Hybrid Deep Learning Framework for Glaucoma Detection Using Fundus Images

Royce Dcunha[1], Aaron Rodrigues[1], Cassandra Rodrigues[1], Kavita Sonawane[2]

[1] Research Associates, St. Francis Institute of Technology
[2] Professor, IEEE Senior Member, St. Francis Institute of Technology

Abstract. Glaucoma is a chronic eye condition that develops because intraocular pressure in the eye damages the visual nerve. One of the causes of blindness around the globe is due to it. Glaucoma does not initially cause vision loss, but if the condition worsens, it may leave a person permanently blind. Measurement of intraocular pressure, testing of the visual field, or inspection of the optical disc of fundus pictures are all methods used in the clinical setting to diagnose glaucoma. Early detection of glaucoma is crucial in reducing the risk of eye damage. VGG19, VGG19+LSTM, Inceptionv3, and Inceptionv3+LSTM are used to study the identification of glaucoma. ACRIMA is the dataset used, and it consists of 705 fundus images (396 glaucomatous images and 309 healthy images). The models are worked using data augmentation and K-fold cross-validation. The extracted features classify the input image as glaucomatous or healthy. The VGG19+LSTM model performed the best out of all the models.

Keywords: Deep learning, Machine Learning, Artificial Intelligence, Fundus Image, ConvNet.

1 Introduction

Glaucoma, a chronic eye condition, primarily caused by intraocular pressure, poses a significant threat to global eye health [12], affecting individuals worldwide [22]. This paper introduces a novel approach to early glaucoma detection, addressing the limitations of existing diagnostic techniques. In clinical settings, diagnosis traditionally involves measuring intraocular pressure, assessing visual fields, and examining fundus images. However, these methods are labour-intensive and may not be readily accessible to all populations. According to the World Health Organization (WHO), it currently affects over 80 million individuals globally, with an anticipated increase of reaching 111.8 million people by 2040 [21]. High myopia, diabetes, eye surgery, and hypertension are all factors that contribute to this illness. The advantages and limitations of several papers are studied in this paper. We present a comparative analysis of four architectures: Inceptionv3, Inceptionv3+LSTM, VGG19, and VGG19+LSTM.

Each model undergoes K-fold cross-validation and data augmentation. This is done to overcome the limitation of having a small dataset [17]. The proposed models extract attributes from input fundus images [4] to classify them as healthy or glaucomatous. Performance evaluation parameters are used to compare the models and assess their accuracy in early glaucoma detection. In this study, we employ the ACRIMA dataset, comprising 705 fundus images with a 90-10 split for training and testing. The aim is to contribute to the early detection of ocular diseases, particularly glaucoma, offering a promising approach [19] to combat this widespread and potentially blinding condition.

2 Literature Review

C. Sharmila and N. Shanthi [1] investigated the application of transfer learning. The approach involved reusing a pre-existing model developed for one task as a starting point for another. The study used the Inceptionv3 model pre-trained on the ImageNet dataset for glaucoma diagnosis. Transfer learning was implemented using both feature extraction and fine-tuning techniques. The training and testing of the automated glaucoma diagnostic model used the ORIGA dataset. It achieved an accuracy of 91.36% in predicting the two classes: glaucoma and not glaucoma. The evaluation included sensitivity, specificity, and accuracy parameters, resulting in 82.60% sensitivity and 95.30% specificity. Higher accuracy was achievable with minimal training epochs due to the small dataset size. However, further studies using additional datasets are necessary to enhance the accuracy of the automated glaucoma detection algorithm.

In another study by Arkaja Saxena, Abhilasha Vyas, Lokesh Parashar, and Upendra Singh [2], developed a deep learning-based architecture for reliable glaucoma diagnosis using CNNs. The CNNs provided a hierarchical visual structure for discriminating between glaucoma-affected and healthy human eyes. The suggested method of testing consisted of six layers. Each of these layers included tens of thousands of photos. The usage of a dropout mechanism improved the approach's performance. The objective was to find the most comparable patterns in healthy and glaucoma-affected eyes. SCES and ORIGA were the datasets used. It yielded a detection rate of 82.2% for ORIGA and 88.2% for SCES. The results showed that the ORIGA dataset outperformed SCES in diagnosing stages of glaucoma.

Ali Serener and Sertan Serte [3] used deep convolution neural networks in the study to detect distinct stages of glaucoma in fundus pictures. The fundus pictures utilized in the study are either healthy (no glaucoma), early glaucoma, or advanced glaucoma. The classification used two deep learning models, which are ResNet50 and GoogLeNet. The models were trained using a single NVIDIA GeForce GTX 1080Ti GPU running the Caffe deep learning framework. The training was performed on a unique dataset to address the limitation of limited testing data. The RIM-ONE dataset assessed the performance of the ResNet50 and GoogLeNet models in accuracy, sensitivity, specificity, and area under the ROC curve. The results reveal that GoogLeNet beats ResNet-50 for early, advanced, and total glaucoma detection.

Table 1. presents a comprehensive comparison of research papers focused on glaucoma. The analysis aims to identify the most promising model for achieving improved performance compared to existing approaches. We have highlighted key metrics and insights derived from these studies to guide our selection process.

Table 1. Literature Review

No	Algorithm & Year of Issue	Advantages	Datasets	Accuracy%	Evaluation Parameters
1	Inceptionv3 (2021) [1]	Classification of early glaucoma	ORIGA	91.36	Sensitivity (Sen%): 82.60, Specificity (Spe%): 95.30
2	CNN (2020) [2]	Higher detection capability and high accuracy	SCES, ORIGA	82.2 to 88.2	Sen%: 21 to 29, Spe: 91 to 93
3	GoogLeNet and ResNet (2019) [3]	Large training dataset	RIM-ONE	85 to 86	Sen%: 21 to 29, Spe%: 91 to 93, ROC: 0.75
4	CNN + LSTM (2021) [4]	Reduced Glaucoma prediction time and high accuracy	RIM-ONE, DRISHTI GS, DRIONS	Around 90	Sen%: 95.4, Spe%: 96.7, AUC: 0.984
5	MobileNet and Inceptionv3 (2021) [5]	High accuracy	ORIGA, SCES	86 for MobileNet and 90 for Inceptionv3	Precision, Recall, F1 Score: 0.87 to 0.90, AUC: 0.831 to 0.887
6	Inceptionv3 (2021) [6]	Reduced Glaucoma prediction time and high accuracy	ACRIM-A, LAG	85.29	Sen%: 95.4, Spe%: 96.7, AUC: 0.984
7	AlexNet, SVM (2020) [7]	High accuracy	HRF, ORIGA	91.21	Sen%: 90.8, Spe%: 85
8	VGG, ResNet (2021) [8]	Uses backward propagation and forward LAG	LAG	80 to 87. Best accuracy: 86.9	Precision: 0.869
9	Mnet, DeNet (2019) [9]	Detection of datasets with different brightness	ORIGA SCES	Around 85	Sen%: 76 to 84, Spe%: 83

3 Methodology

3.1 Design

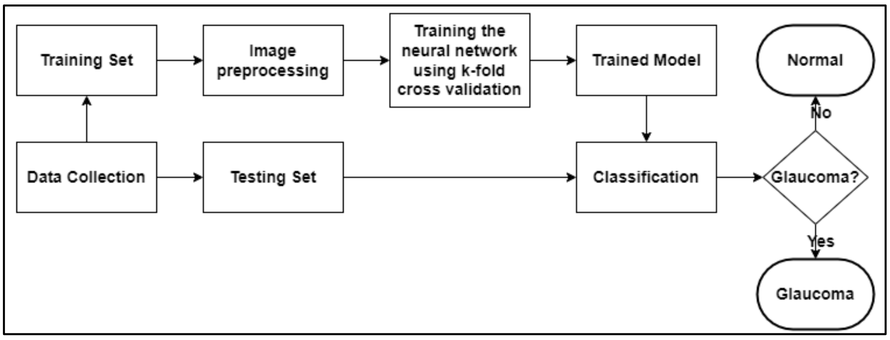

Fig. 1. Proposed architecture system

Fig. 1. shows the system overview of the proposed architecture system. The data is collected and divided into a Training set and a Testing set. The images from the training dataset further undergo Image pre-processing. The models are trained with K-fold cross-validation and data augmentation. The extracted features are used to classify the input image and projected to be either glaucomatous or normal.

3.2 Architecture

A comparison study is done between four architectures: Inceptionv3, Inceptionv3+LSTM, VGG19, and VGG19+LSTM. These architectures are chosen because they have much experience with medical image categorization.

Inceptionv3 Architecture. The purpose of Inceptionv3 is to reduce computing resource usage by modifying previous Inception models [14, 15]. It has a lower error rate compared to its predecessors and has 42 layers. Inception Networks (GoogLeNet/Inceptionv1) are computationally more efficient when compared to VGGNet, both in terms of the associated financial cost (memory and other resources) and the number of parameters generated by the network. The Inceptionv3 model can achieve more than 78.1% accuracy on the ImageNet dataset. Convolutions, average pooling, max pooling, concatenations, dropouts, and fully linked layers are the symmetric and asymmetric building components that make up the model itself [23].

VGG19 Architecture. A convolution neural network that has 19 layers is called VGG19. The VGG19 model contains 16 convolution layers, 5 MaxPool layers, 3 fully linked layers, and a sigmoid layer. The first 16 layers are convolution and maximum pooling layers and extract the spatial features. The final three layers are for Image categorization. The input to a VGG19 network is a fixed RGB image with a size of (224*224). Hence, the matrix has a shape of (224,224,3). For instance, in 112*112*128, 128 is the number of filters or kernels, and 112*112 is the size. The convolution layers' filter size is 3*3, and the stride is 1. The max pooling layers' filter sizes are 2*2, and the stride is 2. After the final pooling layer, 7*7*512 volume flattens into a Fully connected (FC) layer with 4096 channels. The sigmoid classifies an image as Glaucomatous or Normal [24].

VGG19+LSTM & Inceptionv3+LSTM Architecture. Spatial and temporal data extraction is done by a combination of CNN (Inceptionv3 and VGG19) and RNN (LSTM) architecture [25]. Recurrent neural networks are a particular kind of artificial network with loops that enable data storage. RNNs use knowledge of older events to make predictions. The completion of tasks that use visual sequences, therefore, necessitates a sophisticated architecture. As a result, the CNN-RNN architecture is chosen [16]. The CNN extracts spatial data from each video by converting it into consecutive pictures. The outputs detect temporal properties inside the image sequence using a recurrent sequence learning model (LSTM). Finally, the aggregated features are sent to a fully linked layer that predicts categorization for the input sequence [26].

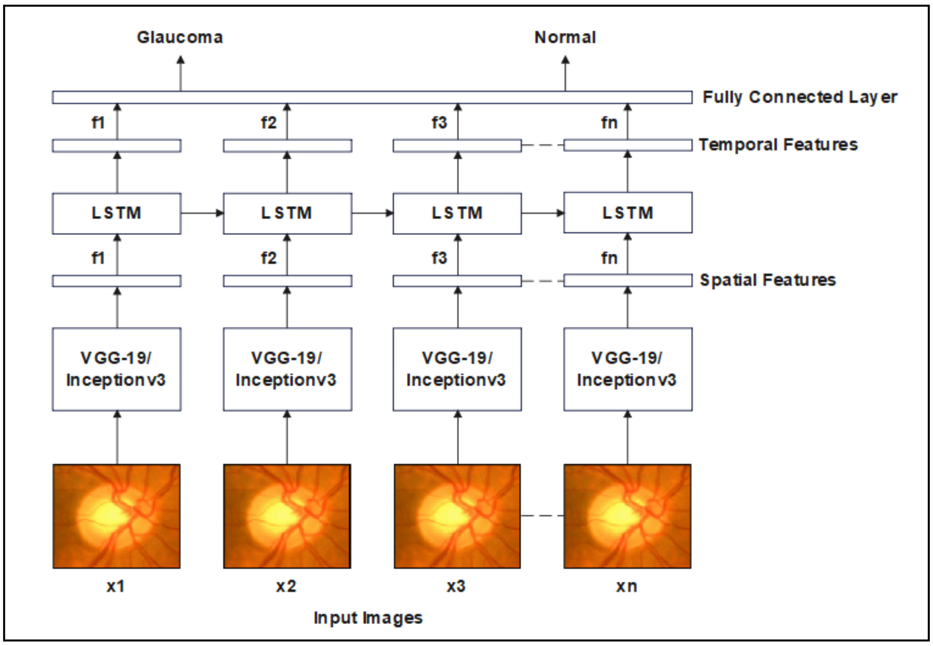

Fig. 2. VGG19+LSTM & Inceptionv3+LSTM Architecture [Gheisari, S., Shariflou, S., Phu, J. et al.,2021][20]

3.3 Working of the Project

Fig. 2. illustrates the architecture of the proposed model used in this paper. This method for glaucoma detection combines the capabilities of the Long Short-Term Memory (LSTM) recurrent neural network and the VGG19 convolutional neural network (CNN). This hybrid design enables glaucoma detection through the analysis of ocular pictures. The overview of the algorithm is below:

Data Preprocessing:

- Obtained a collection of eye photographs classified as having glaucoma or not.
- Created training and testing sets from the dataset.

VGG19 Model:

- Loaded the pre-trained VGG19 model and eliminated the fully connected layers.
- Froze the convolutional layer weights to preserve the learned features.
- Included a new connected layer with appropriate classification units.
- Compiled the model using the proper optimizer and loss function.

LSTM Model:

- Designed an LSTM model for sequence classification.
- Pre-processed the eye image data to create sequential input data for the LSTM.
- Defined the LSTM architecture with a suitable input shape and LSTM units.
- Added fully connected layers and output layers for classification.
- Compiled the LSTM model with an appropriate loss function and optimizer.

Training:

- Fed the eye images into the VGG19 model to extract visual features.
- Used these features as input to the LSTM model for glaucoma detection.
- Trained the combined VGG19+LSTM model using the labeled training data

Testing and Evaluation:

- Evaluated the trained model using the labeled testing data.
- Calculated performance metrics such as accuracy, precision, recall, and F1 score.

Prediction:

- Used the trained model to predict the presence of glaucoma for new eye images.
- Pre-processed the new eye image and extracted visual features with VGG19.
- Fed these features into the LSTM model to obtain the glaucoma prediction.

4 Results and Discussions

4.1 Experimental Setup

The ACRIMA dataset is used for this research. It contains 705 fundus images (396 glaucomatous and 309 normal images). For training, 632 images are used. For testing, 73 images are used. The dataset has a 90-10 split [10]. The sample Glaucoma images are displayed in Fig. 3. The sample normal images are displayed in Fig.4.

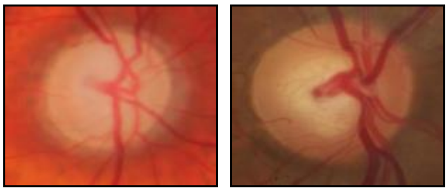

Fig. 3. Glaucomatous Image

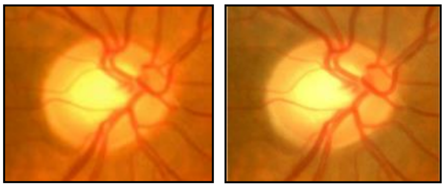

Fig. 4. Normal Image

4.2 Performance Evaluation Parameters

Accuracy. The proportion of the correct predictions to the overall number of predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \tag{1}$$

F1-Score. The harmonic mean of the precision and recall of the model.

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{2}$$

Precision. It divides the fraction of true positives by the total number of true positives and False Positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

Recall. It is determined by dividing the total number of true positives and false negatives by the number of true positives and false negatives.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

4.3 Results

A few samples have been taken from the ACRIMA and RIM-ONE datasets and tested against the proposed model and the results are in Table 2.

Table 2. Test case results

Test No	Test Case (Actions performed)	Expected result	Actual Outcome
1	ACRIMA dataset sample	Normal	Normal
2	RIM-ONE dataset sample	Normal	Glaucomatous
3	ACRIMA dataset sample	Glaucomatous	Glaucomatous
4	ACRIMA dataset sample	Glaucomatous	Glaucomatous
5	RIM-ONE dataset sample	Glaucomatous	Glaucomatous

VGG19 model observation. The model exhibited a precision of 0.85 for normal images and 1.00 for glaucoma images. The recall rates were 1.00 for normal images and 0.84 for glaucoma images. Regarding the F1 Score, normal images scored 0.92, while glaucoma images scored 0.91. Overall, the model attained an accuracy of 91.78%. The model performed better on normal images.

VGG19+LSTM model observation. The model exhibited a precision of 0.90 for normal images and 1.00 for glaucoma images. The recall rates were 1.00 for normal images and 0.89 for glaucoma images. Regarding the F1 Score, normal images scored 0.95, while glaucoma images scored 0.94. Overall, the model attained an accuracy of 94.52%. The model performed better on normal images.

Inceptionv3 model observation. The model exhibited a precision of 0.88 for normal images and 0.92 for glaucoma images. The recall rates were 0.91 for normal images and 0.90 for glaucoma images. Regarding the F1 Score, normal images scored 0.90, while glaucoma images scored 0.91. Overall, the model attained an accuracy of 90.41%. The model performed better on glaucoma images.

Inceptionv3+LSTM model observation. The model exhibited a precision of 0.91 for normal images and 0.95 for glaucoma images. The recall rates were 0.94 for normal images and 0.93 for glaucoma images. Regarding the F1 Score, normal images scored 0.93, while glaucoma images scored 0.94. Overall, the model attained an accuracy of 93.15%. The model performed better on glaucoma images.

The highest precision is for the VGG19-based models for glaucoma images at 0.91. Likewise, the VGG19+LSTM model achieved the highest recall for normal images at 1.00. The highest F1 Score is achieved by the VGG19+LSTM model, with a score of

0.95 for normal images. Ultimately, the VGG19+LSTM model achieved the highest overall accuracy of 94.52%.

Table 3. The performance results of the proposed models

Model	Class	Precision	Recall	F1 Score	Accuracy (%)
VGG19	Normal	0.85	1.00	0.92	91.78
VGG19	Glaucoma	1.00	0.84	0.91	91.78
VGG19+LSTM	Normal	0.90	1.00	0.95	94.52
VGG19+LSTM	Glaucoma	1.00	0.89	0.94	94.52
Inceptionv3	Normal	0.88	0.91	0.90	90.41
Inceptionv3	Glaucoma	0.92	0.90	0.91	90.41
Inceptionv3+LSTM	Normal	0.91	0.94	0.93	93.15
Inceptionv3+LSTM	Glaucoma	0.95	0.93	0.94	93.15

The VGG19-based models perform better on normal images, and Inceptionv3-based models perform better on glaucoma images. Each row in Table 3. corresponds to various approaches used during training. The k-fold cross-validation technique is for training purposes with k=3. After training the model for 35 epochs, the average training accuracy achieved was 96% and 99% for VGG19-based and Inceptionv3-based models, respectively. The average testing accuracy was 94.52% and 93.15% for VGG19-based and Inceptionv3-based models, respectively. The addition of LSTM to VGG19 and Inceptionv3 helped to increase the training as well as testing accuracy. The VGG19+LSTM model has the best results with the highest accuracy.

Table 4. compares the accuracy of the proposed approach with the existing approaches. It is noticeable that the proposed method has resulted in a higher accuracy compared to the other existing approaches to detect glaucoma.

Table 4. Comparison study between various approaches

Author	Model	Dataset	Accuracy (%)
Sharmila C. et al [1]	Inceptionv3	ORIGA	91.36
Arkaja Saxena et al [2]	CNN	SCES	82.20
Arkaja Saxena et al [2]	CNN	ORIGA	88.20
Ali Serner et al [3]	ResNet	RIM-ONE	86.00
Ali Serner et al [3]	GoogLeNet	RIM-ONE	85.00
Proposed Approach	VGG19	ACRIMA	91.78
Proposed Approach	VGG19+LSTM	ACRIMA	94.52
Proposed Approach	Inceptionv3	ACRIMA	90.41
Proposed Approach	Inceptionv3+LSTM	ACRIMA	93.15

5 Conclusion

Conclusion. The mechanism used is a combination of CNN and RNN. The models used are VGG19, VGG19+LSTM, Inceptionv3, and Inceptionv3+LSTM. After performing a comparative study on the ACRIMA dataset, it is noticeable that VGG19+LSTM is the best-performing model. The VGG19+LSTM model predicted two classes (glaucoma and non-glaucoma) with an accuracy of 94.52%. Accurate results are due to transfer learning and data augmentation. Data augmentation helped us tackle the problems while training CNNs. The VGG19-based models perform better on normal images, and Inceptionv3-based models perform better on glaucoma images. This project aims to provide an effective, fast, and efficient solution for exposure to glaucoma in the eye. Because a glaucoma detection model plays a crucial role in early identification, efficient screening, and improved management of glaucoma cases. It has the potential to save vision, reduce healthcare costs, and enhance overall eye healthcare delivery.

Future Scope. This model will be beneficial to both ophthalmologists and patients. Real-life data and larger datasets could be collected from hospitals all over India to analyze any changes in the retina due to different geographical locations. Also, we can work on the severity categories of glaucoma [13]. While these advancements show promise, further research, validation, and regulatory approvals are mandatory before widespread implementation in clinical practice [11, 18].

References

1. Sharmila, C., Shanthi, N. (2021): Retinal Image Analysis for Glaucoma Detection Using Transfer Learning. *Advances in Electrical and Computer Technologies*. Springer, Singapore, pp. 235-244, https://doi.org/10.1007/978-981-15-9019-1_21
2. Saxena, A., Vyas, A., Parashar, L., Singh, U. (2020): A Glaucoma Detection using Convolutional Neural Network, *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2020, pp. 815-820, https://doi.org/10.1109/ICESC48915.2020.9155930
3. Serener, A., Serte, S. (2019): Transfer Learning for Early and Advanced Glaucoma Detection with Convolutional Neural Networks. *2019 Medical Technologies Congress (TIPTEKNO),* 2019, pp. 1-4. https://doi.org/10.1109/TIPTEKNO.2019.8894965
4. Demir, F., Taşcı, B. (2021): An Effective and Robust Approach Based on R-CNN+LSTM Model and NCAR Feature Selection for Ophthalmological Disease Detection from Fundus Images. *Journal of Personalized Medicine.* vol. 11(12):1276. https://doi.org/10.3390/jpm11121276
5. Olivas, L.G., Alférez, G.H. & Castillo, J. (2021) Glaucoma detection in Latino population through OCT's RNFL thickness map using transfer learning. *International Ophthalmology,* vol. 41(11), pp. 1-15. https://doi.org/10.1007/s10792-021-01931-w
6. Afroze, T., Akther, S., Chowdhury, M. A., Hossain, E., Hossain, M. S., Andersson, K. (2021): Glaucoma Detection Using Inception Convolutional Neural Network V3. *Springer International Publishing*. Cham, pp. 17-28. https://doi.org/10.1007/978- 3-030-82269-9_2
7. Ajitha, S., Judy, M. V.,. Meera, N., Rohith, N. (2020): Automated Identification of Glaucoma from Fundus Images using Deep Learning Techniques. *European Journal of Molecular & Clinical Medicine*. vol. 7(2).
8. Sallam, A., Gaid, A.S.A., Saif, W.Q.A., Kaid, H.A.S., Abdulkareem, R.A., Ahmed, K.J.A., Saeed, A.Y.A., Radman, A (2021): Early Detection of Glaucoma using Transfer Learning from Pre-trained CNN Models. In: *2021 International Conference of Technology, Science and Administration (ICTSzA),* pp.1-5. https://doi.org/ 10.1109/ICTSA52017.2021.9406522
9. Fu, H., Cheng, J., Xu, Y., Liu, J. (2019): Glaucoma Detection Based on Deep Learning Network in Fundus Image. *Advances in Computer Vision and Pattern Recognition.* pp. 119-137. https://doi.org/10.1007/978-3-030-13969-8_6
10. Diaz-Pinto, A., Morales, S., Naranjo, V., Köhler, T., Mossi, J., Navea, A. (2019): CNNs for automatic glaucoma assessment using fundus images: An extensive validation. *BioMedical Engineering OnLine* vol. 18(1). https://doi.org/10.1186/s12938-019-0649-y
11. Garg, H., Gupta, N., Agrawal, R. Shivani, S., Sharma, B. (2022): A real-time cloud-based framework for glaucoma screening using EfficientNet. *Multimedia Tools and Applications* vol. 81(24), pp. 34737-34758. https://doi.org/10.1007/s11042-021- 11559-8
12. Li, L., Xu, M., Liu, H., Li, Y., Wang, X., Jiang, L., Wang, Z., Fan, X., Wang, N. (2020). A Large-Scale Database and a CNN Model for Attention-Based Glaucoma Detection. In: *IEEE transactions on medical imaging*, vol. 39(2), pp. 413-424 https://doi.org/10.1109/TMI.2019.2927226
13. Dhillon, A., Verma, G.K. (2020): Convolutional neural network: a review of models, methodologies, and applications to object detection. *Progress in Artificial Intelligence,* vol. 9, 85–112 https://doi.org/10.1007/s13748-019-00203-0
14. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z. (2016): Rethinking the Inception Architecture for Computer Vision. In: *2016 IEEE Conference on Computer Vision and*

15. *Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 2818-2826. https://doi.org/10.1109/CVPR.2016.308.
16. Islam, M. Z., Islam, M. M., & Asraf, A. (2020): A Combined Deep CNN-LSTM Network for the Detection of Novel Coronavirus (COVID-19) Using X-ray Images. *Informatics in Medicine Unlocked*, vol. 20, p. 100412. https://doi.org/10.1101/2020.06.18.2013471
17. Hinton, G.E., Srivastava, N., Krizhevsky, A., Sutskever, I., Salakhutdinov, R.R. (2012): Improving neural networks by preventing co-adaptation of feature detectors. In: *arXiv 2012*. https://doi.org/10.48550/arXiv.1207.0580
18. Tu, Z., Bai, X. (2010). Auto-context and its application to high-level vision tasks. In: *IEEE Transactions on pattern analysis and machine intelligence*, vol. 32(10), 1744–1757. https://doi.org/10.1109/TPAMI.2009.186
19. Xu, Y., Duan, L., Lin, S., Chen, X., Wong, D.W.K., Wong, T.Y., Liu, J. (2014). Optic Cup Segmentation for Glaucoma Detection Using Low-Rank Superpixel Representation. In: Golland, P., Hata, N., Barillot, C., Hornegger, J., Howe, R. (Eds.) *Medical Image Computing and Computer-Assisted Intervention (MICCAI) 2014*, Part I. LNCS, vol. 8673, pp. 788–795. Springer, Heidelberg. https://doi.org/10.1007/978-3-319-10404-1_98
20. Cheng, J., Liu, J., Wong, D.W.K., Yin, F., Cheung, C.Y., Baskaran, M., Aung, T.,Wong, T.Y. (2011). Automatic Optic Disc Segmentation with Peripapillary Atrophy Elimination. In*: IEEE International Conference Engineering in Medicine and Biology Society*., pp. 6224–6227. https://doi.org/10.1109/IEMBS.2011.6091537
21. Gheisari, S., Shariflou, S., Phu, J., Kennedy, P.J., Agar, A., Kalloniatis, M., Golzan, S.M. (2021). A combined convolutional and recurrent neural network for enhanced glaucoma detection. *Scientific Reports* 11(1), 1945. https://doi.org/10.1038/s41598-021-81554-4
22. *Epidemiology of Glaucoma: The Past, Present, and Predictions for the Future*, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7769798/. Accessed 3 Sept. 2021.
23. "Glaucoma: Causes, Types, Symptoms, Diagnosis, and Treatment." *WebMD*, WebMD, https://www.webmd.com/eye-health/glaucoma-eyes. Accessed 21 Sept. 2021.
24. Narein, A. T., "Inception V3 Model Architecture." *OpenGenus IQ: Computing Expertise & Legacy*, OpenGenus IQ: Computing Expertise & Legacy, 8 Oct. 2021, https://www.iq.opengenus.org/inception-v3-model-architecture/. Accessed 23 Nov. 2021.
25. Kaushik, A. Understanding the VGG19 Architecture. OpenGenus IQ: Computing Expertise & Legacy (2020). https://iq.opengenus.org/vgg19-architecture/. Accessed 16 Dec. 2021.
26. Brownlee, J. CNN Long Short-Term Memory Networks, 14 Aug. 2019, https://www.machinelearningmastery.com/cnn-long-short-term-memory-networks/. Accessed 14 Jan. 2022.