2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science

# Performance Analysis of Deep Learning Models for Accurate Glaucoma Detection

Sambhav Dixit
Information Technology
Indian Institute of Information Technology
Bhopal, India
indosambhav@gmail.com

Bhupendra Singh Kirar
Electronics and Communications Engineering
Indian Institute of Information Technology
Bhopal, India
bhup17@gmail.com

Dheraj Kumar Agrawal
Electronics and Communications Engineering
Maulana Azad National Institute of Technology
Bhopal, India
profdheerajagrawal@gmail.com

2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS) | 979-8-3503-4846-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/SCEECS61402.2024.10482336

*Abstract*- **The realm of healthcare, machine learning has emerged as an especially profound, is easy to use and fairly accurate method for easy solutions and making medical procedures more and more accurate. This research study focuses on glaucoma, which is one of the more common and yet less spoken of visual disorders in the country and in the world. Seeing the predicted increased load on the health system with this disease we propose of flurry of comparison between potential machine learning solutions and deep learning models that can detect easily and accurate glaucoma within patients reducing the doctor's workload is proposed. The potential models picked for this work are inceptionv3, ResNet50, VGG16, VGG19, Xception and a custom convolutional neural network (CCNN) as well. The obtained accuracy (in %) for glaucoma detection is 99.43 using VGG19. This may provide an effective application and solution for glaucoma detection.**

**Keywords- Glaucoma, Dataset, Machine learning, Deep Learning, Models.**

## I. Introduction

The realm of healthcare, deep learning has emerged as an especially profound, is easy to use and fairly accurate method off of easing solutions and making medical procedures more and more accurate. This research study focuses on glaucoma, which is one of the more common and yet less spoken of visual disorders in the country and in the world. According to the national Institute of health, approximately 11.2% 40 years and older have glaucoma in India. The primary open angle is estimated a problem of effect in about 6.4% whereas the problem of effect with primary angle closure glaucoma is 2.54 million [1]. Roughly speaking, animated prevalence of glaucoma in adults aged 40 years and above is between 2.5 percent amongst Indians [2]. According to studies Glaucoma is estimated to affect 27.8 by 2040 in Asia alone, amongst which India and China being the bearers of maximum population concentrated areas in the region will most likely have to be the maximum load [3].

Glaucoma is a defect of the vision of the eye. That is often developed involving the conditions of the optic nerve the eye. The optic nerve in the eye is responsible for sending signals the received from the retina and forming the image in the brain [4] The harm to the optic nerve is often due to high pressure created in the eye. However, glaucoma can also develop in an eye with normal pressure. As far as the symptoms of glaucoma concern glaucoma can occur usually with a persistence of age in errors usually occurring in adults aged 60 or above. Due to the first modern lifestyle and its effects on the visual prowess of the upcoming generations glaucoma has started to develop spins the age of 40 and even in early teens as well [5].

There are various types of glaucoma that you might encounter in the research studies conducted on the subject. Include open angle glaucoma, acute angle closure glaucoma, normal tension glaucoma, Etc. The symptoms for glaucoma include patchy blind sports inside vision, peripheral vision, difficulty in seeing objects using central vision, severe headache, eye pain, nausea, redness in eye, increased blinking, hypermetropia, lighted halos Etc. There are ways to prevent glaucoma such as getting regular eye examinations, using the 20 20 20 rules, keeping a check at family health eye history, wearing eye protection, prescribed eyedrops and caring for visual cues [6].

The aim of this paper is to provide a basic approach and a comparative study to detect glaucoma using deep learning models. We will be testing potential candidates such as inceptionV3, ResNet50, VGG16, VGG19, Xception, and a custom convolutional neural network (CCNN) to look at eye samples from patients and classify or predict whether the sad patients suffer from glaucoma or not. So, there will be a review of existing methods and will pay away to give approaches that will be highly accurate and will give efficient results in the future based on the models developed.

## II. Literature Survey

In the last decade, in line with a wider medical trend, machine learning algorithms have been applied to datasets in recent research to identify glaucoma.

From 2014 to 2019, substantial advances in glaucoma diagnosis approaches were made. In 2015, Noronha et al. [7] published a method that used higher-order spectra cumulants and support vector machine (SVM) classification, whereas Acharya et al. [8] used Gabor Transform features for glaucoma dataset classification. Singh et al. [9] proposed a wavelet-based technique in 2016, while Maheshwari et al. [10] used the variational mode decomposition (VMD) methodology on the RIM-ONE dataset in 2017 [11]. Soltani et al. [12] developed a fuzzy logic-based strategy that took into account numerous risk indicators, and Mohamed et al. [13] (2019) presented a cup and disc segmentation algorithm based on the RIM-ONE [11] dataset.

Later studies use VGG19 and CNN to extract features using the two-dimensional empirical mode decomposition (BEMD) technique, and PCA is used to reduce dimensionality. Combining these features with an SVM-based classifier yields an astounding 98.92% accuracy on the ACRIMA [14] dataset and a remarkable 98.31% overall accuracy [15].

Additionally, the study blends machine learning and deep learning on raw fundus images using a novel CNN model for deep feature extraction. On the ACRIMA dataset, the hybrid model-that is, the CNN and Adaboost combination-performs admirably with an accuracy of 92.96%, an F1 score of 93.75%, and an AUC value of 0.928 [16].

For the diagnosis of glaucoma, Kirar et al. [17-22] used a variety of methods, including support vector machines (SVM), quasi-bivariate variational mode decomposition (QB-VMD), compact variational mode decomposition (CVMD), discrete wavelet transforms (DWT), and empirical wavelet transform (EWT). Notably, SS-QB-VMD was particularly implemented with SVM by Kirar et al. [22]. Using a collection of 705 photos, this study is focused on the ACRIMA repository [14].

Table I, which is provided below, shows the highest level of accuracy that each paper's methodology managed to achieve. It also gives a thorough summary of all the literature that has been reviewed in previous research works.

TABLE I. SUMMARY OF THE LITERATURE.

| Refe. | Year | Dataset and Classifiers | Accuracy |
|---|---|---|---|
| [5] | 2014 | TOPCON / NB, SVM | 72.00% |
| [8] | 2015 | Kasturba Medical College/ SVM, Bhattacharya space algo. | 84.00% |
| [9] | 2016 | Venu Eye Research Center/ Random Forest, NB, KNN | 94.7% |
| [10] | 2017 | RIM-ONE/ LS-SVM | 95.19% |
| [12] | 2018 | Pvt.ONH/ SVM | 96.00% |
| [14] | 2019 | ACRIMA/ CNN | 79.97% |
| [15] | 2023 | ACRIMA/ VGG19, CNN and SVM | 98.92% |
| [16] | 2023 | ACRIMA/ CNN | 92.96% |

## III. PROPOSED METHODOLOGY

### A. Dataset

To effectively build glaucoma detection techniques, it is imperative to secure a well-labeled dataset. Finding these databases is difficult, though, mostly because there aren't many samples available and patient privacy must be respected. In this case, we have surmounted these obstacles by employing the well-established and trustworthy ACRIMA Dataset [14]. The dataset contains images of either gluconic eye or normal eye. The said dataset contains 310 images of the normal eye and 395 images of the gluconic eye, in total making a sample of 705 sample images of the eye. Typical images of both classes are shown in Fig. 1.

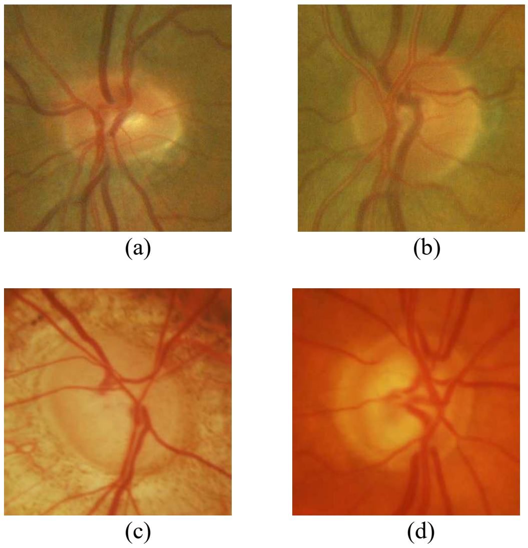


Fig. 1. Typical images for binary class: (a) & (b) Healthy, and (c) & (d) glaucoma.

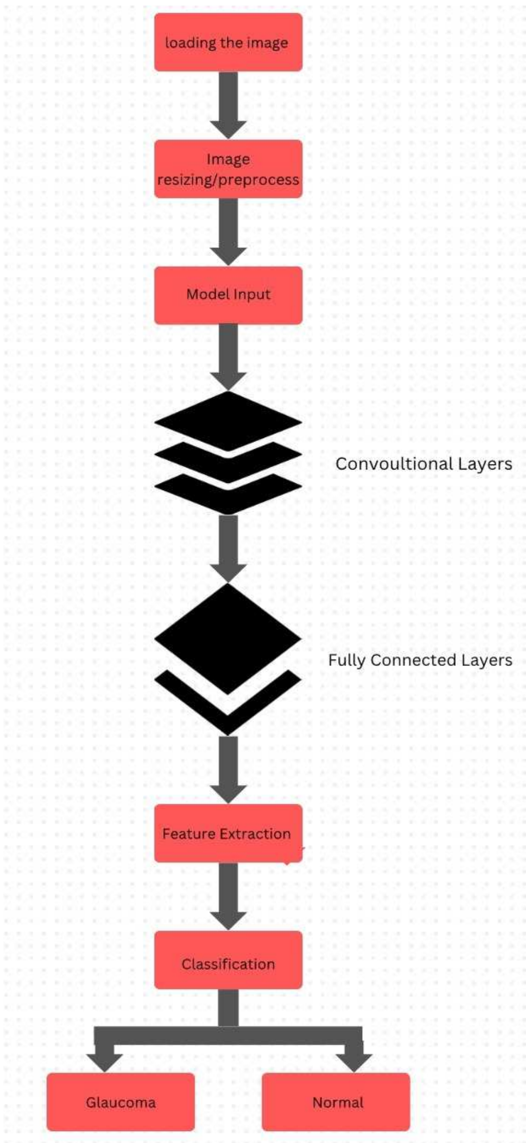


Fig. 2. Representation of proposed method.

### B. Methodology

The methods utilized in this investigation is depicted in Figure 1. We suggest using pretrained machine learning models in conjunction with deep learning to detect glaucoma. To standardize the model inputs, image processing is conducted at the start of this multi-step procedure. The data is then trained using six models that are taken into consideration, specifically:

1. InceptionV3
2. ResNet50
3. VGG16
4. VGG19
5. Xception
6. Custom CNN

### C. Feature Extraction

Attributes are converted into linear combinations of mutually orthogonal features throughout the feature extraction process. This transformation improves the model's accuracy and efficiency while also decreasing the complexity of the data. In our case, the features that are extracted out of the image are the disjoint subsections of pixels around the region of the optical neve, specifically looking for a break in the flow or damage in the section of the pixels or pixel density of the same.

### D. Training and classification

We have used 6 models in this work, namely, InceptionV3, ResNet50, VGG16, VGG19, Xcpetion and a custom convolutional neural network (CCNN). An InceptionV2 model was built on the inceptionV1 or the GoogLeNet model aiming accuracy and efficiency using inception modules for the same. ResNet50 is a convolution layer-based model, where ResNet stands for residual network, as the network uses 50 layers of Residual Network to attain accuracy and efficiency. The VGG16 is a Visual Graphics Models which is the relatively simplistic model with layers of stacked convolutional models embedding their outputs on one another. The VGG19, on the other hand is more of a boosted version of the VGG16, with more stacking, more pooling and more embeddings between adjacent layers. The Xception model is an acronymic name for Extreme Inception model. built more like an inceptionV3, it uses stacking layers to improve efficiency and accuracy of the prediction. The custom CNN model is built with 4 CNN layers and 2 fully connected layers to give model predictions.

### E. Performance Matrices

Equations (1-4) have been used in this work to evaluate the accuracy, precision, sensitivity, and Matthews Correlation Coefficient (MCC) performance matrices:

$$Accuracy = (TN + TP)/(FN + FP + TN + TP) \quad (1)$$

$$Precision = TP/(TP + FP) \quad (2)$$

$$Sensitivity = TP/(FN + TP) \quad (3)$$

$$\mathrm{MCC} = \frac{\mathrm{TP}\times\mathrm{TN}-\mathrm{FN}\times\mathrm{FP}}{\sqrt{(\mathrm{TP+FN})(\mathrm{TP+FP})(\mathrm{TN+FN})(\mathrm{TN+FP})}} \times 100 \quad (4)$$

where the normal meanings of TP, TN, FP, and FN are used.

## IV. Experimental Setup and Parameter Choice

In this paper, deep learning models for accurate glaucoma detection are implemented with the better parameter choice as mentioned in Table II. After performing the experiment, the models yielded the confusion matrix values as Shown in Fig. 3 for 6 types of deep learning models.

TABLE II. PARAMETER CHOICE FOR MODELS.

| SN | Model | Input Layers size | Number of Convolution Layers | Number of Fully Connected Layers | Output Layer | Trainable Parameters | Non-Trainable Parameters | Memory |
|---|---|---|---|---|---|---|---|---|
| 1 | InceptionV3 | 299x299x3 | 4 | 3 | softmax | 21772450 | 34432 | 83.19 MB |
| 2 | ResNet50 | 229x229x3 | 8 | 2 | softmax | 23538690 | 53120 | 90 MB |
| 3 | VGG16 | 299x299x3 | 5 | 3 | softmax | 14715714 | 0 | 56.14 MB |
| 4 | VGG19 | 299x299x3 | 5 | 3 | softmax | 20025410 | 0 | 76.39 MB |
| 5 | Xception | 299x299x3 | 5 | 3 | softmax | 20811050 | 54528 | 79.60 MB |
| 6 | Custom CNN | 299x299x3 | 4 | 2 | softmax | 60608449 | 0 | 231.20 MB |

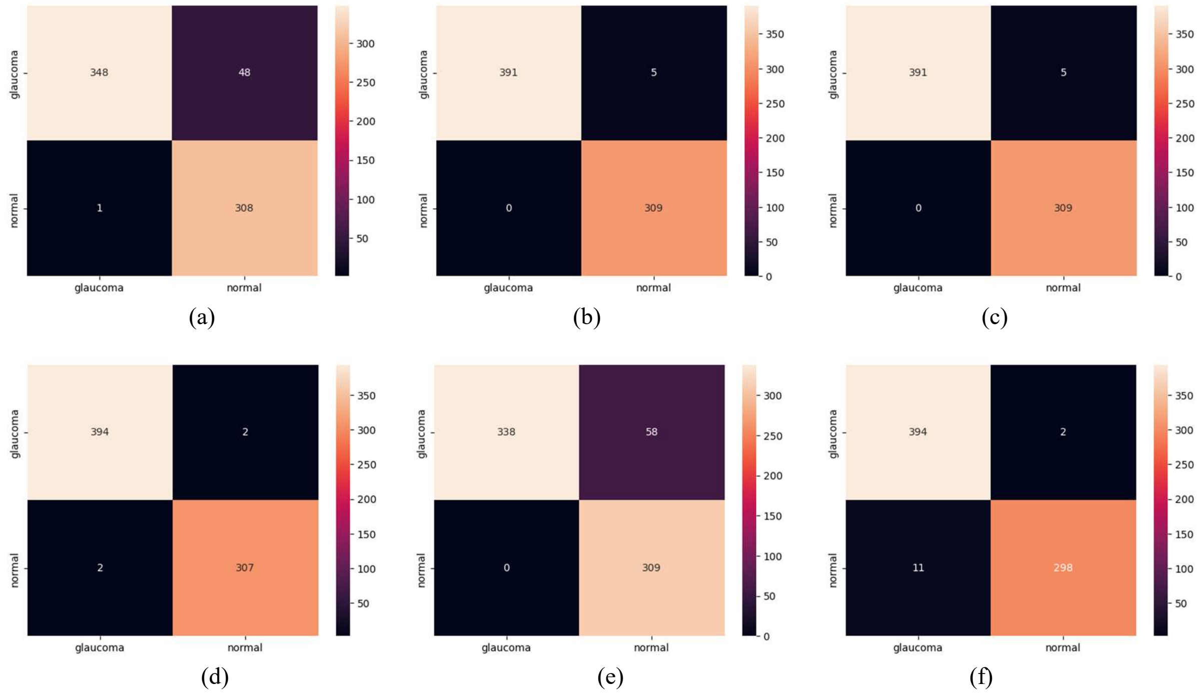


Fig. 3. Confusion matrices: (a) InceptionV3, (b) ResNet50, (c) VGG16, (d) VGG19,(e) Xception,(f) Custom CNN.

Figure 3 is a collection of the confusion matrices of all the models on all the 705 images, indicating the true positive, true negative, false positive and false negative images. This indicates the amount and nature of the error in the predictions being made by the model.

## V. Results and Discussion

In this paper, deep learning models for accurate glaucoma detection. In the first step, the image has been processed to fit the size requirements of the models. This is followed by passing on the said preprocessed images to the model for input where they are first passed to the convolutional layers, followed by the fully connected layers finally extracting the features and making classification on their basis.

The obtained accuracy (in %) for glaucoma detection are 91.77, 93.05, 98.16, 99.29, 99.29, 99.43, using deep learning models Xception, InceptionV3, Custom CNN, ResNet50, VGG16, and VGG19, respectively. Performances measures of the proposed models using ACRIMA dataset have been mentioned in Table III.

The results shed light on how well various techniques perform in the diagnosis of glaucoma. Above all, the Custom CNN and VGG19 models stand out for their exceptional sensitivity in detecting genuine positive cases and their strong MCC of 96.28% and 98.85%, respectively, demonstrating their all-around effectiveness. In the meantime, the models ResNet50, VGG16, and Xception demonstrate perfect specificity at 100%, demonstrating their accuracy in identifying genuine negative cases. Moreover, InceptionV3 and VGG19 exhibit excellent specificity. These complex results highlight the necessity of carefully weighing model priorities in the context of glaucoma diagnosis, whether that means reducing false positives or maximizing overall accuracy. Further the graphical representation for all performance matrices has been shown in Fig. 4.

TABLE III. PERFORMANCES MEASURE OF THE PORPOSED MODELS

| Methods | Acc (%) | Sen (%) | Spe (%) | MCC (%) |
|---|---|---|---|---|
| Xception | 91.77 | 85.35 | 100.00 | 84.77 |
| InceptionV3 | 93.05 | 87.88 | 99.68 | 86.89 |
| Custom CNN | 98.16 | 99.49 | 96.44 | 96.28 |
| ResNet50 | 99.29 | 98.74 | 100.00 | 98.57 |
| VGG16 | 99.29 | 98.74 | 100.00 | 98.57 |
| VGG19 | 99.43 | 99.49 | 99.35 | 98.85 |

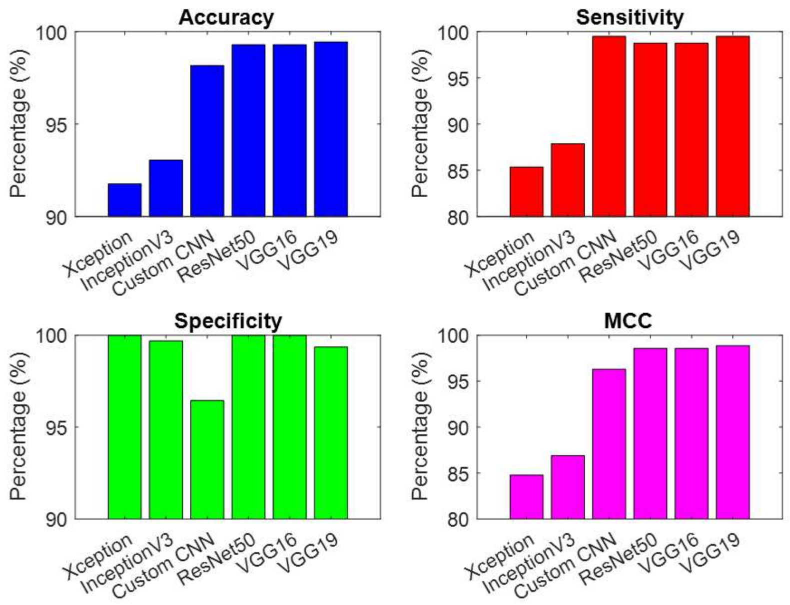


Fig. 4. Performance measures for the proposed models.

Figure 4 is a graphical comparative drawn between all of the individual models on the basis of the performance measuring metrics mentioned in this paper, including accuracy, sensitivity, specificity and MCC. This will help us to decide the best performing model across the board in terms of overall performance.

In discussion section, with an astounding accuracy of 99.43%, the suggested VGG19 model outperforms CNN, GoogleNet, and SVM models, as the discussion highlights. The accuracy of CNN models reported in [14], [24], [25], and [15] varies, with [15] having the highest accuracy at 98.92%. According to [23], GoogleNet lags behind at 65.0%, suggesting possible constraints. According to [20], SVM performs competitively at 92.06%.

The remarkable precision of the VGG19 model implies that it is effective in detecting glaucoma, underscoring the significance of model selection for the best possible diagnostic results. The comparison for glaucoma detection models have been mentioned in Table IV and Fig. 5.

TABLE IV. PERFORMANCES COMPARISON OF MODELS

| Reference | Year | Machine / Deep Learning Models | Accuracy |
|---|---|---|---|
| [14] | 2019 | CNN | 79.97% |
| [23] | 2019 | GoogleNet | 65.00% |
| [24] | 2019 | CNN | 95.31% |
| [25] | 2020 | CNN | 96.64% |
| [20] | 2022 | SVM | 92.06% |
| [15] | 2023 | CNN | 98.92% |
| [16] | 2023 | CNN | 92.96% |
| Proposed | 2024 | VGG19 | 99.43% |

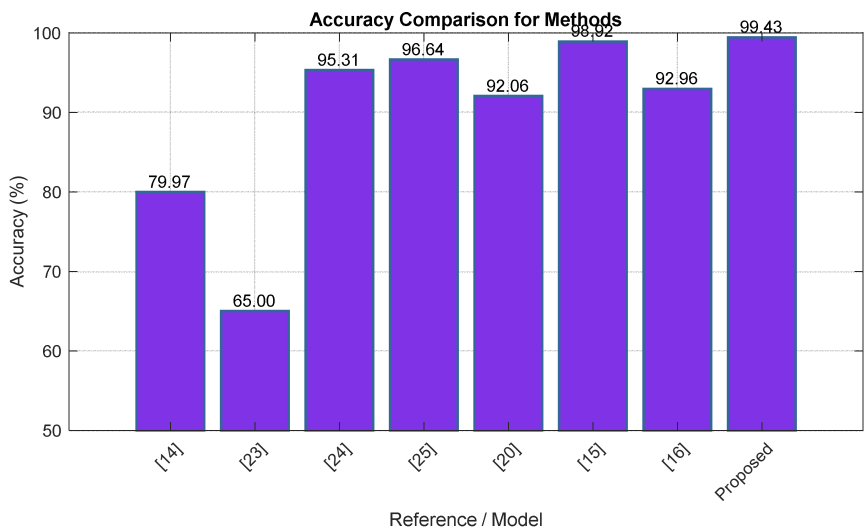


Fig. 5. Performances comparison of models

## V.Conclusion

Glaucoma is a disease found in people of all ages. It is one of the leading causes of vision loss. Early detection of this disease can help mitigate the damages and preserve vision over time. Deep learning models can play a decisive role in detection of glaucoma.

In this work we have proposed deep learning models for accurate glaucoma detection. We have used 6 different deep learning models ACRIMA dataset. Among all 6, VGG19 model reported best glaucoma accuracy with 99.43%.

## REFERENCES


[1] R. George, R. S. Ve, and L. Vijaya, "Glaucoma in India: estimated burden of disease," J Glaucoma, vol. 19, no. 6, pp. 391-397, Aug. 2010.

[2] P. Rewri, "Towards better management of glaucoma in India," Indian J Ophthalmol, vol. 71, no. 3, pp. 686-688, Mar. 2023. Published online Mar 3, 2023.

[3] Y.-C. Tham, X. Li, T. Y. Wong, H. A. Quigley, T. Aung, and C.-Y. Cheng, "Global prevalence of glaucoma and projections of glaucoma burden through 2040: a systematic review and meta-analysis," Review Ophthalmology, vol. 121, no. 11, pp. 2081-2090, Nov. 2014.

[4] K. Boyd, "What Is Glaucoma? Symptoms, Causes, Diagnosis, Treatment," Dec. 04, 2023. Available: https://www.aao.org/eye-health/diseases/what-is-glaucoma

[5] "Glaucoma," https://my.clevelandclinic.org/health/diseases/4212-glaucoma.

[6] "Glaucoma Prevention methods," https://www.cdc.gov/visionhealth/resources/features/glaucoma-awareness.html#:~:text=Open%2Dangle%20glaucoma%20does%20not,avoid%20vision%20loss%20from%20glaucoma.

[7] K. P. Noronha, U. R. Acharya, K. P. Nayak, R. J. Martis, and S. V. Bhandary, "Automated classification of glaucoma stages using higher order cumulant features," Biomed Signal Process Control, vol. 10, pp. 174–183, 2014.

[8] U. R. Acharya, E. Ng, L. W. J. Eugene, K. P. Noronha, L. C. Min, K. P. Nayak, and S. V. Bhandary, "Decision support system for glaucoma using Gabor transformation," Biomed Signal Process Control, vol. 15, pp. 18–26, 2015.

[9] A. Singh, M. K. Dutta, M. ParthaSarathi, V. Uher, and R. Burget, "Image processing based automatic diagnosis of glaucoma using wavelet features of segmented optic disc from fundus image," Comput Methods Prog Biomed, vol. 124, pp. 108–120, 2016.

[10] S. Maheshwari, R. B. Pachori, V. Kanhangad, S. V. Bhandary, and U. R. Acharya, "Iterative variational mode decomposition based automated detection of glaucoma using fundus images," Comput Biol Med, vol. 88, pp. 142–149, 2017.

[11] F. Fumero, S. Alayón, J. L. Sanchez, J. Sigut, and M. Gonzalez-Hernandez, "Rim-one: An open retinal image database for optic nerve evaluation," in 2011 24th International Symposium on Computer-based Medical Systems (CBMS), pp. 1–6, IEEE, 2011.

[12] A. Soltani, T. Battikh, I. Jabri, and N. Lakhoua, "A new expert system based on fuzzy logic and image processing algorithms for early glaucoma diagnosis," Biomed Signal Process Control, vol. 40, pp. 366–377, 2018.

[13] N. A. Mohamed, M. A. Zulkifley, W. M. D. W. Zaki, and A. Hussain, "An automated glaucoma screening system using cup-to-disc ratio via simple linear iterative clustering superpixel approach," Biomed Signal Process Control, vol. 53, p. 101454, 2019.

[14] A.D. Pinto, S. Morales, V. Naranjo, T. Kohler, J. Mossi, and A. Navea, "CNNs for Automatic Glaucoma Assessment Using Fundus Images: An Extensive Validation", Biomed Eng Online, Vol.18, No.29, pp. 1-19, 2019.

[15] A. Elmoufidi, A. Skouta, S. Jai-Andaloussi, and O. Ouchetto, "CNN with Multiple Inputs for Automatic Glaucoma Assessment Using Fundus Images," International Journal of Image and Graphics, vol. 23, no. 01, 2023.

[16] T. Aydin Oguz and M. Yaganoglu, "A CNN-based hybrid model to detect glaucoma disease," Multimedia Tools and Applications, 2023.

[17] B.S. Kirar, and D.K. Agrawal, "Glaucoma Diagnosis using Discrete Wavelet Transform and Histogram Features from Fundus Image", International Journal of Engineering & Technology(UAE), Vol.7, No.4, pp.2546-2551, 2018.

[18] B.S. Kirar, and D.K. Agrawal, "Computer Aided Diagnosis of Glaucoma Using Discrete and Empirical Wavelet Transform from Fundus Images, IET Image Processing, Vol.13, pp.73-82, 2019.

[19] B.S. Kirar, and D.K. Agrawal, "Current Research on Glaucoma Detection Using Compact Variational Mode Decomposition from Fundus Images", International Journal of Intelligent Engineering and Systems, Vol.12, No.3, pp.1-10, 2019.

[20] B.S. Kirar, R.S.R. Gosula, and D.K. Agrawal, "Glaucoma Detection Using SS-QB-VMD Based Fine Sub Band Images from Fundus Images," IETE Journal of Research, Vol.68, No.6, pp. 4421-4428 2022.

[21] D.K. Agrawal, B.S. Kirar, and R. B. Pachori, "Automated Glaucoma Detection Using Quasi-Bivariate Variational Mode Decomposition from Fundus Images", IET Image Processing Vol.13, pp. 2401-2408, 2019.

[22] B.S. Kirar, D.K. Agrawal, and S. Kirar "Glaucoma Detection Using Image Channels and Discrete Wavelet Transform," IETE J. Research, doi:10.1080/03772063.2020.1795934.

[23] S. Serte, and A. Serener, "A Generalized Deep Learning Model for Glaucoma Detection," In: Proc. Of 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, pp. 1-5, 2019.

[24] M. Claro, R. Veras, A. Santana, F. Araújo, R. Silva, J. Almeida, D. Leite, "An Hybrid Feature Space from Texture Information and Transfer Learning for Glaucoma Classification", Journal of Visual Communication and Image Representation, Vol.64, 2019,

[25] P. Elangovan, and M.K. Nath, "Glaucoma assessment from color fundus images using convolutional neural network", Int J Imaging Syst Technol, pp. 1-17, 2020.