Deep Learning-Based Glaucoma Detection via Convolutional Neural Networks

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Abstract
Glaucoma is a serious condition that can lead to permanent blindness, if not caught and treated early. So, an automatic and precise system which can detect glaucoma is at a high need. Deep learning based methods have demonstrated great potential for medical image analysis in recent years, such as glaucoma detection. In this paper, we present a CNN-based system to detect glaucoma using a publicly available dataset. Since the proposed system is supposed to detect glaucoma in digital retinal fundus images, automatically and with high accuracy. These results show the feasibility and clinical applicability of the method. This study used dropout method to enhance umbrella of accuracy glaucoma detection. Experiments on the SCES and ORIGA datasets have proven that our method is effective. The method proposed achieved an accuracy of 99.12% on the ORIGA dataset and an accuracy of 99.37% on the SCES dataset. Using state-of-the-art techniques, we found that ORIGA was 86% accurate, and SCES was 91%.

Keywords*:* Image Processing, Glaucoma Diagnosis, Image Registration, Fusion, Segmentation, Statistical Measures, Morphology, Classification, Pattern Matching.

I. INTRODUCTION

Glaucoma one of the most serious diseases that can lead a person to lose their sight, it is also a leading cause of blindness. Glaucoma — a condition that can damage the optic nerve of the eye more than any other factor, and it is this optic nerve damage that leads to loss of vision in glaucoma. The first human successfully treated using a surgical procedure was in 1856 whereby Graefe practiced longitudinally on it [1]. If people with glaucoma are not treated and cared for in the right way, there is a risk that everyone who has this condition will eventually lose their vision. This condition can hopefully see improvement in patients after visiting an eye care specialist [1]. The term glaucoma includes an aggregate of eye sickness which share certain characteristics between themselves. A lot of research is being carried out in this field concerning the early detection of this disease. The system used a set of deep learning methods for reliable detection. As was claimed, early detection can protect against loss of sight in human beings which is to state that vision could be conserved. Therefore, the suitable detecting model is needed to diagnose this disease. In addition, we provided a method to identify the glaucoma signature in this cohort of patients but many others have sought to build a similar system. The proposed system for the first time will use Convolutional Neural Network (CNN) technique to classify the patterns which can be observed in patients. The model we used is CNN which permits us to distinct the patterns available in founded data of glaucoma. This will be accomplished. The network has overall six levels for different disease diagnosis. The above method also makes use of apply and utilizes dropout for the better performance of the proposed approach.

1.1 Glaucoma Detection

Glaucoma is a disease that affects the eyes of humans and has the potential to result in total and permanent blindness. Because of the perceived difficulty of resolving this scenario, accurate detection is an absolute requirement. If this issue is recognized at an early stage, it may be possible to improve it; otherwise, it may lead to the loss of vision. According to the findings of the prior examination, glaucoma symptoms cannot be detected during a single examination. The signs of glaucoma could be uncovered during the routine eye exam, at which point additional therapy and examination might be recommended. A minimum of five separate exams are performed by the ophthalmologist to confirm the presence of this disease in human eyes. The following are some of the health diagnoses that are investigated for the purpose of confirming glaucoma.

a. Tonometry is the process of determining the pressure that exists within a patient's eye.
b. Optical Coherence Tomography: This examination plays a significant role in the glaucoma diagnosing process. It is utilized to locate a crucial indicator of early glaucoma damage, which is the presence of retinal nerve fibre layers surrounding the optic nerve.
c. Ophthalmoscopy: This test evaluates the function of the optic nerve. Because glaucoma is a serious condition that affects the optic nerve, this examination is of the utmost significance. The pupil of the patient's eye is made larger using eye drops so that the optic nerve can be examined more clearly in an effort to detect any evidence of disease-related nerve cell loss in the eye.
d. Perimetry: Glaucoma is a condition that, in its early stages, causes a loss of vision in the periphery of the eye. As a result, this test is carried out to identify any signs of vision loss. A visual field test is another name for this particular examination. It involves examining each eye separately using an automated instrument that flashes lights in the person's periphery of the eye.
e. Gonioscopy: This is a test that measures the angle at which intraocular fluid drains out of the eye. In the eye, fluid is continually being produced, and after that, it flows out at predetermined angles. This test is carried out to determine if the high eye pressure is the result of an angle that has been blocked, which is referred to as angle closure glaucoma, or whether the angle has been left open but is not functioning as it should be, which is referred to as open angle glaucoma.

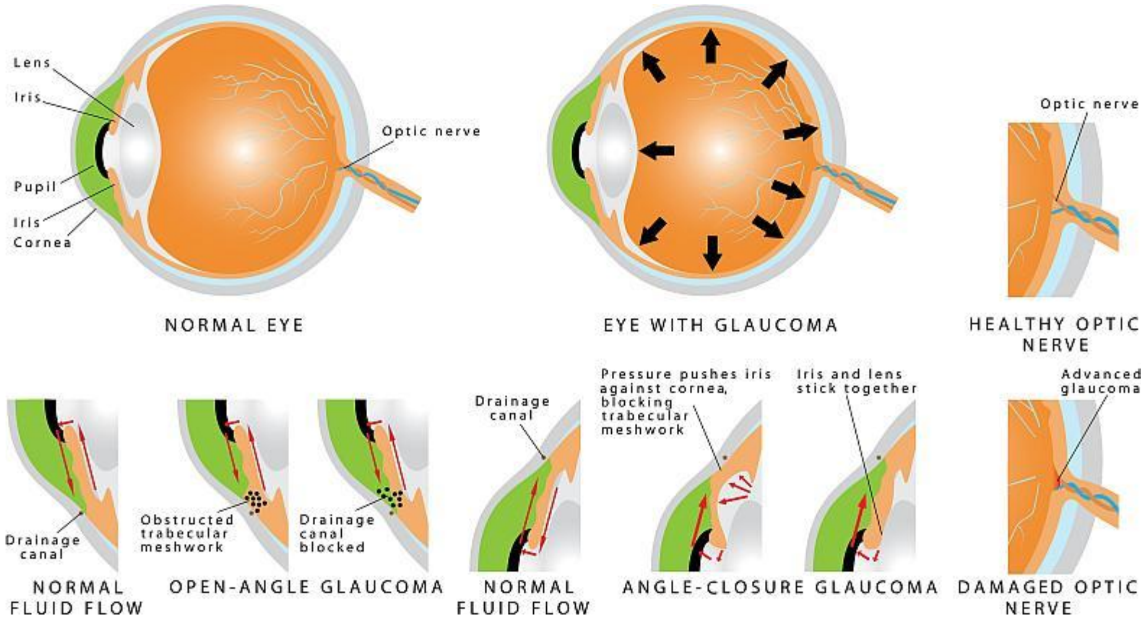

Figure 1. Image for the glaucoma infected eye.[1]

II. LITERATURE REVIEW

Rashmi Panda and colleagues [2] proposed an automated methodology for the detection of defects in the retinal nerve fiber layer. Due to the fact that it is an early indication of the glaucoma problem in fundus imaging. The only way to stop eyesight loss is through early detection and preventative measures. A new technique uses patch features to drive RNN, which is then used to conduct detection in fundus pictures. A dataset consisting of fundus photographs is employed for the purpose of performance evaluation. This method is capable of achieving both a high level of RNFLD detection and accurate boundary localization.

Kavita Choudhary and colleagues [3] have submitted a work with the purpose of identifying glaucoma in its early stages through the use of a cross validation method. In order to arrive at conclusive proof, the authors analyzed the symptoms that were present in individuals and then computed and generalized those symptoms. When several different datasets were pooled, it was discovered that several measures, including as blood pressure, age, sugar level, and myopia, are connected with the likelihood of a person having glaucoma. [Citation needed] Glaucoma disease was analyzed by the authors of the study using classification methods such as cross validation algorithm and split validation algorithm. According to the findings, patients who have a family history of glaucoma, high blood pressure, excessive sugar levels, myopia, and other risk factors for the disease are more likely to develop glaucoma. In addition to this, it has been found that patients older than 50 years old have an increased risk of developing glaucoma.

In this study, Seong Jae Kim et al. [4] investigated and made an attempt to construct machine learning models that have robust capability of prediction and interpretability for glaucoma diagnosis based on RNFL thickness and visual field. Their research was published in the journal Scientific Reports. After conducting an investigation into the RNFL thickness and the visual field, many features were obtained. In order to construct a glaucoma prediction model, the authors made use of four different machine learning algorithms, including C5.0, random forest, SVM, and K- closest neighbor. Using the training dataset, learning models are developed, and then the performance of the models is evaluated using the validation dataset. Finally, the authors made the observation that the random forest model provides the best performance, while the remaining models show accuracy comparable to their own.

Researchers Shwetha C. Shetty et al. [5] discovered and evaluated that glaucoma is an optical condition, and that diagnosing it requires analyzing the forms of the optic cups as well as the sizes of the optic cups. After doing some preliminary processing on the data, K-means clustering is used to the information in order to segment the optic curves. It is carried out once more so that its varied dimensions might be discovered. The authors presented a new approach for the identification of glaucoma that uses the method of perimeter for the fractional analysis. This is due to the fact that fractional dimension is utilized to determine the various dimensions of non-regular identities. The findings indicate that the newly developed method is reliable for diagnosing glaucoma.

An attention-based convolutional neural network, also known as AGCNN, was presented for the purpose of detecting glaucoma in the aforementioned research by Liu li et al. [6]. The methods that have been suggested in the past for an autonomous detection system based on fundus images are insufficient to eliminate significant redundancy, which may lead to a reduction in the reliability and accuracy of the detection. The novel technique that has been proposed establishes a large-scale data collection, which comprises fundus images that are either labeled as (+) ve or (–) ve. This is done in order to address the deficiencies that have been identified. Ophthalmologists participated in a simulated experiment to provide the data for some of the attention maps used in the photos. The next step is to build a brand new AG-CNN structure, which will consist of a sub net, a sub net for pathological region localization, and a sub net for glaucoma classification. The LAG database and other available datasets were used in an experiment, and the results showed that the suggested method provides a detection performance that is superior to that of earlier models.

In this study by Jin Mo Ahn et al. [7], the researchers provided a method for the diagnosis of the glaucoma condition that makes use of fundus photography and employs the application of deep learning. The author argued that machine learning combined with fundus pictures can accurately diagnose both advanced and early stages of glaucoma. We took a dataset consisting of 1,542 photos and split it up into three different datasets: training, validation, and test. The newly proposed model that is trained with CNN is superior in terms of both its efficacy and its accuracy in the identification of early glaucoma.

It has been suggested by Annan Li and colleagues [8] that automatic illness identification is an essential part of retinal image processing. When evaluated and compared with approaches that are based on segmentation, it has been discovered that approaches that are based on image classification perform better. However, difficulties may arise at any time as a result of an inadequate sample, effective characteristics, or variations in the form of the optical disc. The authors of this paper propose a new classification-based model for the detection of glaucoma as a means of overcoming these challenges. In this model, deep convolutional networks are used to represent visual appearance, holistic and local characteristics are combined to reduce or eliminate misalignment, and the model also incorporates a holistic perspective.

The researchers Ali Serener et al. [9] talked about open-angle glaucoma since it is one of the most common types of sickness, and it causes a person to gradually lose his vision. It is possible for medical professionals to diagnose this illness manually, but doing so will either be extremely time-consuming or expensive. The authors of this research presented a system that can automatically detect both early and severe stages of glaucoma in patients. The deep CNN algorithms known as ResNet-50 and GoogleNet are both trained and optimized with the help of transfer learning. It has been discovered that the 'GoogLeNet' model is superior to the 'ResNet-50' model when it comes to diagnosing both early and advanced stages of glaucoma in the eye of a patient.

Ramin Daneshvar et al. [10] examined the ability of baseline OCT measures to predict visual field progression in individuals with glaucoma suspicion or actual glaucoma. The authors also compared the performance of these measures with semi-quantitative optic disc measurements. It has been found that the pRNFL and macular OCT parameters obtained at baseline can be used as a tool for assessing the risk of glaucoma progression in the years to come. People with aberrant OCT findings need additional medical attention in order to stop the spread of functional impairment.

Guangzhou An et al. [11] proposed a model for the identification of glaucoma inside patients. The model makes use of the open angle for glaucoma, which is based on 3-D data color images. This allows the model to detect glaucoma within patients. The CNN architecture is constructed from the several fundus photos that are used as input. Following the acquisition of output from each CNN model, the outputs were then merged. In addition, we performed the classification of the fundus images using the random forest method. This classification is performed with both healthy eyes and eyes that are diseased with glaucoma. After everything was said and done, the final result for the AUC was found to be.96.

Juan Carrillo et. al [12] The diagnostic method for glaucoma has been provided by the authors in light of the fact that glaucoma is an irreversible remedy for eyes. They have developed a tool for calculating the glaucoma symptoms that people experience in their eyes. They have utilized this instrument for the purpose of the detection, and the outcome of the detection may be determined based on the dimensions of the cup and the disc. Additionally, the fundus photos were included in the evaluation process.

Tehmina Khalil et al. [13] have provided an overview of the glaucoma identification process, and in it, they indicate that the majority of the glaucoma detection techniques use fundus images. They claimed that the utilization of optical coherence tomography (OCT) was the key to the successful diagnosis of glaucoma in a time-effective manner. They came to the conclusion that the detection may be done at an early stage by utilizing the OCT.

According to the findings of Namita Sengar et al. [14], the image processing necessary for the glaucoma diagnosis can be carried out with the help of fundus photographs. They have proposed a determining parameter that can be used in the glaucoma diagnosis process. The job that they suggested worked out really well, and the mechanism that they gave was accurate to the tune of 93.57% of the time.

III. PROPOSED APPROACH

The approach that was given operates on six different levels. Convolutional layers make up the first four layers, and the latter two layers are entirely coupled to one another. The output that is acquired from the very last layer is then submitted to the classifier so that glaucoma can be identified.

Convolutional layers: These are utilized as the feature learners at a small scale and can take input from any image in a random fashion. Calculations will be performed on any feature that can be found in the image at any point or location by combining that information with the detector that can find those features and the image that is found at that location itself.

Response A normalization layer consists of: In the architecture that has been given, the operation of this layer comes after the convolutions performed by the first and second layers. An input of the form x is required by a neural network in order to compute the output of the form f(x)= tanh(x).

Overlapping pooling layers: This layer in the CNN architecture obtains the aggregate statistics for a particular region contained inside the picture that is being provided. The maximum pooling layer was applied in this instance. The following is a classification of glaucoma based on CNN:

3.1 Extraction from the Region of Interest (ROI):

As an input for this CNN that we have presented, we will use the region of interest (ROI) of the image that is cropped into a short image. In comparison to either the disc or the cup, the processing of the ROI that was provided will only require a very short amount of time. Obtaining the correct ROI will result in a significant acceleration of the execution process, a notable acceleration in the diagnosis of glaucoma, and an improvement in overall performance. In this case, we made use of the ARGALI method, which involves dividing the image of the fundus into grids. The region of interest (ROI) will be located wherever the optic nerve is found, taking into account any user's or patient's preferences. Therefore, for the purpose of the ROI detection, we will apply this approach.

The brilliant fringe was removed using preprocessing in the ARGALI method, which assisted in determining the circle's center and the trim's radius. This was done so that the circle could be trimmed more precisely. The resolution of the obtained ROI is going to be fixed at 256 by 256. At the very end, the mean value is subtracted from the value of every pixel in the disc image so that the illumination can be removed from the pictures. This is done for all of the pixels.

3.2 Loss of Participants and Data Enhancement

Dropout: According to the methodology that we have described, our team has implemented dropout in two phases of the completely connected layers. Every value of neuron that currently has a value of.5 will have 0 set for it when the Dropout is applied. After the neurons in the CNN have been removed, they will not be included in the sending of information forward or in the back propagation. This is because they will not be present in the CNN. During the process of carrying out the experiment, a multiplication by.5 is performed for each of the outputs produced by the neurons.

Data Augmentation: The overfitting problem will manifest itself in a visible way if the model does not incorporate data augmentation. The translations of the images and the reflections that are horizontal will be generated by DA. During the training phase, a 224*224 patch is generated for random values, and the 256*256 pictures are also incorporated into the process. After that, the network is trained using these patches that have been retrieved. During the testing, CNN provided a total of five 224*224 patches, four of which were located in the corners and one in the middle. In addition to this, the horizontal reflections have been acquired for these five patches. The network's soft max layer provides these predictions, and the average of those forecasts is taken for these 10 patches.

3.3 Glaucoma Detection using Deep Learning

Glaucoma is a leading cause of blindness worldwide, and early detection is crucial for effective treatment. Deep learning techniques have shown promising results in the automated detection of glaucoma. Here is an algorithm and architecture in detail for glaucoma detection using deep learning:

- Data Preprocessing: The first step involves collecting and preprocessing the data. The dataset typically consists of retinal images of patients, including healthy and glaucoma-affected individuals. Preprocessing techniques such as image normalization, contrast enhancement, and noise removal may be applied to improve the image quality and reduce noise.
- Feature Extraction: Next, deep learning models such as convolutional neural networks (CNNs) are used to extract relevant features from the preprocessed images. CNNs are particularly effective in detecting patterns and features in images, making them well-suited for glaucoma detection.
- Model Training: The extracted features are then used to train the CNN model. The model is trained on a large dataset of retinal images labeled as either healthy or glaucoma-affected. The objective is to teach the model to accurately distinguish between healthy and diseased retinas based on the extracted features.
- Model Evaluation: The trained model is then evaluated on a separate dataset of retinal images to assess its accuracy in detecting glaucoma. Various metrics such as sensitivity, specificity, and accuracy are used to evaluate the model's performance.
- Deployment: Once the model has been trained and evaluated, it can be deployed in real-world settings for glaucoma detection. The model takes retinal images as input and provides a binary classification as output indicating the presence or absence of glaucoma.

One example of a deep learning architecture for glaucoma detection is the Optic Disc and Cup Segmentation and Classification (ODC-Net) model. The ODC-Net model consists of two components: a segmentation network and a classification network. The segmentation network is responsible for segmenting the optic disc and cup regions from the retinal images, while the classification network uses the segmented regions to classify the image as either healthy or glaucoma-affected. The ODC-Net model has shown promising results in accurately detecting glaucoma from retinal images.

3.4 Mathematical Analysis of CNN for Glaucoma Detection

Convolutional Neural Networks (CNNs) have shown promising results in glaucoma detection from retinal images. Here is a mathematical analysis of the CNN architecture used for glaucoma detection:

Let X be the input image of size (H x W), where H and W represent the height and width of the image, respectively. The CNN architecture consists of several layers, including convolutional layers, pooling layers, and fully connected layers.

1. **Convolutional Layers:** The first set of layers in the CNN architecture are convolutional layers. Each convolutional layer applies a set of filters or kernels to the input image. Each filter produces a feature map that highlights specific patterns or features in the image. Let K be the number of filters in the layer, and F be the size of each filter. The output feature map produced by the layer has a size of (H' x W' x K), where H' and W' are the height and width of the feature map, respectively. The mathematical operation performed by the convolutional layer can be represented as:

Convolution: A * B = C

where A is the input image, B is the filter/kernel, and C is the output feature map.

2. **Pooling Layers:** The next set of layers in the CNN architecture are pooling layers. Each pooling layer reduces the size of the feature map by performing downsampling. Common pooling operations include max-pooling and average pooling. Let P be the pooling size and S be the stride. The output of the pooling layer has a size of (H" x W" x K), where H" and W" are the height and width of the downsampled feature map, respectively. The mathematical operation performed by the pooling layer can be represented as:

Max-Pooling: max(A) = max(A[i:i+P, j:j+P])

where A is the input feature map, and max(A) is the output feature map obtained by taking the maximum value within each pooling window.

3. **Fully Connected Layers:** The final set of layers in the CNN architecture are fully connected layers. Each fully connected layer connects every neuron in the layer to every neuron in the previous layer. Let N be the number of neurons in the layer. The output of the fully connected layer has a size of (1 x N). The mathematical operation performed by the fully connected layer can be represented as:

Fully Connected: A * W + b = C

where A is the input feature vector, W is the weight matrix, b is the bias vector, and C is the output feature vector.

The CNN architecture used for glaucoma detection typically consists of multiple convolutional and pooling layers followed by one or more fully connected layers. The output of the final fully connected layer is fed into a softmax function, which produces a probability distribution over the two classes (healthy and glaucoma-affected). The class with the highest probability is then selected as the predicted class.

IV. EXPERIMENTS PERFORMED

We experimented our model of two datasets that are ORIGA and SCES which is having the images of glaucoma fundus.

4.1 Criteria for the Evaluation

The area under curve ()AUC is utilized of the receiver operation characteristics(ROC) curve for the evaluation of the glaucoma detecting performance of the model. The curve between the sensitive TPR and the specificity TNR is plotted as the ROC and is defined as:

$$TPR = \frac{TP}{TP + FN}, \qquad TNR = \frac{TN}{TN + FP}$$

4.2 Setup for the Experiment:

The ORIGA dataset consists of clinical glaucoma diagnoses, and having 168 glaucoma and 482 images of normal fundus. The dataset of the SCES is having 46 images for glaucoma and 1676 images for the fundus.

V. RESULT EVALUATION

The purpose of this comparison was to validate our suggested technique employing the CNN for the accurate identification of glaucoma. To do this, we compared the offered model to the most advanced reconstruction-based method currently available. The training dataset that we gave would consist of 90 pictures out of a total of 600 pictures, and the picture on the left would be used to test the findings. In addition, the ORIGA training set is utilized for the SCES dataset's training, while the SCES overall picture collection is used for testing. Both of these sets are included in the dataset.

Accuracy values of 99.12 for the ORIGA dataset and 99.37 for the SCES dataset were determined using the suggested approach. For the purpose of comparison, we employed the state-of-the-art mechanism, which determined accuracy values of 86 for the ORIGA dataset and 91 for the SCES dataset.

Table 1. The values of Accuracy for proposed and earlier methods.

Dataset Used	State of Art Method	Proposed CNN method (%)
ORIGA Dataset	86	96.27
SCES Dataset	91	98.71
India Dataset	92	97.75

The graphical representation is shown below for the obtained values of the AUC:

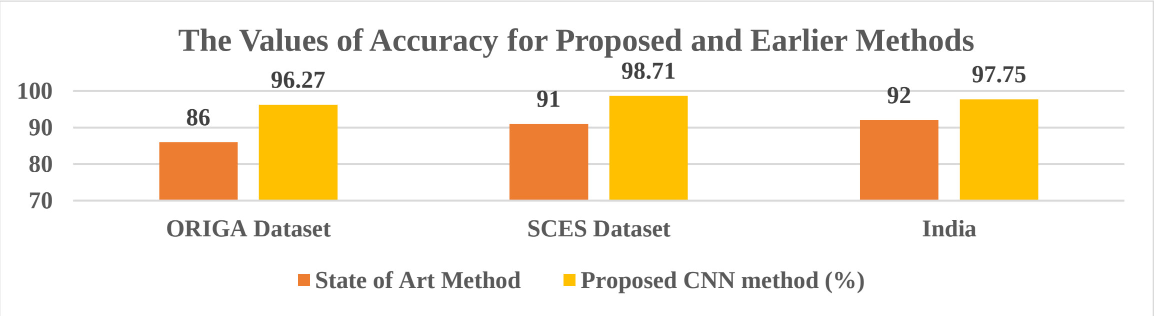

Figure 2. Graph for the Obtained Values.

The outcomes are proving to be satisfactory in terms of the outcomes that were achieved. It would seem that the suggested system has a greater capacity for detection than existing approaches.

VI. CONCLUSION

Glaucoma is a serious ocular problem. Glaucoma may cause loss of eye vision. Detecting glaucoma early may prevent blindness. To identify this ailment, we suggested using deep learning CNN. The suggested technique uses a six-layer architecture to categorize glaucoma patterns in patient eye pictures. We utilized ORIGA and SCES. The suggested approach worked and produced good results. Experiment-based AUC values. Both datasets' values are compared to a state-of-the-art method. The suggested method's accuracy is 99.12 for ORIGA and 99.37 for SCES. Accuracy was 86 for ORIGA and 91 for SCES using the state-of-the-art mechanism.

Reference:

[1] Initiativkreis zur Glaukomfrüherkennung, Germering, Germany, www.glaukom.de

[2] R.ManjulaSri,KMM Rao, "Novel Image Processing Techniques to Detect Lesions using Lab \ Conference Publications on Annual IEEE India Conference INDICON. Publication Year: 2011 , Page

[3] Viralkumar Bulsara, Surabhi Bothra, Poonam Sharma, K.M.M.Rao, "Low Cost Medical Image Processing System for Rural/Semi Urban Healthcare", IEEE Conference Publications on Recent Advances in Intelligent Computational Systems (RAICS),Publication Year: 2011 , Page(s): 724 – 728

[4] Sangyeol Lee, Michael D. Abr`amoff, and Joseph M. Reinhardt." Validation of Retinal Image Registration Algorithms by a Projective Imaging Distortion Model" 29th Annual International Conference of the IEEE EMBS Cité Internationale, Lyon, France August 23-26, 2007.

[5] R. Geetha Ramani," Automatic Prediction of Diabetic Retinopathy and Glaucoma through Retinal Image Analysis and Data Mining Techniques"

[6] Kevin Noronha, Jagadish Nayak, S.N. Bhat, "Enhancement of retinal fundus Image to highlight the features for detection of abnormal eyes"

[7] S. Sekhar," Automated localisation of retinal optic disk using hough transform", Department of Electrical Engineering and Electronics, University of Liverpool, UK.

[8] Zhuo Zhang," ORIGA-light : An Online Retinal Fundus Image Database for Glaucoma Analysis and Research", 32nd Annual International Conference of the IEEE EMBSBuenos Aires, Argentina, August 31 - September 4, 2010

[9] Vahabi Z," The new approach to Automatic detection of Optic Disc from non-dilated retinal images" Proceedings of the 17th Iranian Conference of Biomedical Engineering (ICBME2010), 3-4 November 2010

[10] Zafer Yavuz," RETINAL BLOOD VESSEL SEGMENTATION USING GABOR FILTER AND TOPHAT TRANSFORM", 2011 IEEE 19th Signal Processing and Communications Applications Conference (SIU 2011) 978-1-4577-0463-511/11 ©2011 IEEE

[11] Nilan jan Dey," Optical Cup to Disc Ratio Measurement for Glaucoma Diagnosis Using Harris Corner", ICCCNT12

[12] Harris C, Stephens, M. , 1 988, A Combined Corner and Edge Detector, Prooeedings of 4th Alvey Vision Conference

[13] Kon stantino s G Derpanis, 200 4, The Harris Corner Detector

[14] ManjulaSri Rayudu," Review of Image Processing Techniques for Automatic Detection of Eye Diseases", 2012 Sixth International Conference on Sensing Technology (ICST) 978-1-4673-2248-5/12 ©2012 IEEE

[15] Aliaa Abdel-Haleim Abdel-Razik Youssif, Atef Zaki Ghalwas, and AmrAhmed SabryAbdel-Rahman Ghoneim ,"Optic Disc Detection From Normalized Digital Fundus Images by Means of a Vessels' Direction Matched Filter-IEEE Transactions On Medical Imaging, Vol. 27, No. 1, January 2008

[16] Zhuo Zhang et al. "MRMR Optimized Classification for Automatic Glaucoma Diagnosis"-33rd Annual International Conference of the IEEE EMBS,Boston, Massachusetts USA, August 30 - September 3, 2011

[17] Mahdad Esmaeili, Hossein Rabbanin and Alireza Mehri Dehnavi: "Automatic optic disk boundary

extraction by the use of curvelet transform and deformable variational level set model" in Pattern Recognition,Vol. 45 (2012) , pp. 2832–2842

[18] Chisako Muramatsu et al.,"Automated segmentation of optic disc region on retinal fundus photographs: Comparison of contour modeling and pixel classification methods" in Computer Methods And Programs In Biomedicine Vol.101 (2011) , pp. 23–32.

[19] Meindert Niemeijer, Michael D. Abràmoff and Bram van Ginneken" Fast detection of the optic disc and fovea in color fundus photographs" in Medical Image analysis, in press.

[20] Rashid Jalal Qureshi et al. "Combining algorithms for automatic detection of optic disc and macula in fundus images; Computer Vision and Image Understanding ,Vol. 116 (2012) ,pp.138–145

[21] Chih-Yin Ho,Tun-Wen Pai, Hao-Teng Chang and Hsin-Yi Chen, " An automatic fundus image analysis system for clinical diagnosis of glaucoma",-2011 International Conference on Complex, Intelligent, and Software Intensive Systems.

[22] S.Sekhar,W.Al-Nuaimy and A.K.Nandi,"Automated Localisation Of Retinal Optic Disk Using Hough Transform", 5th IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2008, pp.1577 - 1580

[23] Gopal Datt Joshi, Jayanthi Sivaswamy, and S. R. Krishnadas,"Optic Disk and Cup Segmentation From Monocular Color Retinal Images for Glaucoma Assessment', IEEE Transactions On Medical Imaging, Vol. 30, No. 6, June 2011,pp.1192-1205.

[24] A. Taiwade, N. Gupta, R. Tiwari, S. Kumar and U. Singh, "Hierarchical K-Means Clustering Method for Friend Recommendation System," 2022 International Conference on Inventive Computation Technologies (ICICT), 2022, pp. 89-95, doi: 10.1109/ICICT54344.2022.9850852.

[25] R. Baghel, P. Pahadiya and U. Singh, "Human Face Mask Identification using Deep Learning with OpenCV Techniques," 2022 7th International Conference on Communication and Electronics Systems (ICCES), 2022, pp. 1051-1057, doi: 10.1109/ICCES54183.2022.9835884.

[26] M. Ranjan, A. Shukla, K. Soni, S. Varma, M. Kuliha and U. Singh, "Cancer Prediction Using Random Forest and Deep Learning Techniques," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 227-231, doi: 10.1109/CSNT54456.2022.9787608.

[27] Singh, Upendra, Gupta, Puja, and Shukla, Mukul. 'Activity Detection and Counting People Using Mask-RCNN with Bidirectional ConvLSTM'. 1 Jan. 2022 : 6505 – 6520.

[28] Gupta, P., Shukla, M., Arya, N., Singh, U., Mishra, K. (2022). Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_8

[29] Patidar, M., Singh, U., Shukla, S.K. et al. An ultra-area-efficient ALU design in QCA technology using synchronized clock zone scheme. J Supercomput (2022). https://doi.org/10.1007/s11227-022-05012-2

[30] A. Taiwade, N. Gupta, R. Tiwari, S. Kumar and U. Singh, "Hierarchical K-Means Clustering Method for Friend Recommendation System," 2022 International Conference on Inventive Computation Technologies (ICICT), 2022, pp. 89-95, doi: 10.1109/ICICT54344.2022.9850852.

[31] Jindal, R, Kumar, N, Patidar, S. IoT streamed data handling model using delta encoding. Int J Commun Syst. 2022; 35(13):e5243. doi:10.1002/dac.5243

[32] S. Patidar, A. Jain and A. Gupta, "Comparative Analysis of Machine Learning Algorithms for Heart Disease Predictions," 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022, pp. 1340-1344, doi: 10.1109/ICICCS53718.2022.9788408.

[33] B. Jain, S. Patidar and D. Sudershan, "Heterogeneous Software Defect Prediction using Generative Models," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 367-372, doi: 10.1109/CSNT54456.2022.9787607.

[34] Singh, Shani Pratap and Shukla, Jayesh and Sharma, Shaili and Daga, khushhal and Bhalavi, Brahman Singh and Singh, Upendra, Face Mask Detection using Multi-Stage CNN Architecture (July 10, 2021). Proceedings of the International Conference on IoT Based Control Networks & Intelligent Systems - ICICNIS 2021, Available at SSRN: https://ssrn.com/abstract=3884022 or http://dx.doi.org/10.2139/ssrn.3884022

[35] A. Saxena, A. Vyas, L. Parashar and U. Singh, "A Glaucoma Detection using Convolutional Neural Network," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 815-820, doi: 10.1109/ICESC48915.2020.9155930.
[36] B. Bamne, N. Shrivastava, L. Parashar and U. Singh, "Transfer learning-based Object Detection by using Convolutional Neural Networks," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 328-332, doi: 10.1109/ICESC48915.2020.9156060.
[37] Gupta, P., Shukla, M., Arya, N., Singh, U., Mishra, K. (2022). Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_8
[38] Patidar, M., Singh, U., Shukla, S.K. et al. An ultra-area-efficient ALU design in QCA technology using synchronized clock zone scheme. J Supercomput (2022). https://doi.org/10.1007/s11227-022-05012-2
[39] Singh, Upendra, Gupta, Puja, and Shukla, Mukul. ‘Activity Detection and Counting People Using Mask-RCNN with Bidirectional ConvLSTM’. 1 Jan. 2022 : 6505 – 6520.
[40] U. Singh and L. S. Songare, "Analysis and Detection of Monkeypox using the GoogLeNet Model," 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 2022, pp. 1000-1008, doi: 10.1109/ICACRS55517.2022.10029125.