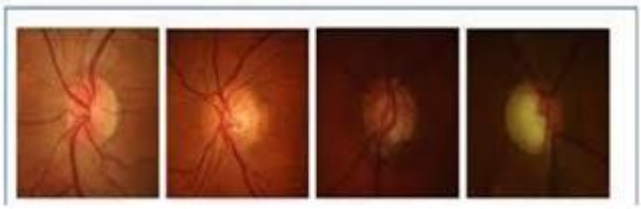

Figure3:Data Classification

B. Pre-Processing:As a preprocessing step for achieving high accuracy, we performed the following: CNN worked on a dataset of fundus images that were of different sizes and aspect ratios. Prior to preprocessing, all images are resized and downsized to 256 x 256 images. Convert the images into green channel images before putting them into the architecture for classification. And then, apply filters for salt and pepper noise removal. Microaneurysms (MAs), and vessels can be seen in the monochrome images of the fundus. In a microaneurysm (MA), there is an area of swelling on the vessel wall. MAs are found in the retina of people with diabetes. The MA is an important indicator of DR. Candidates who have the greatest contrast in the fundus have the highest chance of DR. An equalization filtering algorithm was employed for contrast adjustment.

C. Feature Extraction: The pre-processed image is given as an input to the CNN model which consists of an input layer, convolution layers and a fully connected layer. The input image of 256x256pixel acts as the input layer The first convolution layer generates 16 feature maps from 16 filters of 3x3 size kernel each by sliding one by one through the position. This is called feature extraction.A 2x2 window size Max Pooling layer for each input variable below zero is applied on the output of the ReLU layer, resulting in down-sampling of the resulting feature..The output of the last convolution layer acts as an input for the next convolution layer. The next convolution layer contains of 32 3x3 scale kernel filters that are applied to each of function maps retrieved from the last layer. Specific operations like ReLU and max pooling are carried out to generate 64x64 pixel down-sampled data..The same operations are performed on the third layer which is the last layer where 64 filters of 3x3 size kernels are used which produce 32x32 pixel data.The third convolution layer has an output of 64 32x32 pixel feature maps. These features are then leveled to a single 32x32x64= 65536 long vector, that acts as an input to a fully-
connected layer. These features are then used to evaluate the image type whether it is an healthy eye or glaucoma- infected eye..

D. Classification: After all the feature extraction has been done, now we are going to perform binary classification. Here we have used deep neural nets with two input layers, a total of three layers, one representing the output. For this we have created a feed-forward backpropagation network (newff) . Here the terms 'newfit' is for 'regression' and 'newpr' is for 'classification'. They together are called 'newff' the generic name which is still available and gives better output in our classification. First of all we have created a two later feed forward network. The first layer consists of three 'transig' neurons and the second layer has one 'purelin' neuron. Thuswehave,net =ewff(p,t,[3,1],{'tansig','purelin'});Here, p is the matrix of input vectors and t is the matrix for target vectors. For the inputs vectors we have used three components namely, optic disk mask, artifacts mask and exudates mask. Then the network is simulated and its output is plotted. Thus we have y = sim(net,p); We need to mention here that the network is trained for 5000 epochs, train- parameter goal is 0.01.When the training has been done a **.**mat file is created and further loaded to test our datasets. Once loaded we are able to distinguish our image as a good one and as a bad one. Then the corr2 library function is used to find the correlation between four classes of images. The test image belongs to the class with which it correlates most.

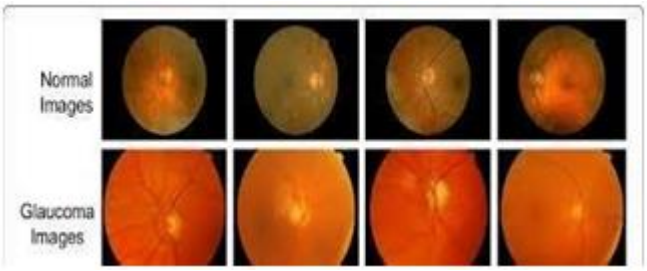

Figure4: Classification

V. CONCLUSION

we have proposed a novel convolutional neural organize strategy for diabetic retinopathy discovery based on transfer learning. In this method, retinal patches are automatically extracted before preprocessing to improve results. For DR classification, the proposed technique outperformed other CNN models, including the VGG16. According to our experiments, we found that an Inception CNN model performed better for classification and successfully represented retinal pathological features. Referral DR with 96.29 percent accuracy on Messidor database was the best result achieved. Future, First steps to standardizing the detection of diabetic retinopathy were discussed. It is a difficult database, but it mirrors the reality in practice: the images are uncalibrated, expert evaluation is free form, and the displays used to view the images are uncalibrated. We will, however, continue to develop our database and evaluation methods in the future.

Several steps will be taken in the development process: 1. It was necessary to calibrate the fundus camera and optics due to known, and the photometric information is identical between images). A calibration level of 1 has been achieved. Secondly, There is a predefined set of directives provided to the experts for different types of findings. By introducing directives, the usage of free-form descriptions is prevented, allowing subjective interpretations to be controlled. Findings are classified by the confidence level indicated by the expert (high, medium, low). The findings are independently verified by a number of experts. The fourth point is crucial. Experts will be evaluated on how display calibration impacts their performance. The fifth point. Measures of sensitivity and specificity will be improved (sensitivity/specificity function). The data will also contain the location of normal findings and a protocol for evaluating the accuracy of their localization.

REFERENCES

[1] U. R Acharya, S Dua, Xian Du, S Vinitha Sree, and Chua Kuang Chua. Automated diagnosis of glaucoma using texture and higher order spectra features. IEEE Transactions on Information Technology in Biomedicine, 15(3):449–455, 2011.

[2] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top- down attention for image captioning and visual question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[3] Jimmy Ba, Volodymyr Mnih, and Koray Kavukcuoglu. Multiple object recognition with visual attention. arXiv preprint arXiv:1412.7755, 2015.

[4] Hao Chen, Qi Dou, Xi Wang, Jing Qin, and Pheng Ann Heng. Mitosis detection in breast cancer histology images via deep cascaded networks. In The AAAI Conference on Artificial Intelligence, pages 1160–1166, 2016.

[5] Xiangyu Chen, Yanwu Xu, Damon Wing Kee Wong, Tien Yin Wong, and Jiang Liu. Glaucoma detection based on deep convolutional neural network. In Engineering in Medicine and Biology Society (EMBC), 37th Annual International Conference of the IEEE, page 715, 2015.

[6] S Dua, U. R. Acharya, P Chowriappa, and S. V. Sree. Wavelet-based energy features for glaucomatous image classification. IEEE Transactions on Information Technology in Biomedicine, 16(1):80–7, 2012.

[7] A Esteva, B Kuprel, R. A. Novoa, J Ko, S. M. Swetter, H. M. Blau, and S Thrun. Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639):115– 118, 2017.

[8] Xinyang Feng, Jie Yang, Andrew F Laine, and Elsa D Angelini. Discriminative localization in cnns for weaklysupervised segmentation of pulmonary nodules. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 568–576. Springer, 2017.

[9] F. Fumero, S. Alayon, J. L. Sanchez, J. Sigut, and M. Gonzalez-Hernandez. Rim-one: An open retinal image database for optic nerve evaluation. In International Symposium on Computer-Based Medical Systems, pages 1–6, 2011.

[10] R Gargeya and T. Leng. Automated identification of diabetic retinopathy using deep learning. Ophthalmology, 124(7):962–969, 2017.

[11] Zongyuan Ge, Sergey Demyanov, Rajib Chakravorty, Adrian Bowling, and Rahil Garnavi. Skin disease recognition using deep saliency features and multimodal learning of dermoscopy and clinical images. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 250–258. Springer, 2017.

[12] Waleed M Gondal, Jan M Kohler, Ren ¨ e Grzeszick, Gernot A ´ Fink, and Michael Hirsch. Weakly-supervised localization of diabetic retinopathy lesions in retinal

fundus images. In Image Processing (ICIP), 2017 IEEE International Conference on, pages 2069–2073. IEEE, 2017.

[13] V Gulshan, L. Peng, M Coram, M. C. Stumpe, D. Wu, A Narayanaswamy, S Venugopalan, K Widner, T Madams, and J Cuadros. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. Jama, 316(22):2402, 2016.

[14] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In Proceedings of the IEEE international conference on computer vision, pages 1026– 1034, 2015

[15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 770–778, 2016.

[16] Xun Huang, Chengyao Shen, Xavier Boix, and Qi Zhao. Salicon: Reducing the semantic gap in saliency prediction by adapting deep neural networks. In IEEE International Conference on Computer Vision, pages 262–270, 2015.