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RESEARCH ARTICLE - PHYSICS

Glaucoma Disease Classification based on Convolutional Neural Network Architecture Method

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Abstract

Glaucoma refers to a class of eye disorders which often associated with the increase in intraocular pressure that can damage the eye by destroying the nerve cells in the retina in addition to the optic nerve of the eye. The need for detecting and recognizing glaucoma eye disease increased worldwide. The current paper presents a novel Convolutional Neural Network based on an intelligent pattern categorization method upon ACRIMA dataset images. The proposed technique for detecting and classifying the glaucoma in fundus images consisted of a multi-layer deep neural network model with convolutional and classification layers. The main contribution of the current study focuses on the proposed model's achievement in classifying funds images, verify the impact of the number of filters upon two values of Epoch (50 and 100) and analysis the variation of confusion matrices with increasing the number of filters through the two mentioned Epoch values. The role of the dropout layer affects upon classification procedure and hence a robust CNN model resulted such that highest values of TP and TN lie in the range (0.97-0.99) and (0.99-1) respectively for all used filters, otherwise Fp and FN recorded the lowest values and hence the proposed model at final succeeded with significant advancement in comparison with other related studies in classifying glaucoma disease.

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Keywords: Convolutional Neural Network; Epoch; Glaucoma; Sensitivity; Accuracy.

1. Introduction

The inequalities in health coverage, prevention services, treatment and rehabilitation, made the adequate attention to eye condition is not present. According to the report of the World Health Organization (WHO) in 2019, one thousand two hundred million people were infected by eye conditions. Eye problems are severe concern worldwide since they are problematic in developing countries in which access to technology and financing is limited [1]. Refraction errors, eye cataracts, glaucoma, corneal opacities, macular degeneration, diabetic retinopathy and presbyopia are some types of these conditions [2].

A class of eye conditions known as glaucoma refers to a category of eye disorders which often associated with increased intraocular pressure that can damage the eye by destroying the nerve cells in the retina in addition to the optic nerve of the eye. Although the exact origin of the most prevalent forms of glaucoma is unknown, medications that lower eye pressure can assist in delaying the progression of the condition because high eye pressure is a common feature in glaucoma patients. There are several varieties of glaucoma, congenital glaucoma and angle-closure glaucoma are two less prevalent varieties. Most people refer to open-angle glaucoma when they discuss glaucoma because it is the most prevalent kind in the United States as an example [3].

Nowadays, the difficulties of recognizing eye conditions are resolved with the aid of pattern recognition task that involves classification. The fundamental goal of the classification approach is to group similar features from any creature, object, occurrence, or event that is a part of the real or abstract universe. Convolutional Neural Network (CNN) is one of the artificial neural network types that can be used in data mining, machine learning and intelligent pattern classification. Moreover, analog algorithms are applied also in diagnosing diseases in human bodies in ophthalmology and medicine [4].

The anatomy of the human eye is depicted in Fig. 1. The retina, choroid, macula, fovea, blood vessels and optic disc positioned in region called 'fundus'; the outermost structure which is far away than the opening of the eye. The color of the fundus varies both between and within species [3]. The retina for example is blue, green, yellow, orange and red; only the human fundus (from a lightly pigmented blond person) are red. For the eye, there are several parts positioned in the fundus, these are [5, 6]:

Retina – The region where a layer of cells called photoreceptors lie on the back of the eye. The photoreceptors usually response of light conversion into electrical signals. Then the signals sent to the brain and hence make the person see the scene.

Macula – It is retina’s center which is responsible for central vision.

Fovea – It is the small depression where the vision is the sharpest part inside the macula.

Choroid – It is the white part of the eye that contains the blood vessels which are responsible to send nutrients to the eye. It is located between the sclera and the retina.

Optic disc – It is the area where retina connects to the optic nerve. The optic nerve is critical since it connects to the brain and hence affects the ability of the person to see.

The blood vessels that support the inner retina is called retinal blood vessels. The oxygen and nutrients supplied the retina through blood from the central retinal artery and its branches while carbon dioxide and waste removed away by the central retinal vein and its branches. Healthy role of the parts of the eye is important in being able to see. In front of the eye, cornea and lens work in focusing the light enters the eye. When the later hits fundus, a light conversion takes place to electrochemical impulses by the retina and then go to the brain through the optic nerve [6].

The current work presents a novel convolutional neural network based on an intelligent pattern categorization method. According to previous results [5], Epoch values 50 and 100 seem to be the best values of Epoch in classification performance. The originality of the current study focuses on the proposed model’s achievement in classifying funds images, verify the impact of the number of filters (i.e nf=16,32,64,128) upon two values of Epoch (50 and 100) and analysis the variation of confusion matrices with increasing the number of filters through the two mentioned Epoch values to help doctors at final in diagnosing glaucoma eye condition. The next section shall display the most related works in the field of detecting glaucoma disease followed by a brief description of the Convolutional Neural Network architecture technique. The proposed technique can be described in section four followed by its results and discussion in section five and finally the most important remarks will be presented in conclusion section.

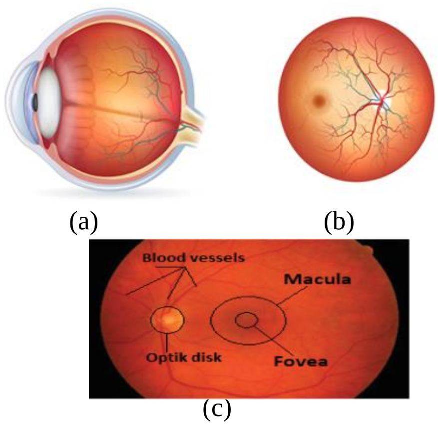


Fig. 1. The anatomy of the eye: (a) Cross section of the eye [7] (b) View of the fundus [7] (c) Annotated structure of retina [8]

2. Related Works

Many researchers investigated the problem of eye diseases toward detecting and diagnosing such conditions. A. Serener et al. in [9] suggested a protocol to recognize glaucoma in its advanced stages. Their study employed ResNet-50 and GoogLeNet Deep Convolution Neural Network (DCNN) to classify glaucoma. Their trial stage included three types; early, advanced and absence of glaucoma. Their results indicated the outer performance of GoogLeNet than ResNet-50 through their average accuracy which recorded 83% and 79% respectively. For automatic glaucoma detection, A. Diaz et al. employed five different ImageNet-trained models; Xception, ResNet50, InceptionV3, VGG19 and VGG16. A significant improvement resulted by using Xception through an average specificity, accuracy and sensitivity equal to 0.8580, 0.9605 and 0.9346, respectively [10].

M. R. Hossain et al. [11] proposed a DCNN based system where 5718 fundus images were used. This technique used for the presence and absence of cataract detection. Their results yielded a precision equal to 96.25%, sensitivity recorded a value of 94.43% and specificity 98.07%. R. Krishnan et al. [12] proposed a glaucoma detection system. The utilized dataset contained 101 cases, 50% for training and 51% for testing. Their investigation used a support vector machine model with an RBF kernel and yielded F1 score equal to 86%. By using Faster R-CNN and DenseNet Regression, M. Aljazaeri et al. [13] proposed a technique to detect glaucoma by using MESSIDOR which contained 460 images and Magrabi with 94 images. Their proposed method yielded good performance up to 71% reduction in the mean absolute value. Their proposed model recorded a value of mean square error equal to 0.0008 for MESSIDOR and 0.0098 for the Magrabi datasets. A DeepLabv3+ architecture used by S. Sreng et al. [14] to segment the optic disc region first with multiple deep convolutional neural networks by substituting the encoder module. Three proposals were used for the classification stage; transfer learning, support vector machine to learn the feature descriptors and establishing the ensemble for the previous two methods. The authors evaluated their proposals upon five different database consisting of 2787 retinal images. The ensemble of methods performed better than the conventional techniques for ACRIMA, DRISHTI-GS1, ORIGA and RIM-ONE with an accuracy equal to 99.53%, 86.84%, 90.00% and 97.37%, respectively and 95.59% by using REFUGE dataset

A technique for detecting melanocytic tumors of the iris introduced by A. Sinha et al. [15]. They used deep learning techniques through the use of LeNet architecture. Their results showed an accuracy of 98% for normal images and 95% for abnormal cases. X. Luo et al. [16] suggested a procedure in diagnosing Age-related Macular Degeneration (AMD), cataracts and glaucoma. In their experiment, 5000 fundus images were utilized from OIA-ODIR and served CNN and Adam as optimizer. The highest accuracy recorded for AMD, Cataract and Glaucoma equal to 90.08%, 99.45% and 84.7%, respectively.

A. Elmoufidi and S. Jai-andaloussi [17] described an approach for automatic glaucoma detection by using six dataset images (i.e. RIM-ONE, sjchoi86-HRF, ACRIMA, Drishti-GS1, REFUGE and ORIGA-light). They implemented CNN architecture VGG19 to get features from the decomposed Bi-dimensional Empirical Mode Decomposition components. By training the model on REFUGE, the overall accuracy recorded 96.43%, 98.60%, 98.31%, 95.24%, 98.61% and 96.67%, respectively and 98.27%, 96.36%, 98.92%, 96.97%, 99.06% and 97.10%, respectively when using a model training on ACRIMA. Also, a classification technique based on Deep CNN architectures proposed by A. U. Rehman et al. in [18] used Inceptionv3, InceptionResNetV2, NasNet-Large and AlexNet. The results of sensitivity specificity, accuracy and AUC gave 99.4%, 99.3%, 97.8% and 99.1% respectively. Their results found that NasNet-Large architecture is the best one for glaucoma classification.

For glaucoma detection, A. Patra et al. [19] developed Majority-Voting-Ensemble (MVE) learning approach which used various machine learning techniques by the use of two publicly datasets; REFUGE and ORIGA. Results showed accuracy values equal to 88.48% and 99.86% on the ORIGA and REFUGE datasets.

3. Convolutional Neural Network Architecture Method

A particular class of machine learning model is known as Convolutional Neural Network (CNN). It is a deep learning technique that is particularly well-suited for the analysis of visual data. CNNs, also known as convents, extract features and recognize patterns in images using concepts from linear algebra, specifically convolution processes. CNNs can be configured to handle audio and other signal data, even if processing images are their primary function. The deep learning algorithm can classify classes, even so, deep learning networks can speed up the classification process with considerably correct results [8]. In real-time disease classification, the CNN Model can utilized some statistical parameters to evaluate the results of the CNN model to mark the efficacy of the system being developed [20]. Figure 2 depicts the CNN layers which can be explained as follow [21]:

Input Layers: A resolution of 200 × 200 pixels was applied to the processed images.

Convolution Layers: The input image passes via three phases; the two-dimensional convolution layer process uses 16, 32 and 64 filters that are run in turn using MaxPooling. This layer uses the visuals that are shown on each screen to extract information and significant features.

Max Pooling Layer: It makes the use of 2x2 MaxPooling grid. MaxPooling Layer's goal is to make the final convolution layer's surrounding values smaller. This process is carried out three times with the same dimension while the convolution layer is running concurrently.

Rectified linear unit layer (ReLU): The ReLU activation is used in the construction of the model and it acts as convolution layer activation.

Flattens' layers: This layer followed the completion of the convolution and MaxPooling stages. A two-dimensional matrix's value can be flattened to create a one-dimensional MaxPooling vector. Dense will be used then to classify the generated model's classes using the outcomes of flattening.

Dense: In this layer, the model's categorization is carried out within the built model [22].

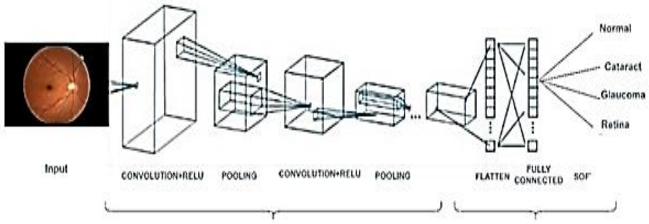


Fig. 2. CNN Architecture [23]

4. Dataset and the Proposed Methodology

The connection patterns found in the human brain, particularly in the visual cortex, are crucial for the perception and processing of visual inputs, which served as a model for CNN design. These models can comprehend the whole images because the artificial neurons in the CNN are constructed to efficiently interpret visual information. A deep neural network model with convolutional and classification layers were designed to analyze images and detect structural changes of fundus images. In this study, the proposed CNN architecture trained, validated and tested by the use of the ACRIMA database found in [24] for automatic glaucoma classification using fundus images shown in Fig. 3 for examples of natural and glaucoma cases. The ACREMA dataset consists of 705 retinal images in total of type JPEG 2048x1536 pixels of which 396 are classified as glaucoma and 309 as normal cases.

(a) (b)

Fig. 3. Examples of normal and glaucoma fundus images [24]

The analysis involved using these retinal images, with 95% of the dataset for training and 5% for validation. The analysis was conducted using MATLAB programming language.

A general diagram of the proposed methodology can be illustrated in Fig. 4. Figure 5 shows the current CNN layers and the training process works on the principle of backpropagation; the network works with several images in succession and simultaneously transmits a target value each time. This value is the associated object class. Each time when an image is displayed, the filter arrays are optimized such that the target and actual values of the target class match. After completion of this process, the network can detect effects in the images such that the observer did not notice the infection through the training process.

The training procedure consists of splitting the database to 95% for training and 5% for testing, augmented the data and define the CNN network layers as explained in Fig. 5. The dropout layer built the CNN model with more robust and hence makes the learning process more efficient. The training rate set to 0.0001 and the validation frequency set to 5. Figure 6 shows the training procedure in the current work.

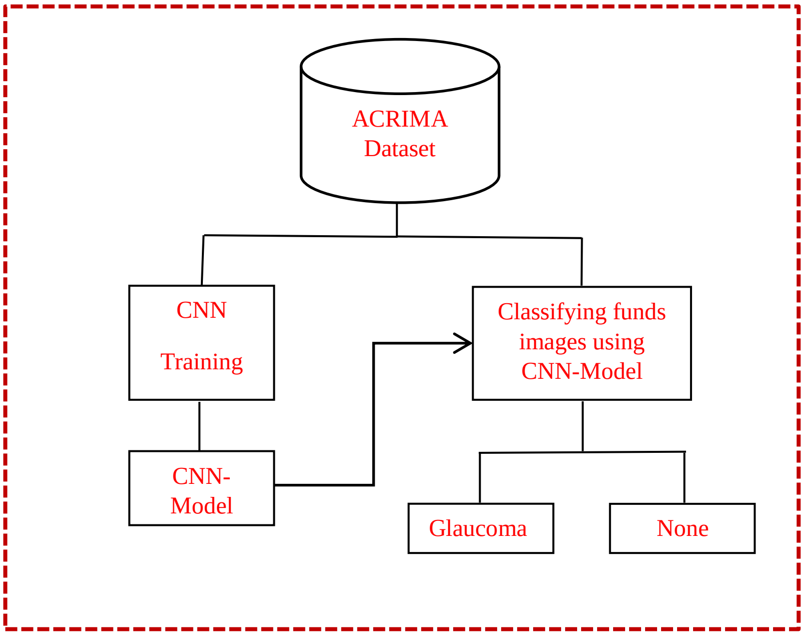


Fig. 4. Block diagram of the proposed methodology

Fig. 5. The current CNN layers

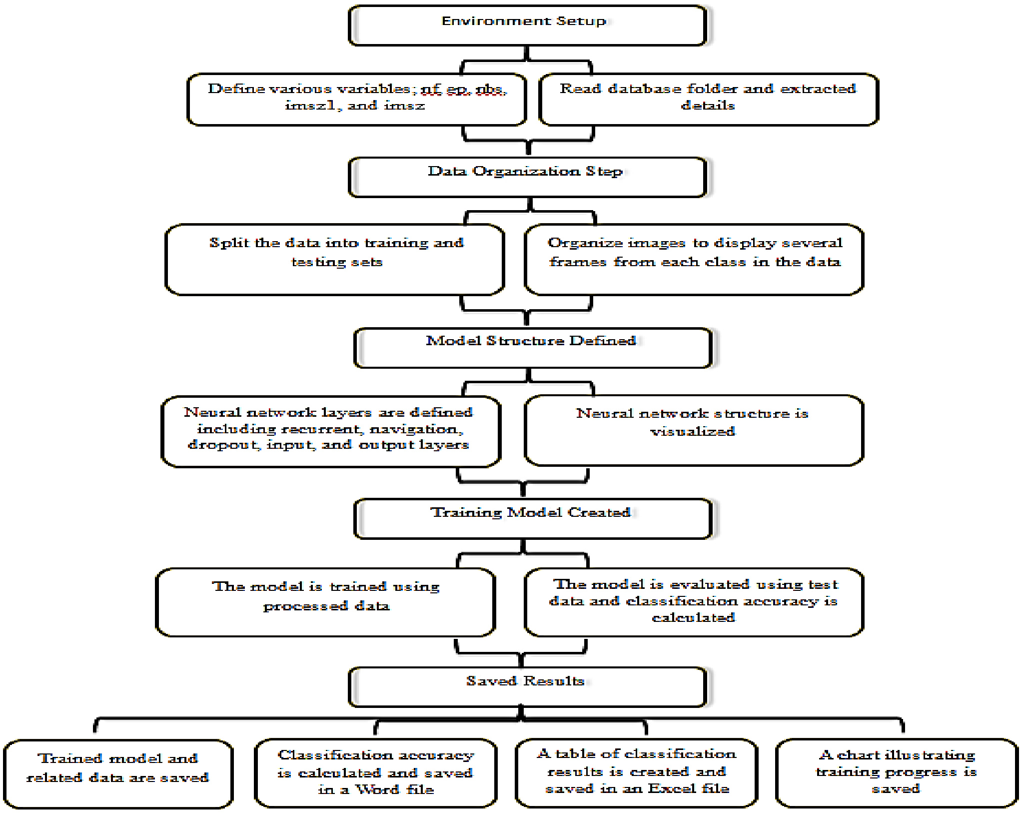


Fig. 6. Layout for the training procedure, where ‘nf’ represents the number of filters, ‘Ep’ epoch value, ‘nbs’ is batch size, ‘imsz1’ is image size and ‘imsz’ is image size in RGB form

The recognition procedure shown below consists of augmenting the input image, classify it by the aid of CNN model and hence estimate the confusion matrix. The threshold value (th) set to a value of 0.9.

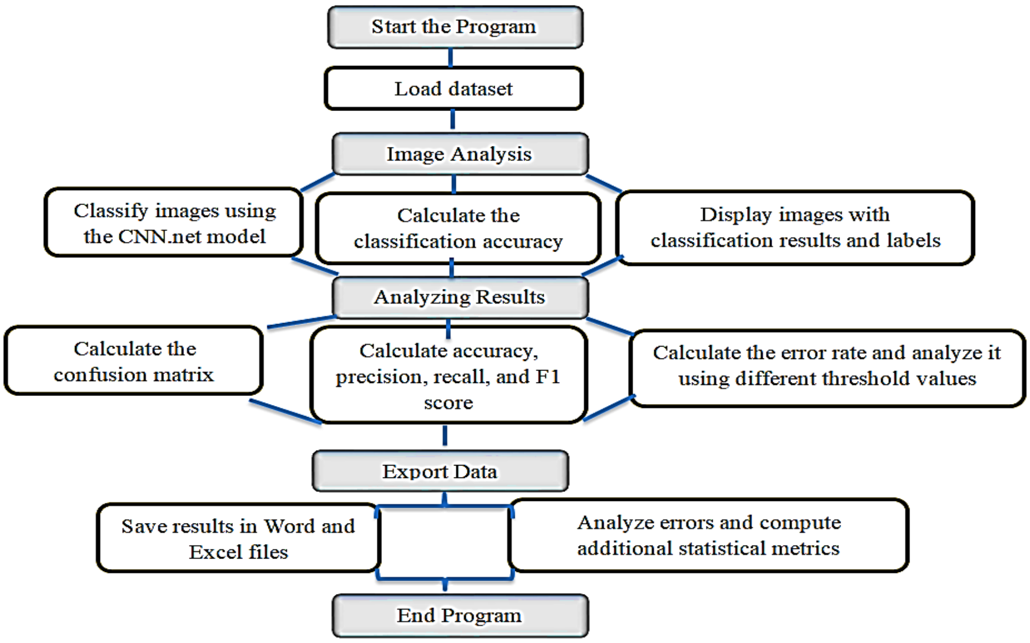


Fig. 7. Layout for the recognition procedure

5. Results and Discussion

In order to measure the CNN performance in glaucoma classification, the next measures can be expressed by the following equations [25-28]:

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

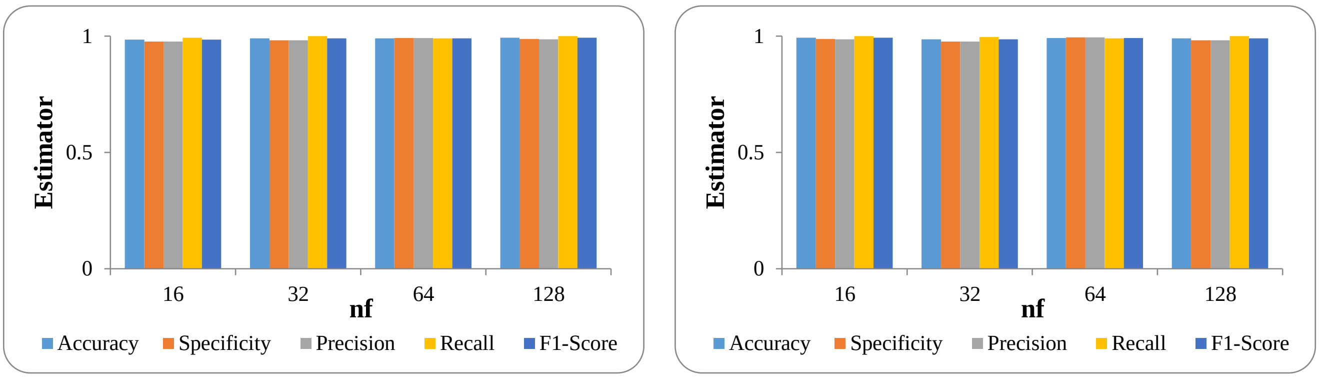
$$F1-Score = \frac{2TP}{2TP+FN+FP} \quad (6)$$

where TP represents the cases in which the model predicted the presence of the eye condition correctly. FN represents the cases where glaucoma was present, but the model failed to detect it. FP represents the cases where no target is present, but the model predicts it as present and TN presents the cases where no glaucoma present and the model predicted it as negative.

In the current search, several models resulted by varying the number of filters (nf) for each specified epoch value (Ep) each time through the discrimination algorithm and the confusion matrices resulted as seen in Table 1. For all used filters, one can noticed the highest values of TP and TN shown in Table 1 lie in the range (0.97-0.99) and (0.99-1) respectively, otherwise, Fp and FN recorded the lowest values. The classification evaluation process estimated through accuracy, specificity, precision, recall and F1-Score. The variation of these estimators with increasing the number of filters gave good values for all values of Epoch as shown in Fig. 8.

Table 1. Results of confusion matrix

Epoch Value (Ep)	Filter no.	TP	FN	FP	TN
	16	0.97727	0.0064725	0.022727	0.99353
50	32	0.98232	0	0.017677	1
	64	0.99242	0.0097087	0.0075758	0.99029
	128	0.98737	0	0.012626	1
	16	0.98737	0	0.012626	1
100	32	0.97727	0.0032362	0.022727	0.99676
	64	0.99495	0.0097087	0.0050505	0.99029
	128	0.98232	0	0.017677	1



(a) (b)

Fig. 8. The variation of estimators with increasing the number of filters for Epoch value (a) 50 and (b) 100

Several related studies used ACRIMA dataset in classifying glaucoma; A. Diaz et al. [10], S. Sreng et al. [14] and A. Elmoufidi et al. [17]. Table 2 shows a comparison between the previous related studies and the proposed method through their sensitivity, specificity and accuracy results.

The proposed method presents a state-of-art performance according to the other previous techniques in terms of sensitivity values. Table 3 shows another comparison between the performance of the proposed method and previous study presented by A. Elmoufidi [17], one can noticed the convergent values for accuracy results for the two methods and this ensures the effectiveness and robustness of the suggested CNN architecture method

Table 2. A comparison between the proposed method and other related techniques

Reference	Classifier	Dataset	Sensitivity %	Specificity %	Accuracy %
A.Diaz-Pinto et al. [10]	Xception architecture	ACREMA	68.93	70.20	70.21
S. Sreng et al. [14]	CNNs + transfer learning		NR*	NR*	99.53
	CNNs features + SVM		NR*	NR*	96.23
A.Elmoufidi et al. [17]	CNNs features + SVM		98.87	98.98	98.92
The Proposed Method	CNNs features		99.63	98.53	99.07
A.Sinha et al. [15]	LeNet architecture	Eye cancer and uveal melanoma image databases.	NR*	NR*	97
X. Luo et al. [16]	CNN+Adam optimizer	OIA-ODIR	NR*	NR*	91.41
A.Patra et al. [19]	MVE +SVM+RF+MLP	REFUGE+ORIGA	NR*	NR*	94.17
A.Serener et al. [9]	ResNet-50+ GoogleNet DCNN	RIM-ONE	NR*	NR*	81
A.U. Rehman at al. [18]	DCNN	ACREMA ORIGA-light RIM-ONE AFIO HMC	99.1	99.4	99.3

NR*= Not Reported

Table 3. A comparison between the proposed method and [17] for Epoch values 50 and 100

Reference	Epoch values	Accuracy
A.Elmoufidi et al. [17]	50	0.9824
	100	0.9905
The Proposed Method	50	0.9904
	100	0.9911

6. Conclusion

In the current research, a deep neural network model with convolutional and classification layers have executed upon ACRIMA dataset to detect and classify glaucoma eye disease. The role of the dropout layer affects upon classification procedure and hence a robust CNN model resulted such that the proposed method succeeded at final in classifying glaucoma and yielded highest values in comparison with other methods in terms of sensitivity. Results gave a state-of-art performance in classifying glaucoma and recorded a value of 99.63% for sensitivity. The difficulties in recognizing glaucoma were resolved in the current work by the suggested models of CNN architcheure. More studies need to be investigated in the future to adopt other techniques and dataset images to solve the difficulties in diagnosing other eye conditions.

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References

[1] "World report on vision," Who.int, 08-Oct-2019. Available: https://www.who.int/publications/i/item/world-report-on-vision.
[2] Y.-H. Wang, C. Huang, Y.-L. Tseng, J. Zhong, and X.-M. Li, "Refractive error and eye health: An umbrella review of meta-analyses," Front. Med. (Lausanne), vol. 8, 2021.
[3] D. Križaj, What is glaucoma? University of Utah Health Sciences Center, 2019.
[4] J. Serey et al., "Pattern recognition and deep learning technologies, enablers of industry 4.0, and their role in engineering research," Symmetry (Basel), vol. 15, no. 2, p. 535, 2023.
[5] A. M. Taha, Q. M. M. Zarandah, B. S. Abu-Nasser, Z. K. D. Al Kayyali, and S. S. Abu-Naser, "Gender prediction from retinal fundus using deep learning," Philarchive.org. Available: https://philarchive.org/archive/TAHGPF
[6] "Visual processing: Eye and retina (section 2, chapter 14) neuroscience online: An electronic textbook for the neurosciences," Tmc.edu. Available: https://nba.uth.tmc.edu/neuroscience/m/s2/chapter14.html.
[7] "Anatomy Eye Cross Section View Fundus: vector de stock (libre de regalías) 177901772," Shutterstock. Available: https://www.shutterstock.com/image-vector/anatomy-eye-cross-section-view-fundus-177901772.
[8] T. Kohler, A. Budai, M. F. Kraus, J. Odstrcilik, G. Michelson, and J. Hornegger, "Automatic no-reference quality assessment for retinal fundus images using vessel segmentation," in Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems, 2013.
[9] A. Serener and S. Serte, "Transfer learning for early and advanced glaucoma detection with convolutional neural networks," in 2019 Medical Technologies Congress (TIPTEKNO), 2019.
[10] A. Diaz-Pinto, S. Morales, V. Naranjo, T. Köhler, J. M. Mossi, and A. Navea, "CNNs for automatic glaucoma assessment using fundus images: an extensive validation," Biomed. Eng. Online, vol. 18, no. 1, p. 29, 2019.
[11] M. R. Hossain, S. Afroze, N. Siddique, and M. M. Hoque, "Automatic detection of eye cataract using deep convolution neural networks (DCNNs)," in 2020 IEEE Region 10 Symposium (TENSYMP), 2020.
[12] R. Krishnan, V. Sekhar, J. Sidharth, S. Gautham, and G. Gopakumar, "Glaucoma detection from retinal fundus images," in 2020 International Conference on Communication and Signal Processing (ICCSP), 2020.
[13] M. Aljazaeri, Y. Bazi, H. AlMubarak, and N. Alajlan, "Faster R-CNN and DenseNet regression for glaucoma detection in retinal fundus images," in 2020 2nd International Conference on Computer and Information Sciences (ICCIS), 2020.
[14] S. Sreng, N. Maneerat, K. Hamamoto, and K. Y. Win, "Deep learning for optic disc segmentation and glaucoma diagnosis on retinal images," Appl. Sci. (Basel), vol. 10, no. 14, p. 4916, 2020.
[15] A. Sinha, Aneesh, and Nazneen, "Eye tumour detection using deep learning," in 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII), 2021.

[16] X. Luo, J. Li, M. Chen, X. Yang, and X. Li, “Ophthalmic disease detection via deep learning with a novel mixture loss function,” IEEE J. Biomed. Health Inform., vol. 25, no. 9, pp. 3332–3339, 2021.
[17] A. Elmoufidi and S. Jai-andaloussi, “CNN with Multiple Input for automatic glaucoma assessment using Fundus Images,” Research Square, 2021.
[18] A. U. Rehman, I. A. Taj, M. Sajid and K. S. Karimov, "An ensemble framework based on deep CNNs architecture for glaucoma classification using fundus photography", Math. Biosci. Eng., vol. 18, no. 5, pp. 5321-5346, Jun. 2021.
[19] A. Patra, A. Nandi, M. Z. Lazarus, and S. Lenka, “An Ensemble Framework for Glaucoma Classification Using Fundus Images,” in Soft Computing: Theories and Applications, R. Kumar, A. K. Verma, T. K. Sharma, O. P. Verma, and S. Sharma, Eds., in Lecture Notes in Networks and Systems. Singapore: Springer Nature, 2023, pp. 573–588.
[20] M. M. Taye, “Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions,” Computation (Basel), vol. 11, no. 3, p. 52, 2023.
[21] D. Liciotti, M. Bernardini, L. Romeo, and E. Frontoni, “A sequential deep learning application for recognising human activities in smart homes,” Neurocomputing, vol. 396, pp. 501–513, 2020.
[22] R. Ramya, A. Anandh, K. Muthulakshmi, and S. Venkatesh, “Gender recognition from facial images using multichannel deep learning framework,” in Machine Learning for Biometrics, Elsevier, 2022, pp. 105–128.
[23] M. Aamir et al., “An adoptive threshold-based multi-level deep convolutional neural network for glaucoma eye disease detection and classification,” Diagnostics (Basel), vol. 10, no. 8, p. 602, 2020.
[24] Figshare.com. Available: https://figshare.com/s/c2d31f850af14c5b5232.
[25] J. Shreffler and M. R. Huecker, Diagnostic testing accuracy: Sensitivity, specificity, predictive values and likelihood ratios. StatPearls Publishing, 2023.
[26] O. M. S. Ali, A. A. D. Al-Zuky, and F. E. M. Al-Obaidi, “R-CNN auto-system for detecting text road signs in Baghdad,” IEIE Trans. Smart Process. Comput., vol. 13, no. 2, pp. 140–147, 2024.
[27] S. J. Shahbaz, A. A. D. Al-Zuky, and F. E. M. Al-Obaidi, “Traffic sign recognition by the use of speed up robust features,” in 2nd International Conference of Mathematics, Applied Sciences, Information and Communication Technology, 2023.
[28] S. J. Shahbaz, A. A. D. Al-Zuky, and F. E. M. A.-D. Al-Obaidi, “Evaluation of object detectors in recognizing crossroad intersection triangle sign,” Indones. J. Electr. Eng. Comput. Sci., vol. 29, no. 2, p. 890, 2023.