ARTICLE
JOURNAL OF UNIVERSITY OF BABYLON
For Pure and Applied Sciences (JUBPAS)
Vol.30; No.3.| 2022

Classifying Three Stages of Cataract Disease using CNN

Hind Hadi Ali[1], Ali Yakoob Al-Sultan[2] and Enass Hamood[3]
[1]College of Science for Women, University of Babylon, hind.hussaien.gsci20@student.uobabylon, Hilla, Babil, Iraq.
[2]College of Science for Women, University of Babylon, wsci.ali.yakoob@uobabylon.edu.iq, Hilla, Babil, Iraq.
[2]College of Education for pure science, University of Babylon, pure.anas.ehmod@uobabylon.edu.iq, Hilla, Babil, Iraq.
***Corresponding author email:** wsci.ali.yakoob@uobabylon.edu.iq; mobile: 07832406409

تصنيف ثلاثة مراحل لمرض عتمة العين باستخدام الشبكة العصبية التلافيفية

ايناس حمود محيسن[3]، علي يعقوب السلطان[2]، هند هادي علي[1]
[1] كلية العلوم للبنات، جامعة بابل، hind.hussaien.gsci20@student.uobabylon بابل، العراق
[2]كلية العلوم للبنات، جامعة بابل، wsci.ali.yakoob@uobabylon.edu.iq بابل، العراق
[3] كلية التربية للعلوم الصرفة، جامعة بابل، pure.anas.ehmod@uobabylon.edu.iq بابل، العراق

Received:	6/8/2022	Accepted:	25/9/2022	Published:	30/9/2022

ABSTRACT

Among the many diseases that affect the retina, a cataract. It is one of the most serious pharmacological public health issues in developing nations, it can develop without causing any symptoms. It is one of the prime reasons for blindness or blurred vision for senior citizens. Therefore, accurate and early detection of cataracts depending on the severity of the condition is required to preserve vision and prevent the global increase in blindness caused by cataracts. As with most of the diseases related to the eyes, treatments, and early diagnosis have been shown to prevent visual loss and blindness. Compared with the manual diagnostic methods, automated retinal analysis systems help save patients' time, vision and cost. Artificial intelligence-based cataract detection methods have gained a lot of attention in the scientific community. This research produces an efficient and robust method for the automatic diagnosis of cataract by using Convolution Neural Network (CNN) for detection and classification cataract grading automatically in fundus images. It used Adam optimizer and (ODIR) dataset to train the model. The suggested method beats state-of-the-art cataract detection systems with an average accuracy of 100 % for two classes (Normal, Cataract) ,96.9% for four classes (Normal, Mild, Moderate, Sever) according to experimental results.

Materials and Methods:

Used Convolution Neural Network for detection and classification cataract grading automatically in fundus images.

Results:

The suggested method beats state-of-the-art cataract detection systems with an average accuracy of 100 % for two classes (Normal, Cataract) ,96.9% for four classes (Normal, Mild, Moderate, Sever) according to experimental results.

Conclusion:

The proposed network looked at different layers, activation functions, loss functions, and optimization algorithms in order to reduce computing costs while maintaining model accuracy. The proposed system used multi-image augmentation methods, then implemented the system on these augmented images to decrease the issue of overfitting and to improve the efficiency of the suggested system, as best accuracy obtained for classification 96.9 percent was get for fundus images which augmented of ODIR dataset, but only 94 percent when the system was applied to the original fundus images. When compared to other similar works, this system performed admirably. Because this approach was extremely cost- effective, accurate, and ophthalmologists, time-efficient were able to detect cataract more quickly and accuracy with fewer parameters and less computer power. In retinal fundus images, the suggested approach is able to detect cataract phases. The detection of cataract stages (mild, moderate, and severe) will be done by the DCNNs system.

Key words:

Cataract disease, Automatic Detection, Retinal Images.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com
مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل

الخلاصة

مقدمة:

من بين العديد من الأمراض التي تصيب شبكية العين هو الساد . يعتبر مرض الساد من أخطر مشاكل الصحة العامة الدوائية في الدول النامية. يمكن أن يحدث دون التسبب في أي أعراض. وهو يعتبر أحد الأسباب الرئيسية للعمى أو عدم وضوح الرؤية لكبار السن. لذلك ، فإن الاكتشاف الدقيق والمبكر لإعتام عدسة العين حسب شدة الحالة مطلوب للحفاظ على الرؤية ومنع الزيادة العالمية في العمى الناجم عن إعتام عدسة العين. كما هو الحال مع معظم الأمراض المتعلقة بالعيون، فقد ثبت أن العلاجات والتشخيص المبكر يمنعان فقدان البصر . و بالمقارنة مع طرق التشخيص اليدوية، تساعد أنظمة تحليل الشبكية الأوتوماتيكي في تقليل وقت للمرضى وتقليل التكلفة. اكتسبت طرق الكشف عن مرض عتمة العين المبنية على استخدام الذكاء الاصطناعي اهتمامًا كبيرًا في المجتمع العلمي. ينتج هذا البحث طريقة فعالة وقوية للتشخيص التلقائي لإعتام عدسة العين باستخدام الشبكة العصبية التلافيفية (CNN) لاكتشاف وتصنيف الساد تلقائيًا في صور قاع العين. يستخدم محسن آدم ومجموعة بيانات (ODIR) لتدريب النموذج. تتفوق الطريقة المقترحة على أحدث أنظمة الكشف عن المياه البيضاء بمتوسط دقة 100٪ لفئتين (عادي، إعتام عدسة العين)، 96.9٪ لأربع فئات (عادي، خفيف، معتدل، شديد) وفقًا للنتائج التجريبية.

طرق العمل:

باستخدام شبكة Convolution العصبية (CNN) لاكتشاف وتصنيف إعتام عدسة العين تلقائيًا في صور قاع العين..

الاستنتاجات:

حيث يقترح هذا البحث نظام التشخيص الآلي لإعتام عدسة العين باستخدام الشبكة العصبية العميقة (DCNN). تمت معالجة مجموعة بيانات الساد لصور قاع العين مسبقًا وتحسينها لجعل مجموعة البيانات أكثر ملاءمة لتغذية الشبكة العميقة في البداية. تعمل الشبكة المقترحة في طبقات مختلفة، ودوال التنشيط ، ودوال الخسارة، وخوارزميات التحسين من أجل تقليل تكاليف الحوسبة مع الحفاظ على دقة النموذج. استخدم النظام المقترح طرق تكبير متعددة للصور ، ثم طبق النظام على هذه الصور المعززة لتقليل مشكلة فرط التجهيز وتحسين كفاءة النظام المقترح ، حيث تم الحصول على أفضل دقة لتصنيف 96.9 بالمائة لصور قاع العين التي تمت زيادتها قاعدة بيانات ODIR ، ولكن بنسبة 94 في المائة فقط عند تطبيق النظام على صور قاع العين الأصلية. عند مقارنته بأعمال أخرى مماثلة، كان أداء هذا النظام رائعًا. نظرًا لأن هذا النهج كان فعالًا للغاية من حيث التكلفة وتوفير الوقت اللازم لطبيب العيون، فقد كان فعالاً من حيث الوقت، قادراً على اكتشاف إعتام عدسة العين بشكل أسرع ودقيق مع عدد أقل من المعاملات المستخدمة في الشبكة وطاقة كمبيوتر أقل. كذلك في صور قاع الشبكية، فإن الطريقة المقترحة قادرة على اكتشاف مراحل الساد. وتم الكشف عن مراحل إعتام عدسة العين (خفيفة، معتدلة، وشديدة) بواسطة نظام DCNNs المقترح.

الكلمات المفتاحية:

مرض الساد، الكشف التلقائي ، صور الشبكية.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

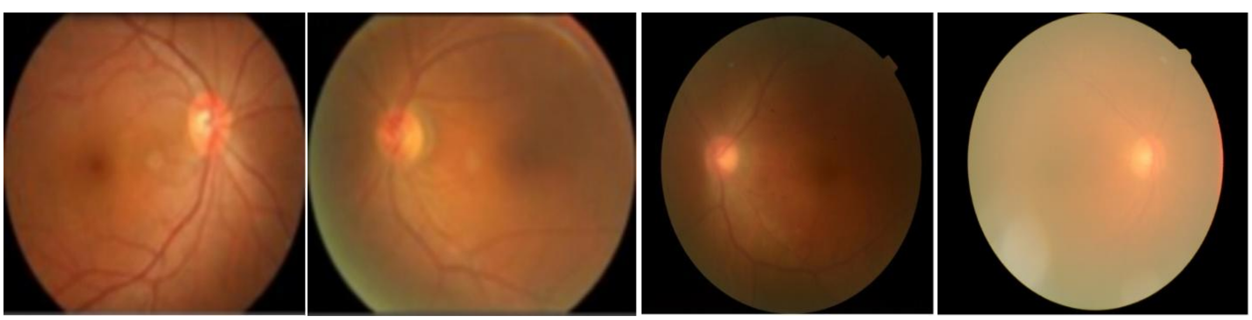
Introduction

The human eye is a complex system made up of interconnected organs such as the lens, retina, iris, pupil, optic nerve, and cornea [1]. There are several diseases (ocular diseases) related to different components of the eye; Cataract is among the most common ones [2, 1]. When ocular diseases are diagnosed late, it is difficult to effectively repair vision, which can lead to vision loss [1]. Despite the fact that cataract can be cured [2], it is still one of the major issues in pharmacological public health in both developed and developing countries [3, 4, 5, 6, 7, 8, 9], It is also the leading cause of blindness the majority of countries [9, 1, 10]. Studies show that 36 million people worldwide have blindness, and more than 12 million cases are diagnosed with cataract [5, 8]. It is expected that this number will rise to 13.5 million people in 2025 [8, 9]. In 2015, about 3 million cataract surgeries were performed in the United States alone [2, 4]. Given the large number of people affected and the associated healthcare costs, determining the presence and severity of cataracts is critical for diagnosing and monitoring the disorder's progression [4, 5, 6, 7, 8].

There are three levels of cataract:)1) Mild, (2) Moderate, and (3) Sever [11]. As seen in Figure (1).

Where Figure (1.a) shows a normal eye. Presents a healthy retina, in which the optic disc, main vessels, capillary vessels, and even choroid can be clearly observed. Figure (1.b) shows an eye with cataract in early stage. where the optic disk and main vessels are visible, while the choroid and capillary vessels are only faintly visible. Figure (1.c) shows intermediate stage in cataract disease. Where only the main blood vessels and optic disc are visible. While Figure (1.d) shows the late stage, where no retinal structures can be observed.

With more severe cataracts, it is possible to see fewer retinal structures.



(a) **(b)** **(c)** **(d)**

Figure (1) Image for Normal and Cataract stages. a) normal, b) Mild, c) Moderate and d) sever Cataract retinal.

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل
ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

Traditional image feature extraction approaches are limited by the researchers' prior experience. Deep learning algorithms have advanced exponentially in computer vision in recent years, with vastly improved results when compared to traditional approaches. The model of convolutional neural network (CNN) is interesting because of Its high representation efficiency compensates for the shortcomings of traditional feature extraction techniques. CNNs can automatically obtained high-level image feature knowledge and have demonstrated promising results in object detection, image recognition, and other areas.

2. Related Works

A number of studies have been conducted to cover the most related work and to provide a summary of the work for detection of cataract. The suggested cataract detection system can be implemented using the bypass neural network (CNN) algorithm. In the following, the description of this research:

- S. Jayachitra , et al. in 2021 introduced cataract disease classification using U-Net to detect and grad cataract automatically. The obtained accuracy is 93.5% [12] .
- Turimerla Pratap, et al. in 2019 introduced a way by utilized a pre-trained CNN as transfer learning for classification cataract automatically. The final classification was carried out using feature extraction, and an SVM classifier. The four-stage classification accuracy obtained is 92.91% [13].
- Md Rajib Hossain, et al. in 2020 suggested detection system for cataract using (DCNNs). Experimental result shows that the proposed system can detect eye cataract with best accuracy: 95.77% [14].
- Ely Sudarsono, et al. in 2020 introduced cataract detection system by classify the fundus image of cataract using CNN and optimize it using diffGrad optimizer. The classes are normal fundus images and cataract fundus images with accuracy 97.5% [15].
- Mas Andam Syarifa, et al. in 2020 introduced cataract detection system by classify the fundus image of cataract using CNN and optimize it using diffGrad optimizer. The classes are normal fundus images and cataract fundus images with accuracy 97.5% [16].
- Weni, et al. in 2021 using a deep learning, (CNN) which is used for pattern recognition which can help to classify images automatically . When using the epoch value equal 50, reached accuracy 95% which represent the highest value [17].
- Ram ,et al, In 2020 used the deep convolutional neural network topology with N-Way fully connected layers. This investigation's main emphasis was on the classification of normal, cataract, AMD, and myopia. As the network's feature extraction component (i.e. the convolutional net) is trained, the feature mapping component (i.e. the linear net) of the network is also trained to different specifications. The greatest level of accuracy obtained was (0.819), and the highest level of specificity was (0.663), with a sensitivity of (0.714), and a specificity of (0.663) [18].

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

- Islam ,et al, In 2019 introduced new technique for identifying malignant tumours. The convolutional neural network (CNN) has been used to diagnose eight different kinds of eye disorders, and the performance of the CNNs has been assessed. Some standard pre-processing is carried out before the data is transmitted to the network for rigorous categorization to be carried out. The greatest level of accuracy was obtained with an F-score of (0.85), a Kappa score of (0.31), and the value of AUC (0.80). [19]
- Jing ,et,al. in 2020 at this method one or more fundus diseases may be diagnosed based on CNN-style model imaging of fundus images that does not need any extra labeling information. The first half of the solution relies on an efficient net-based feature extraction network, while the second half is a customized classification neural network that is suitable for multi-label classification scenarios. Finally, in order to determine the final recognition result, multiple models' output probabilities are merged. Then producing satisfactory results. (0.89) Accuracy, Recall is (0.58). AUC is (0.73). and Precession is (0.63) [20].

- Cao Lvchen, et al. in 2020[21]: Offered an automated cataract detection method using the Haar wavelet which improved based on the properties of retinal images. Retinal images of normal (non-catarac)t, as well as mild, moderate, and severe cataracts, are recognized automatically using the improved Haar wavelet. The accuracies of the two-class classification (cataract and non-cataract) and four-class classification are 94.83% and 85.98%, respectively.
- Linglin Zhang, et al. in 2017 [22]: Introduced a way of classification of cataract disease using Deep Convolution Neural Network (DCNN) to detect and grad cataract automatically. The best accuracy, this method achieved, is 93.52% and 86.69% in cataract detection and grading tasks separately.

This paper aim to suggest automatic system which be able to detect cataract disease by classification fundus images to (Normal) and (mild, moderate and severe) which represent the grading of cataract severity using retinal images.

3. Methodology

The proposed system is divided into three steps. **The first stage** (preprocessing stage) involves performing the Augmentation method on the dataset, color images converting to greyscale images, altering the size of the image to (256*256) pixels , and using (Mean Filtering) to reduce noise.The contrast will advanced by using the contrast limited adaptive histogram equalization (CLAHE) approach, then divide the photo's pixels by 255 to scale them (normalization). **The second stage** involves utilizing CNN to extract features from many fundus images in order to identify them, and the **third stage** involves classifying fundus images (based on previously recovered features) as (Normal, Mild, Moderate, and Sever). Figure (2) depicts the proposed system.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

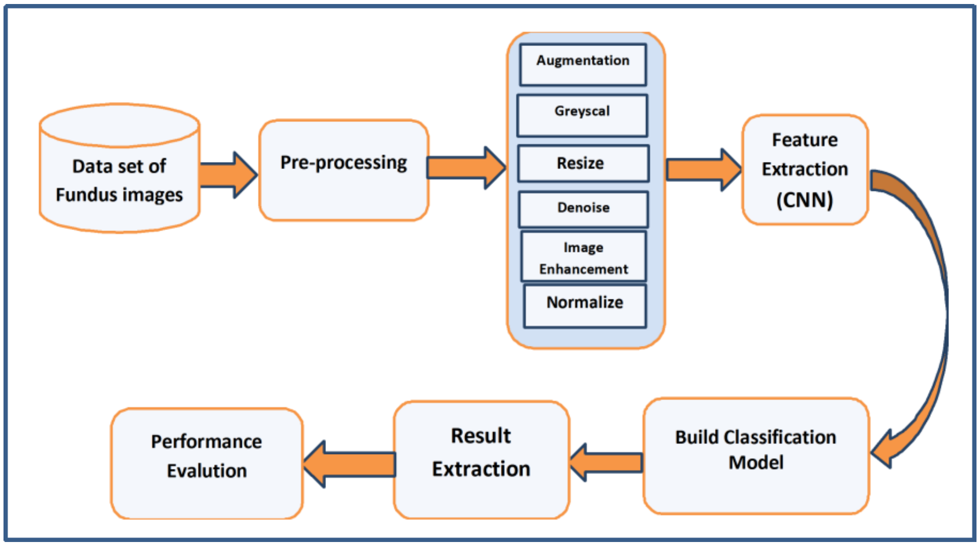


Figure (2): Our approach methodology is depicted in this figure in broad strokes.

3.1 Ocular Disease Intelligent Recognition (ODIR)

(**ODIR**) is a well-organized ophthalmic database of 5,000 patients with age, colour fundus photographs for left and right eyes and doctors' diagnostic keywords from doctors.This dataset represents the "real-life" set of patient information collected by Shanggong Medical Technology Co., Ltd. from different hospitals/medical centres in China. In these institutions, fundus images are captured by various cameras in the market, such as Canon, Zeiss and Kowa, resulting in varied image resolutions. Trained human readers labelled annotations with quality control management. They classify patient into many (eight) classes, including: [Cataract (C(- Diabetes (D) - Glaucoma (G) - Normal (N) - Age-related Macular Degeneration (A) - Hypertension (H) - Pathological Myopia (M) - Other diseases/abnormalities (O( ].This paper is concentrated on one type of eye disease, Cataract. This database contains 512 fundus images (212 Cataract images and 300 Normal images).Cataract fundus images divided into (51 Mild, 61 Moderate, and 100 Sever) .The dataset is divided into a training and a testing data set. The statistics for dividing the data set are shown in table (1), and they used this data set in a variety of studies.

Table (1) shows dividing ODIR data set

	Normal	Mild	Moderate	Sever	Total
Train	210	35	42	70	357
Test	90	16	19	30	155
Total	**300**	**51**	**61**	**100**	**512**

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية
ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

3.2. Pre-processing Stage

The pre-processing stage is important in cataract detection system. It has been performed on fundus images of dataset to make dataset suitable for training process and to initialize it for the extract the feature. It consist of five steps: Data Augmentation method, convert color fundus images to Gray-Scale images for reduction of data and to speed the processing, resize images to (256*256) pixels, and apply mean filter on the images, fundus images enhancement using CLAHE technology execute the normalization, and finally perform normalization by dividing by 255.

3.2.1 Data Augmentation Step

This step is used in the pre-processing stage to increase the proposed system's efficiency for precise evaluation. It increases the dataset by supplying more images to be used in the training and testing stages. Moreover, it will tackle the problem of overfitting. The observed influence of four common Data Augmentation techniques on the original dataset has been presented and these techniques are: **Horizontal Flip, Zoom Range, Rotation Range and Fill Mode.**

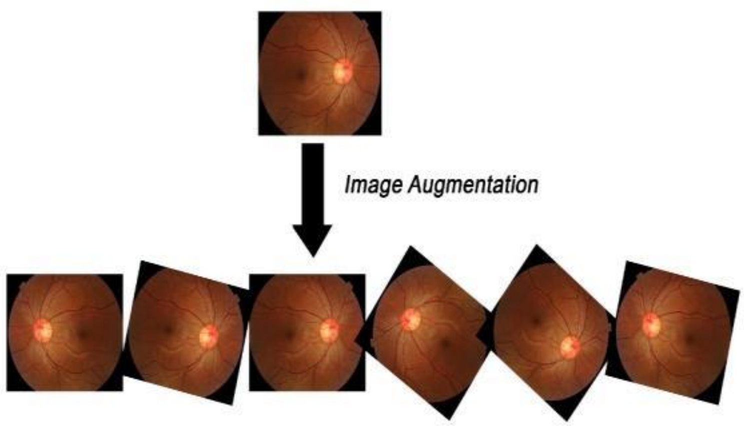


Fig s [17].

Table (2) shows fundus images after the data augmentation is applied on ODIR datasets.

Table (2) Statistics of fundus images divide for ODIR dataset after Augmentation.

	Normal	Mild	Moderate	Sever	Total
Train	**420**	70	84	140	714
Test	**180**	32	38	60	310
Total	**600**	**102**	**122**	**200**	**1024**

3.2.2 Images Converting to Grayscale Step

The data set's initial images as colored images. In other words, the image is represented by three channels (RGB).This will lengthen the time it takes to process the photographs. However, each channel has the characteristics required for this project. As a result, all of the photos are transformed to greyscale to speed up the process while maintaining the needed properties.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل

3.2.3 Image Resize Step

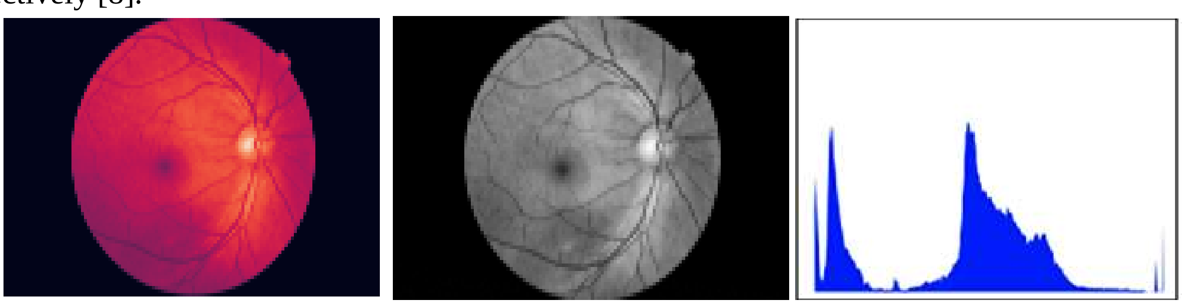
We can define a unified (standard) size for all photographs supplied to chosen AI algorithms because the size of the majority of images captured by a camera and provided to variety of chosen AI algorithm. The fundus images have been scaled down to (256 × 256) pixels in size.

3.2.4 Remove noise (De-noise) Step

During the collection and transmission of images, noise is introduced. The important and major step in the concept of image processing is picture enhancement. It is used to improve the image's quality and brightness. Furthermore, Average (Mean) Filtering, is one of the suitable filters, which used to eliminate noise. The mean filter is a filtering mechanism that is linear in nature. The picture data is smoothed with the mean filter. The performance of each pixel mask is averaged to create unique pixels depend on the itensity value of other pixels; thus, it is known as an mean filter. This mean filter is used to reduce grain noises mostly in images which be photographic .

3.2.5 Images Enhancement Step

The goal of the major image enhancement technique is to handling a selected images ,so that the result is more improved than the source image , this can happen by enhancing the differences between the image's specifics ,observing that the process of improvement(enhancement) is happen after the image process of correction it is completed when deleting the noise of the image. The limited-contrast adaptive histogram equation (CLAHE) technique was used to pre-treat the fundus pictures in this step, CLAHE is a contrast enhancement method that increases image contrast effectively [8].



(a) (b) (c)

Figure (4). Image pre-processing is the suggested technique.Input color fundus image (b) Contrast enhancement of grayscale image (c)the image's histogram having better contrast after CLAHE enhancement.

3.2.6 Normalization Step

It a fundamental step in the images pre-processing. Due to the fact that the CNN receives and processes the images in the range of [0-1]. In order to achieve this result, each pixel is rescaled from the range [0-255] into [0-1] by dividing each pixels by the value of 255.

3.3 Feature Extraction.

It describes pertinent shape data in a pattern, so that model classification becomes easy through a formal procedure. At the recognition of pattern and the processing of image, a feature extraction is a distinct type of dimensional reduction. The primary purpose of feature extraction is to discover most important data from the source data after that with fewer dimension spaces this information will represent. The proposed system will be classified depend on the features extracted.

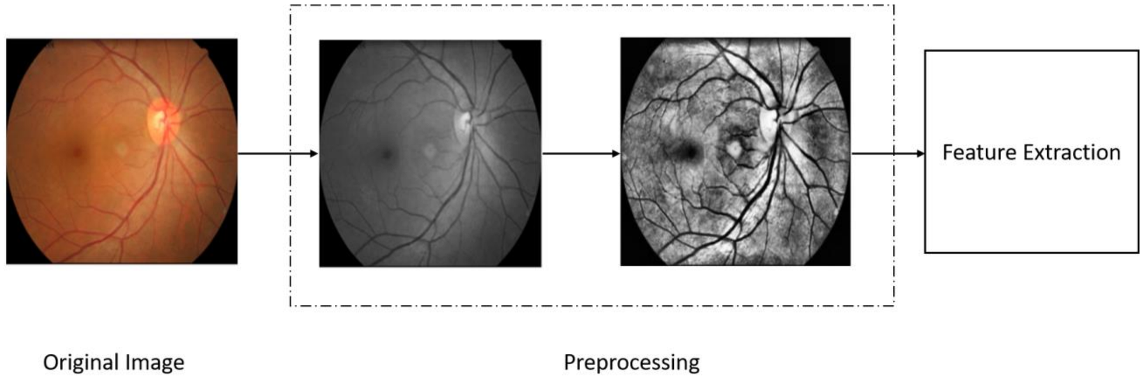


Figure 5. The procedures of extract features from fundus images after preprocessing [26].

Some fundus images of cataract have certain characteristics such as, optic disc, main vessels, capillary vessels, and even choroid. Cataracts develop gradually and can be partial or complete, as well as progressive or stationary. To obtain the optimal procedure for feature extraction, the design of CNN includes various layers. Table (3) the proposed CNN structure, the input and output sizes are described in (row × column × feature maps). The filter size is specified as (row × column).

Table (3) CNN structure for proposed system.

Layer name	Input Layer	Output Layer	Filter Size, Stride
Convolution 1 + ReLU	(256, 256, 1)	(256, 256, 16)	(3×3),1
Max Pooling1	(256, 256, 16)	(128, 128, 16)	(2×2), 2
Convolution 2 + ReLU	(128, 128, 32)	(128, 128, 32)	(3×3), 1
Max Pooling2	(128, 128, 32)	(64, 64, 32)	(2×2), 2
Convolution 3 + ReLU	(64, 64, 64)	(64, 64, 64)	(3×3), 1
Max Pooling3	(64, 64, 64)	(32, 32, 64)	(2×2), 2
Dropout(0.2)	/	/	/
Fully connected layer (Flatten)	(32, 32, 64)	65536	/
Dense layer 1 (128)	65536	258	/
Dense layer 2 (2) SoftMax	258	4	/

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل

ISSN: 2312-8135 | Print ISSN: 1992-0652

info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

The CNN using multiple convolutions layers and Max Pooling layer to know the important characteristics found in photos of the eye fundus, The feature extraction structure will be as follows: Convolutional layers is the first layer contains 16 filters, the filter size is (3,3), and without padding, followed by activation function (ReLU), after which we use Max Pooling layer with a (filter size= (2,2), strides= (2,2)). Next, we use another Convolution layers (the second Convolutional layer contains 32 filters), the filter size for the first and second layers = (3,3), the padding = same, followed by (ReLU) activation function then comes the Max pool layer with filter size = (2,2), steps = (2,2)). Also, it has one Convolution layer (contains 64 filters), size filters = (3,3), padding = same, followed by a Max Pooling layer (Filter Size = (2,2), steps = (2,2)), Followed by the Dropout layer = (0.2), followed by the Flatten layer. The map of feature matrix will be transformed to only a single column (vector) of values by this layer. Then Dense 1ayer in which the number of units (size of output layer) will be 128, finally Dense_layer in which the number of units will be four (Normal, Mild, Moderate, and Sever) classes and the activation function which used (Softmax). Fig. (6) shows the scheme of the CNN architecture:

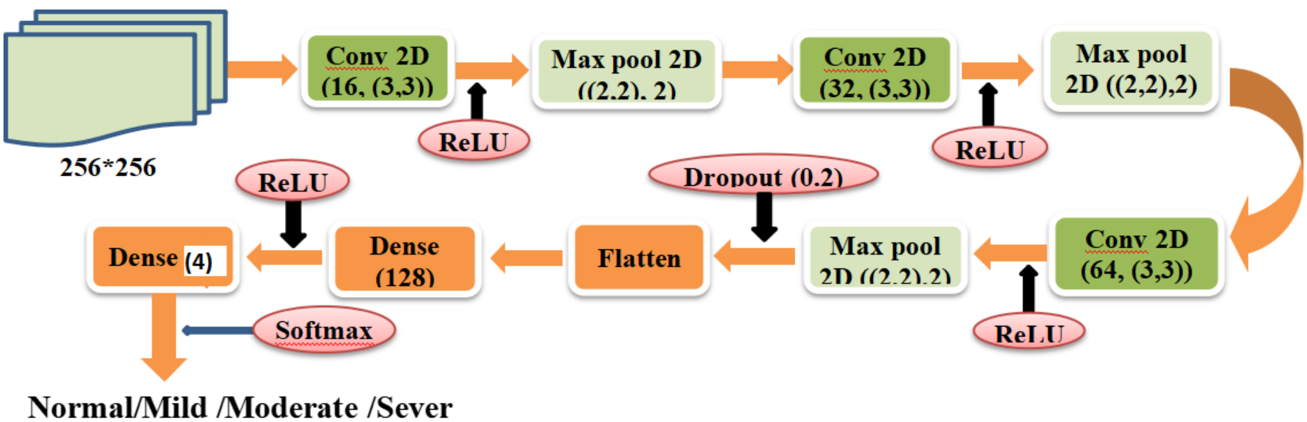


Figure (6) CNN architecture.

An activation function is used after each convolutional layer (Rectified Linear Unit (ReLU)). ReLU is a nonlinear piece wise function, it will be output directly if the input is positive. Otherwise, it will return a value of zero. Many types of neural networks (NN) now use it as their default activation function. Because a model that employs it is simpler to train and frequently provides superior results , as shown in figure (7).

JOURNAL OF UNIVERSITY OF BABYLON
For Pure and Applied Sciences (JUBPAS)
Vol.30; No.3.| 2022

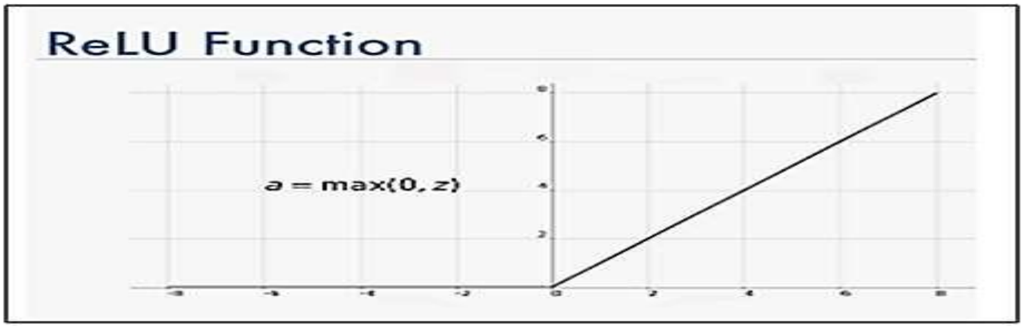


Figure (7) The ReLU activation function

Max Pooling: It is the layer which introduce the approaches for reducing feature maps in order to obtain more apparent features and reduce overfitting. Average and Max pooling are the two most common types of pooling .The Max value for neurons group in the previous layer is used in Max pooling, whereas the Average pooling used average value [23].The Max-pooling attribute was employed in the proposed work to minimize feature maps arising from prior layers [24], as shown in Figure (8).

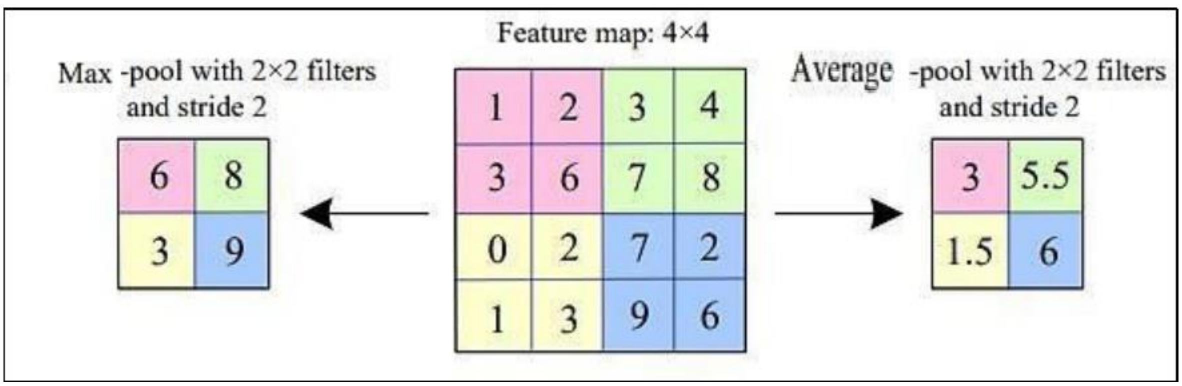


Figure (8) explain pooling operation with (2×2)size of kernel , stride is 2 [23][24]

3.4 Classification

Cataract diagnoses are made by extracting features from fundus images in a dataset in order to extract information will be the most significant from the raw data and characterize it in a space has fewer dimensions. A classification of cataract patients vs. normal is developed rely on these extracted features.There is a thick structural layer with an activation function that is completely connected after the Flatten layer (ReLU). The dense layer, which is utilized for categorization, is the final layer. As an activation function, SoftMax was utilized [25].

3.5 Evaluation Metrices

Performance is measured using a variety of metrics, including:

1. **Accuracy :**Whether the classification findings are favorable or negative, if the categorization is correct, success is accomplished.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية

$$\text{Acc} = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) \quad (1)$$

2. **Sensitevity** : the proportion of positive classes that are correctly labeled .

$$\text{Sen} = \left(\frac{TP}{TP + FN}\right) \quad (2)$$

3. **Specificity:** the proportion of correctly identified Cases that are negative .

$$\text{Spe} = \left(\frac{TN}{TN + FP}\right) \quad (3)$$

4. F1-score: For computing a balanced mean output, displays a combination of precision and sensitivity.

$$F1\_score \;\& = \frac{2TP}{2TP + FP + FN} \quad (4)$$

The classification is right of a correct diagnosis (healthy) categorized as Non-cataract (normal)) is a True Poseitive "TP", and the classification is false of a positive diagnosis (cataract categorized as Non_cataract (normal)) is a False Positive "FP", depending on the images of the eyes (in the (Kaggle and ODIR) datasets) are sampled and examined. True Negative "TN" is proper classification for negative diagnosis (cataract eye categorized as cataract), while False Negative 'FN" is the incorrect classification (Normal categorized cataract). [26]

The quality of the classification algorithm's predictions is measured in the rating report. Tables (4) shows the main classification criteria for the proposed model with ODIR dataset for four classes.

Table (4) The classification reports for ODIR dataset for 4 class.

	Precision	**Recal l**	**F1-score**	**Support**
Normal	0.88	0.97	0.92	30
Mild	0.94	0.79	0.86	19
Moderate	1.00	1.00	1.00	16
Sever	1.00	1.00	1.00	90
Accuracy	96.9		0.97	155

The model was evaluated on ODIR dataset: 70% from the dataset used to train the system (by adjusting Weights and Biases), and 30% from the dataset used to test the system (parameters is improving to get the performance will give best measures made by the system). Finally, utilizing the test results, the system was assessed independently. The (confusion matrix) for the features recovered by DCNN for ODIR datasets is shown in Figure (9).

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية

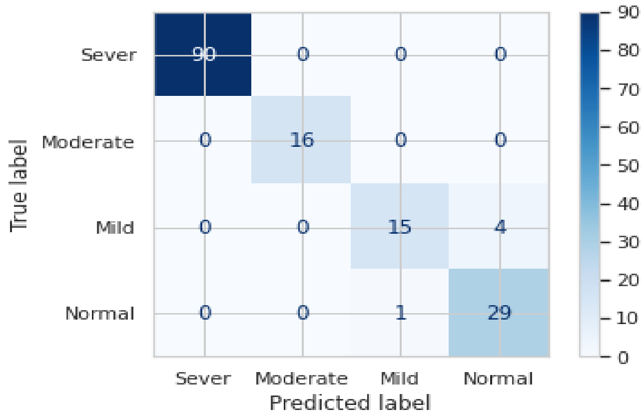


Fig (9) ODIR dataset's Confusion Matrix for4 class.

4.Results and Discussions

The best accuracy will receive from the proposed system which represented by confusion Matrix is Accuracy100%, Sensitivity 100% , specificity 100% by classification fundus images of ODIR dataset to (Normal or Cataract). Also, the best accuracy will receive from the proposed system which represented by Confusion Matrix is Accuracy 97%, Sensitivity100%, specificity 100% by classification fundus images of ODIR dataset to (Normal, Mild, Moderate, Sever). And the same think for ODIR dataset when classification fundus images to 4 class at fig (10) and (11) shown below:

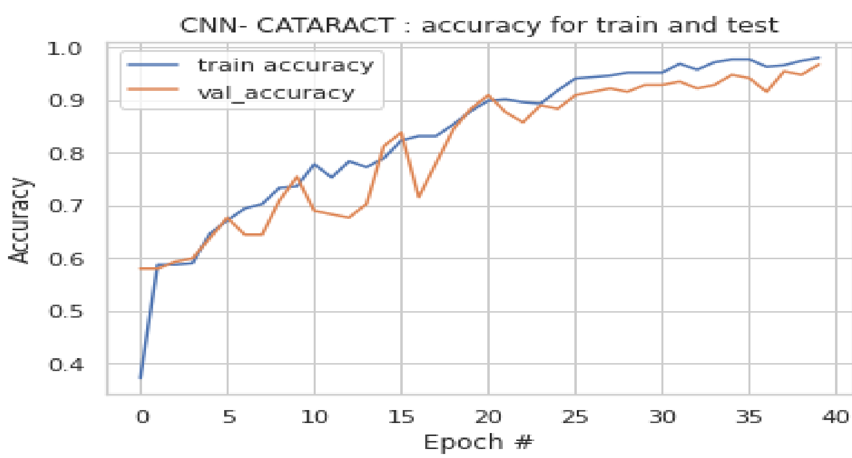


Figure (10) accuracy obtained of ODIR dataset at 4 class.

مـجلـة جـــامعة بـــابـل للعلـــوم الصـــرفـة والتطــبيقيـة مـجلـة جـــامعة بـــابـل للعلـــوم الصـــرفـة والتطــبيقيـة مـجلـة جـــامعة بـــابـل

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

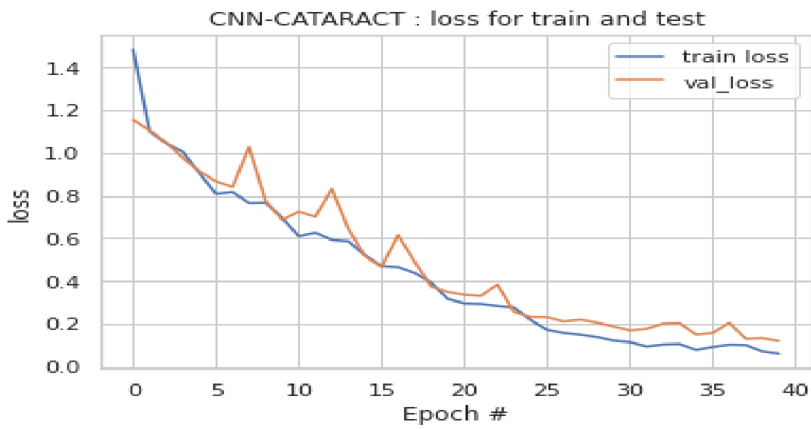


Fig. (11) Loss obtained of ODIR dataset at 4 class.

The graph represent (“accuracy” for train and test (valid) of ODIR dataset) is fig. (10) . And fig.(11) for (“loss function ”for train and test of ODIR dataset) shows fit and good result because as loss for train decreases (the gap between the actual and predicted result is represented by the loss function), we continue to train very well the proposed net to decrease the loss until have high accuracy and best weights .

Table (5) Comparison of various methods of cataract detection.

Authors	Techniques	Data set	Accuracy	AUC	Specificity	Sensitivity
Ram and Reyes et al., 2020 [18]	DCNN topology with N-Way fully connected layers.	**ODIR**	0.819	-	0.66	0.714
Islam et al., 2019 [19]	(CNN) has been used to diagnose eight different kinds of eye disorders.	**ODIR**	0.876	0.805	-	-
Jing et al.., 2020 [20]	CNN-style model imaging of fundus images that does not need any extra labeling information.	**ODIR**	0.89	0.73	-	-
Lvchen Cao1, et al 2020 [22]	This essay utilizes (the improved Haar wavelet).	**Local**	85.9	-	-	89.66
S. Jayachitra , et al. 2021 [12] (**Dense net**)	Dense net to detect and grad cataract automatically.	**Local**	89.5	-	82	75
S. Jayachitra, et al. 2021 [12] (**U net**)	U-Net to detect and grad cataract automatically.	**Local**	93.5		86	80

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

Linglin Zhang, et al. 2017 [22]	using Deep Convolution Neural Network (DCNN) to detect and grad cataract automatically	**Local**	84.9	-	86.9	78.7
Md. R. Hossain, et al **2020[14]**	This paper presents an eye cataract detection system using (DCNNs)	**Local**	95.77	96.25	98.07	94.43
Turimerla Pratap, ET Al. In 2019 [13]	CNN for feature extraction. Then the classification using SVM classifier	**Local**	92	-	-	-
Weni, et al. 2021 [17]	(CNN) classification into normal or cataract	**Local**	95	-	-	-
Ely Sudarsono. et al **2020 [15]**	CNN and optimize it using diffGrad optimizer into cataract and non-cataract	**Kaggle**	97.00	-	-	-
Mas A. Syarifa, et al **2020 [16]**	CNN and optimize it using Lookahead optimizer into cataract and non-cataract	**Kaggle**	97.00	-	-	-
Proposed method	**DCNN**	**ODIR**	**96.9**	**95.0**	**1.00**	**91.2**

5. Conclusion

This research proposes a Deep Convolution Neural Network (DCNN)-based automated cataract diagnosis system. A cataract data collection of fundus images was pre-processed and enhanced to make data set more suitable for feeding the deep network at first. The proposed network looked at different layers, activation functions, loss functions, and optimization algorithms in order to reduce computing costs while maintaining model accuracy. The proposed system used multi-image augmentation methods, then implemented the system on these augmented images to decrease the issue of overfitting and to improve the efficiency of the suggested system, as best accuracy obtained for classification 96.9 percent was get for fundus images which augmented of ODIR dataset, but only 94 percent when the system was applied to the original fundus images. When compared to other similar works, this system performed admirably. Because this approach was extremely cost- effective, accurate, and ophthalmologists, time-efficient were able to detect cataract more quickly and accuracy with fewer parameters and less computer power. In retinal fundus images, the suggested approach is able to detect cataract phases. The detection of cataract stages (mild, moderate, and severe) will be done by the DCNNs system.

Acknowledgments:

We thank college of Science for Women who provided insight and expertise that greatly assisted the research

Conflict of interests.

There are non-conflicts of interest.

References

[1] I. Shaheen, A. Tariq, F. Khan (Eds), M. Jan, and Alam M. Survey analysis of automatic detection and grading of cataract using diffferent imaging modalities. In Applications of Intelligent Technologies in Healthcare, EAI/Springer Innovations in Communication and Computing, page 35. Springer, 2019.

[2] H. Hashemi, E. Hatef, A. Fotouhi, A. Feizzadeh, and K. Mohammad. The prevalence of lens opacities in tehran: the tehran eye study. Ophthalmic epidemiology, 16(3):187, 2009.

[3] C. Cedrone, F. Culasso, M. Cesareo, R. Mancino, F. Ricci, G. Cupo, and L. Cerulli. Prevalence and incidence of age-related cataract in a population sample from priverno, italy. Ophthalmic Epidemiology, 6(2):95, 2009.

[4] T. Li, T. He, X. Tan, S. Yang, J. Li, Z. Peng, H. Li, X. Song, Q. Wu, F. Yang, et al. Prevalence of age-related cataract in high-selenium areas of china. Biological trace element research, 128(1):1, 2009.

[5] GE. Nam, K. Han, SG. Ha, BD. Han, D. H. Kim, Y. H. Kim, YG. Cho, K. Hand Park, and BJ. Ko. Relationship between socioeconomic and lifestyle factors and cataracts in koreans: The korea national health and nutrition examination survey 2008–2011. Eye, 29(7):913, 2015.

[6] R. Varma, M. Torres, Los Angeles Latino Eye Study Group, et al. Prevalence of lens opacities in latinos: the los angeles latino eye study. Ophthalmology, 111(8):1449, 2004.

[7] J. M. Yu, D. Q. Yang, H. Wang, J. Xu, Q. Gao, L. W. Hu, F. Wang, Y. Wang, Q. C. Yan, J. S. Zhang, et al. Prevalence and risk factors of lens opacities in rural populations living at two diffferent altitudes in china. International journal of ophthalmology, 9(4):610, 2016.

[8] S. R. Flaxman, R. RA Bourne, S. Resnikoffff, P. Ackland, T. Braithwaite, M. V. Cicinelli, A. Das, J. B. Jonas, J. Keeffffe, J. H. Kempen, et al. Global causes of blindness and distance vision impairment 1990–2020: a systematic review and meta-analysis. The Lancet Global Health, 5(12):e1221, 2017.

[9] H. Hashemi, R. Pakzad, A. Yekta, MR. Aghamirsalim, M. Pakbin, S. Ramin, and M. Khabazkhoob. Global and regional prevalence of age-related cataract: a comprehensive systematic review and meta-analysis. Eye, page 1, 2020.

[10] C. Xu, X. Zhu, W. He, Y. Lu, X. He, Z. Shang, J. Wu, K. Zhang, Y. Zhang, X. Rong, et al. Fully deep learning for slit-lamp photo based nuclear cataract grading. In International Conference on Medical Image Computing and Computer-Assisted Intervention, volume 11767, page 513, Shenzhen, China, 2019. Springer.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

[11] Campos, Gabriel Fillipe Centini, et al. "Machine learning hyperparameter selection for contrast limited adaptive histogram Equalization." EURASIP Journal on Image and Video Processing 2019.1 (2019): 1-18. doi.org/10.1186/s13640-019-0445-4 .

[12] Jayachitra, S., Kanna, K. N., Pavithra, G., & Ranjeetha, T. (2021, June). A Novel Eye Cataract Diagnosis and Classification Using Deep Neural Network. In Journal of Physics: Conference Series (Vol. 1937, No. 1, p. 012053). IOP Publishing.

[13] Pratap, T., & Kokil, P. (2019). Computer-aided diagnosis of cataract using deep transfer learning. Biomedical Signal Processing and Control, 53, 101533.

[14] Hossain, M. R., Afroze, S., Siddique, N., & Hoque, M. M. (2020, June). Automatic Detection of Eye Cataract using Deep Convolution Neural Networks (DCNNs). In 2020 IEEE Region 10 Symposium (TENSYMP) (pp. 1333-1338). IEEE.

[15] Sudarsono, E., Bustamam, A., & Tampubolon, P. P. (2020, November). An optimized convolutional neural network using diffgrad for cataract image classification. In AIP Conference Proceedings (Vol. 2296, No. 1, p. 020090). AIP Publishing LLC.

[16] Syarifah, M. A., Bustamam, A., & Tampubolon, P. P. (2020, November). Cataract classification based on fundus image using an optimized convolution neural network with lookahead optimizer. In AIP Conference Proceedings (Vol. 2296, No. 1, p. 020034). AIP Publishing LLC.

[17] Weni, I., Utomo, P. E. P., Hutabarat, B. F., & Alfalah, M. (2021). Detection of Cataract Based on Image Features Using Convolutional Neural Networks. Indonesian Journal of Computing and Cybernetics Systems), 15(1), 75-86.

[18] A. Ram and C. C. Reyes-Aldasoro, “The relationship between Fully Connected Layers and number of classes for the analysis of retinal images,” Apr. 2020, [Online]. Available: http://arxiv.org/abs/2004.03624, 2020.

[19] M. T. Islam, S. A. Imran, A. Arefeen, M. Hasan, and C. Shahnaz, “Source and Camera Independent Ophthalmic Disease Recognition from Fundus Image Using Neural Network,” in 2019 IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON), Nov. 2019, pp. 59–63, doi: 10.1109/SPICSCON48833.2019.9065162., 2019, pp. 59–63.

[20] J. Wang, L. Yang, Z. Huo, W. He, and J. Luo, “Multi-Label Classification of Fundus Images With EfficientNet,” IEEE Access, vol. 8, pp. 212499–212508, 2020, doi: 10.1109/ACCESS. 2020. 3040275, 2020.

[21] Cao, L., Li, H., Zhang, Y., Zhang, L., & Xu, L. (2020). Hierarchical method for cataract grading based on retinal images using improved Haar wavelet. Information Fusion, 53, 196-208.

[22] Zhang, L., Li, J., Han, H., Liu, B., Yang, J., & Wang, Q. (2017, May). Automatic cataract detection and grading using deep convolution neural network. In 2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC) (pp. 60-65). IEEE.

[23] J. He, C. Li, J. Ye, Y. Qiao, and L. Gu, ‘Multi-label ocular disease classification with a dense correlation deep neural network’, Biomed Signal Process Control, vol. 63, p. 102167, 2021.

[24] T. Islam, S. A. Imran, A. Arefeen, M. Hasan, and C. Shahnaz, ‘Source and camera independent ophthalmic disease recognition from fundus image using neural network’, in 2019 IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON), 2019, pp. 59–63.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com

[25]. Wang, L. Yang, Z. Huo, W. He, and J. Luo, 'Multi-Label Classification of Fundus Images With EfficientNet', IEEE Access, vol. 8, pp. 212499–212508, 2022.

[26] D. Luo and L. Shen, 'Vessel-Net: A Vessel-Aware Ensemble Network For Retinopathy Screening From Fundus Image', in 2020 IEEE International Conference on Image Processing (ICIP), 2020, pp. 320–324.

ISSN: 2312-8135 | Print ISSN: 1992-0652
info@journalofbabylon.com | jub@itnet.uobabylon.edu.iq | www.journalofbabylon.com