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Cataract Detection and Classification Using Deep Learning Techniques

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Abstract: Detecting eye diseases in the early part can reduce the damage to the eye and get the cure. Using artificial intelligence techniques in medical applications, it can detect and classify eye diseases using deep learning models with color images of the eye. In this paper cataract detection, recognition, and classification have been achieved using Convolutional Neural Network (CNN) deep-learning models applied to retinal fundus color images. A sample of 400 color images dataset has been classified into 300 normal images and 100 cataract images. These datasets were pre-processed automatically using histogram equalization (HE) and contrast limited adaptive histogram equalization (CLAHE) in addition to the segmentation process. There are three models have been used in this work, GoogleNet, ResNet-101, and Densenet201, they are applied in three cases, the first case uses the original images without image preprocess, the second with HE images pre-process, and the third with HE and CLAHE pre-processed images and achieved high testing accuracy exceeding 98% with Densenet201 model and achieved classification accuracy of 90% with GoogleNet model. The experimental results are evaluated using common performance metrics such as accuracy, precision, sensitivity, specificity, and F1-score for both cataract detection and classification cases. The performance of the proposed work makes this model can be used to improve eye health, including accuracy, early detection, training, and future education, and a considerable step toward the automatic detection and classification of cataract efficacy procedures for assisting detection and performing.

Keywords: Artificial Intelligence, Cataract, CNN, Deep Learning, Densnet201

1. INTRODUCTION

According to the American Academy of Ophthalmology, the clouding of the lens refers to the cataract [1]. the most common factors that cause cataracts are indicated in research such as advanced age, diabetes, hypertension, and radiation exposure [2]. There are several types of cataracts, and their reasons and risks are summarized as follows [3]:

a) *Congenital and developmental*: Genetics, prenatal lens development issues, maternal malnutrition, infections, medicines, radiation, fetal/infantile factors, metabolic disorders, birth trauma, malnutrition, birth deformities, and idiopathic. It might start from birth or develop throughout childhood and youth.

b) *Age-related:* Aging, dehydration, systemic diseases, smoking, oxidative stress, and a deficiency in key nutrients. Most of the elderly are beyond the age of 50.

c) *Traumatic:* Physical injury to the eye lens capsule, penetration by foreign substances. Welders and glass furnace workers are examples of people who operate in dangerous environments.

d) *Complicated:* Complications of some chronic inflammatory and degenerative eye disorders Patients with skin conditions, allergies, uveitis, glaucoma, diabetes, emphysema, and asthma.

e) *Metabolic*: Metabolic diseases Diabetes mellitus and galactosemia. Individuals lacking in specific enzymes and hormones Toxic Certain toxicants and drugs— Steroids and NSAIDs People undergoing steroid therapy or taking hazardous medicines.

f) *Radiation and Electrical:* Infrared, X-rays, UV rays, and a strong electric current. Individuals face excessive sunlight, artificial radiation, and high voltage.

This is typically translucent and the refractive lens experiences degenerative changes that result in a loss of transparency and an impairment of optical performance. These alterations eventually give rise to cataracts.

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Cataract-related visual impairments include changes in color perception as well as blurred vision. Fig. 1 shows several classes of cataracts. Colors can seem washed out, desaturated, or faded, making it difficult to distinguish between them accurately. In addition, cataracts may cause an increased sensitivity to light, which can cause glare and halos around light sources, particularly in dimly lit areas or under strong lighting. In addition, people with cataracts often report feeling uncomfortable with their vision, which includes seeing things that are dim or dark. This decreased sensitivity to contrast makes it harder to discern things against backgrounds with identical tonal values, making it harder to see objects in low-contrast environments. Nuclear cataracts are the first type of cataract we encounter. This type impacts the nucleus, which is the lens's center portion close to the eye's inner corner. This area's opacity adds to the cloudiness and brown or yellow tint. This distortion obscures the light's path while also hinting at the physiological alterations taking place inside the lens [4].

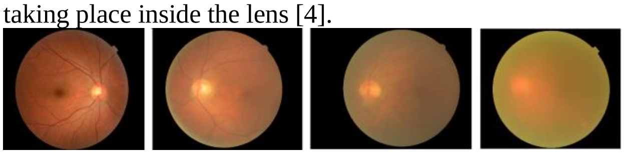

Figure 1. Retinal Fundus Images (a) non-cataract, (b) mild-cataract, (c) moderate-cataract, (d) severe-cataract

According to the World Health Organization (WHO), a cataract is a cloud of the eye [4]. There are an astounding 285 million people worldwide who suffer from vision impairment. 39 million people in this group have visual constriction, whereas the remainder have abnormal visual phenotypes. Cataracts cause 33% of visual weakness cases while 51% represent the blind [5]. The two main types of eye cataracts are nuclear cataracts and cataracts in the cortex [6][7]. Every day the cataract gets worse. There has been a 43.6% increase in recent cataract cases. The nuclear cataracts account for 23.1%, posterior subcapsular cataracts (PSC) for 13.1%, and cortical cataracts for 22%. Only 26.8% of cases had cataract surgery. Recently, a lot of cataract surgeries have been executed and the researches indicate that the rate of patients in females is greater than in males [8]. The location of the crystalline lens opacity determines whether it is a nuclear cataract (NC), a cortical cataract (CC), or a posterior subcapsular cataract. NC implies gradual clouding and hardness of the nuclear area. CC is characterized by white wedge-shaped and radially oriented opacities that grow in a spoke-like pattern from the lens's outside edge to the center [9, 10]. PSC is characterized by granular opacities and symptoms such as little breadcrumbs or sand particles distributed behind the lens capsule [11].

In medical science, Artificial Intelligence (AI) has made a huge impact in recent years in several applications such as breast cancer early detection, lung cancer, fatal blood diseases, COVID-19 detection, gender detection, eye disease (glaucoma and cataracts), and others in ophthalmology [12-15]. Deep learning processes based on artificial intelligence have become commonly used in various applications due to the enormous ability of large computations to extract high-level features of huge and different data, which has prompted many researchers to work on detecting cataracts and classifying the degree of opacity automatically, with high speed and accuracy. A Convolutional Neural Network (CNN) is a prevalent type of neural network commonly applied in the realm of image processing. This network architecture comprises singular or multiple convolutional layers [14, 15]. Deep learning networks use artificial neurons consisting of several layers to replicate the physiological behavior of the human brain so that they can extract features from images, texts, and signals automatically. The significant advantage of CNN over other feature extraction methods is the automatic extraction of features from images without human intervention [12].

The motivation of this study is to develop a machine-learning model aimed at the early detection and classification of various eye ailments. This work provides good support to ophthalmologists to overcome the difficulties in examining and treating visual impairment problems that directly affect large population. To overcome these challenges, pre-trained deep learning networks can be used, through which uncertainty can be effectively managed and the classification process organized accurately and intelligently. The contributions behind this work are summarized as follows:

1) different image pre-processing techniques are applied to the retinal fundus images (dataset) such as histogram equalization (HE), contrast limited adaptive histogram equalization (CLAHE), and segmentation to enhance the quality of images and as a result enhance the performance results.
2) Using pre-trained CNN models for automatic cataract detection such as GoogleNet, ResNet-101, and Densenet201 compare the performance between them and determine the best model for detection.
3) The results from the detection section are applied to the classification section for cataract severity calculation. Calculate the performance evaluation for detection and classification cases.

2. LITERATURE WORK

Most recent works applied the DL pre-trained models with the utilization of computer-aided diagnosis (CAD) system models for both detection and classification. Automatic detection and classification of cataracts from retinal images have garnered significant attention within the medical imaging domain. Various research articles in this discipline highlight that the process typically involves three main stages: preprocessing, feature extraction, and classification.

In a recent study, an active shape model with over 5000 training samples was used and reached 95.00 percent accuracy [16]. A discrete state transition (DST) system based on ResNet was presented by Li et. al. They overcame the vanishing gradient problems and achieved a 94.00% accuracy rate in cataract identification.

In [17], they produced methods of automatic detection and grading for cataracts. They used two proposed CNN models, DST-ResNet and EDST-ResNet. they have experimental results that produce better performance for the combined features than a single type of feature with an accuracy of detection/ grading of 0.94/0.8238 and 0.9143/0.805 for DST-ResNet and EDST-ResNet respectively.

In [18], they assessed a new CAD imaging program for nuclear lens opacity grading using Slit-lamp lens photographs. The experimental results produced a correlation coefficient of 0.96 for the CAD method.

In [19], they worked on automatic cataract classification and grading using a fundus image analysis-based CAD system. The wavelet transforms and sketch-based methods are used in feature extraction from the fundus images. The results are better for wavelet (accuracy approaches 90.9%) than sketch-based methods (86.1%).

In [20], they assessed the automatic detection and classification of nuclear cataracts from slit-lamp images using CNN. They obtained high-level features by using a support vector machine (SVM) for cataract grading with an accuracy of 88.4%.

In [21], they presented an automatic cataract detection using computer science (CNN) with retinal fundus images. they used two methods for cataract classification the SVM and SoftMax with accuracies of 86% and 94.01% respectively.

In [22], they proposed a combined method of CNN and Random Forests (RF) for cataract grading based on fundus images. The experimental results present an average accuracy of 90.69%

In [23], they focused mainly on the detection of cataracts from fundus retinal images using computer-aided diagnosis CAD and pre-trained CNN for cataract classification. They used an image quality selection module before using the SVM for cataract classification and obtained an accuracy of 92.91%.

In [24], they produced a new architecture of CNN named Tournament-based Ranking CNN for solving several problems such as classification and unbalanced datasets that cause performance degradation. The obtained results of the applied structure present a model record of the exact accuracy of 68.36% while the record of ranking CNN and ResNet is 53.40% and 56.12% respectively.

In [25], they proposed a practical machine-learning model for congenital cataracts identification. This case study is performed on 2005 subjects (1274 cataracts and 731 normal) at Zhongshan Ophthalmic Center. The experimental results show an accuracy of validation approaches to 94% using the 4-fold cross-validation.

In [26], the author proposed an automatic detection of eye cataracts using CNN and retinal fundus images. They achieved an accuracy of 95.77%.

In [27], they assessed a computer-aided cataract diagnosis system for the best network selection of CNN under additive white Gaussian noise (AWGN). This method is applied to maintain the best performance from the pre-trained CNN through different noise levels.

In [28], they proposed a cataract detection system using CNN with VGG-19 have acquired an overall 97.47% accuracy where the precision was 97.47% and the loss was 5.2.

In [29], they assessed the classification of cataracts using the pre-trained CNN models using publicly available images. They have the highest validation accuracy approaches 98.17%.

In [30], they presented an automated cataract diagnosis and grading based on CNN deep learning using slit-lamp and retro illumination lens photographs based on the Lens Opacities Classification System (LOCS). The proposed work operates with pre-trained recent CNN models and produces an accuracy of 91.22%.

In [12], they proposed an automatic detection and classification for cataracts in the early stages using CNN and discrete Fourier transform (2D-DFT) with fundus images. The highest accuracy of 93.10% is obtained after making an algorithm for the best color image quality.

In [31], they focused on the detection of cataract abnormalities using machine learning and image processing techniques applied to digital camera images. They worked with the LeNet-CNN model and obtained an accuracy of 96%.

In [32], they presented the automatic grading of nuclear cataracts using slit-lamp images and a Sport Vector Machine (SVM) grading model. They used more than 5000 clinical images for training and achieved a feature extraction rate success of 95% and a mean grading difference of 0.36.

In [6], they applied the algorithms of deep learning on automatic nuclear cataract severity using ocular images (smartphone slit-lamp images). The YOLOv3 is used for nuclear region detection while the combination of ShuffleNet and SVM models are used for cataract grading and evaluation. They achieved accuracy and F1-score of 93.5% and 92.3% respectively.

3. METHODOLOGY

In this section, the proposed methods and algorithms are employed to enhance the effectiveness and precise of automatic cataract detection and classification. Fig. 2 depicts the main structure of the proposed work. It produces the complete vision of how the cataract can be detected and classified automatically. This section contains the dataset acquisition, pre-processing stage, the CNN models stages (detection and classification), and the final decision stage where the lens opacity is identified and categorized.

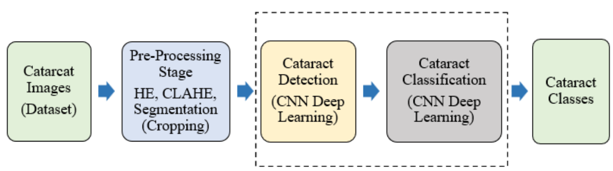

Figure 2. The proposed structure of the automatic cataract detection/classification system

A. Dataset

The availability of sufficient data is one of the essential things to complete this work. Therefore, images of the eye must be available and classified so that they can be used in the training process for various deep learning functions and to obtain appropriate cataract detection and diagnosis. The datasets that have been used in this work are retinal fundus images collected from Kaggle and available at [33]. The dataset consists of 400 images that are divided into 300 normal images and 100 cataract images.

B. Image Pre-Processing

To ensure or enhance the certainty of successful diagnosis or classification of images, pre-processing of the images is conducted. Fig. 3 shows the image enhancement with various image processing techniques. Segmentation of the image is carried out to focus on the eye lens, followed by conversion of the images to grayscale format. Border detection is then carried out, followed by edge enhancement and noise reduction methods. Small items are then removed. The generated images, which depict the eye lens, are used on a white background. The image segmentation represents the end phase that leads to further image improvement techniques such as HE (Histogram Equalization) and CLAHE (Contrast Limited Adaptive Histogram Equalization). The HE and CLAHE are used for contrast improvement and disclose important minor features for accurate diagnosis. There are specific image portions altered with adaptive enhancement while keeping local features. To increase image quality it should reduce artifacts, especially in noisy surroundings. the identification of anatomical features and anomalies can be achieved by Enhanced visibility and image information preservation is significant for ensuring accurate clinical.

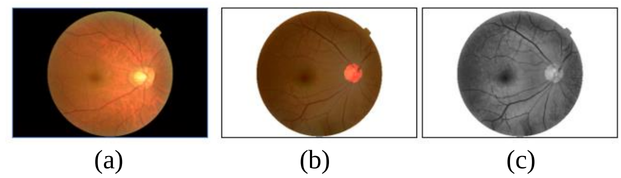

Figure 3. The image processing enhancement before applying CNN algorithms, a) Original image, b) Segmented image, c) Image after HE&CLAHE

C. Cataract Detection and Classification using the CNN model

After making pre-processing techniques for retinal fundus images, the use of deep learning pre-trained models for automatic cataract diagnosing and classification. there are three pre-trained CNN models (GoogleNet , ResNet-101, and Densenet-201) are used in this paper.

One of the commonly used types of CNN is GoogleNet, which consists of 22 complex layers, in addition to its basic structure consisting of three basic layers, which are the convolutional, pooling, and inception layers. The other model is ResNet-101, which consists of 101 layers, including convolutional layers, batch regularization, and pooling layers. The final model, DenseNet-201, is made up of 201 densely connected layers, including batch normalization, activation, and pooling layers. The input images used to train and test these CNN models are 224 x 224 x 3.

The process of diagnosing and classifying cataracts goes through two basic stages: feature extraction and classification. The feature extraction stage is regarded as a crucial and fundamental phase in the execution of the diagnosis and categorization process, owing to its effective role in these procedures. Employing a pre-trained CNN model is deemed a pivotal step in carrying out the automated diagnosis and categorization procedures, given that the parameters of this model are fine-tuned to enhance the accuracy and ease of the training process [34, 35]. As indicated in Table I, the three CNN models undergo optimization. The selection of the suitable optimizer during the model training phase is of utmost significance due to its direct influence on the speed of convergence, model efficacy, and generalization capability. The SGDM optimizer was used to find the fastest path to finding the optimal solution by accelerating the convergence process while collecting the momentum of the previous training. Also, by using intrinsic momentum, it is possible to move away from the minimum and circumvent this problem by giving the optimizer the ability to move away from the minimum. The other criterion in the training process is the percentage of learning rate, and it is set to 0.0001 because of its direct impact on convergence speed, robustness, and in general on the final performance of the model. Finally, a mini-batch size of about 4 was used, which was carefully chosen because of its effect on the speed of training and the stabilization process. Another significant selection is the number of approaches to achieve the equilibrium between underfitting and overfitting. Consequently, the models underwent training for multiple epochs, including 10, 20, 25, and 30. The number 20 was determined to be the most suitable point at which the model exhibited stability across the training curve.

In the stage of classification, the decision was made to employ the SoftMax classifier. The prediction of the cataract classes is achieved by using the SoftMax function. It can be used to transform logarithmic values into probabilities by taking exponential of each output and divided it with the total sum of all values (exponentiated), where the cumulative sum of the output vector equals one. the SoftMax function can be presented in (1) [36]:

$$\text{SoftMax}(Z_j) = \text{Exp}(Z_j) / \sum_{k=1}^{K} \text{Exp}(Z_K), \text{ for } j = 1\ldots,K \quad (1)$$

In this context, Z_j denotes the input applied to the SoftMax function about class j, while the denominator signifies the aggregate of the exponential values of the raw class scores within the output layer. K represents the number of output neurons.

TABLE I. THE TRAINING PARAMETERS OF CNN MODELS FOR CATARACT DETECTION

Configuration	**Value**
Optimizer	SGDM
Learning Rate	0.0001
Minibatch Size	4
Epochs	20
Classification Function	SoftMax

In this study, the fundamental framework is delineated in Fig. 4, illustrating the progression of images through a two-phase pre-processing procedure within CNN architectures. During the initial stage, known as the diagnostic phase, the dataset is instructed to ascertain the presence of cataracts in patients, with the adoption of DenseNet-201. The DenseNet-201distinguishing feature is the parameter efficiency achieved by the dense interconnections, and this can assist feature reusability and reduce redundantly computations. The DenseNet model relies on improving the training process and accelerating convergence over other models with a smaller number of connections. Moreover, the DenseNet model showed high levels of detection performance compared to the rest of the models, achieving a high accuracy rate using fewer parameters.

Three categories of cataracts are classified by using the GoogleNet model, mild cataracts, moderate cataracts, and severe cataracts. GoogleNet 's design enabled efficient parameter consumption by combining various filter dimensions into a single layer. Because of its lesser depth, GoogleNet displayed a very simple training procedure when compared to complicated designs such as DenseNet-201 and ResNet-101. The model produced innovative results and demonstrated strong performance in the domain of picture categorization.

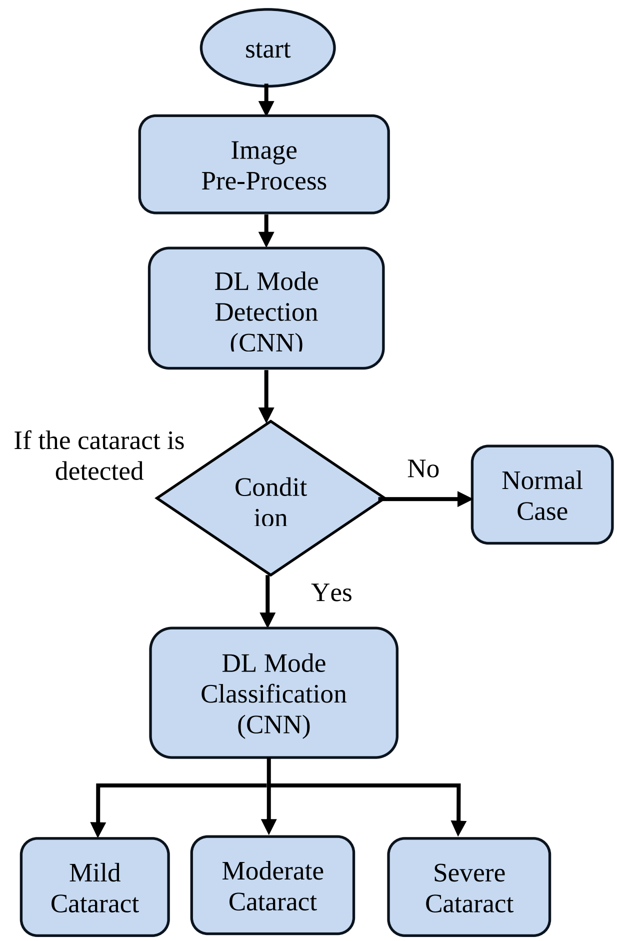

Figure 4. The proposed algorithm for automatic cataract detection and classification

4. RESULTS AND DISCUSSIONS

This section produces the experimental results that are derived from the execution of pre-processing techniques and CNN pre-trained models on the retinal fundus images for automatic cataract identification and classification. The results obtain a lot of performance metrics such as accuracy, sensitivity, and F1-score. This section is divided into three parts, performance evaluation metrics, experimental results of detection, and classification results.

A. Performance evaluation criteria

This part provides the significant evaluation criteria for the performance of the pre-trained CNN models used for detection and classification cases. the performance of the evaluation of these models is based on commonly used metrics such as accuracy, specificity, sensitivity, and F1 score [12]:

Accuracy = (True Positive (TP)+True Negative (TN))/ (True Positive (TP)+True Negative (TN)+False Positive (FP)+False Negative (FN)) (2)

Sensitivity = True Positive (TP) / (True Positive (TP)+False Negative (FN)) (3)

Specificity= (True Negative (TN))/(True Negative (TN)+False Positive (FP)) (4)

Precision= (True Positive (TP))/(True Positive (TP)+False Positive (FP)) (5)

F1-score = 2*(Precision*Sensitivity)/(Precision +Sensitivity) (6)

Test images are usually divided into four categories to determine the evaluation: True positive (TP), true negative (TN), false positive (FP), and false negative (FN). Accuracy and sensitivity are usually the most common and used in evaluation in many types of research specialized in this field, after which the F1 score became commonly used due to the ease of calculating accuracy and sensitivity.

B. Results of detection

The automatic eye cataract detection is carried out using the dataset illustrated in Table II. The dataset is divided into training, validation, and test categories with ratios of 80%, 10%, and 10% respectively. The test set is used for results evaluation after applying three deep-learning models, GoogleNet, RestNet-101, and DenseNet-201 to the dataset. Table III presents the test accuracy results obtained from applying the three CNN models without and with image pre-processing. The second column of Table III represents the results obtained after applying the three CNN models directly without any image enhancements. In this case, the DenseNet-201 confirms 93.33% which dominates by 8% and 3% on the GoogleNet and RestNet-101 models respectively. In the third column of Table III, the results have been obtained after applying the Histogram Equalization (HE) and segmentation processes. the results show a notable enhancement in the accuracy for all the CNN models. the accuracy of the DenseNet-201 model is increased to 96.83% and it also dominates the RestNet-101 and GoogleNet by 1% and 9% respectively. The last column summaries the accuracy of further image enhancements with HE, Contrast Limited Adaptive Histogram Equalization (CLAHE), and the segmentation process. there is a significant improvement where the DenseNet-201 achieved an accuracy of 98.33% which exceeds the GoogleNet and RestNet-101 by 10% and 1% respectively.

From Table III it can be observed that the best model which produces the best performance is the DenseNet-201 model. The performance results (test, validation, training, and overall accuracy) of the best model are presented in Table IV. Table V summaries the performance evaluation metrics of the best model in the detection case. The performance evaluation metrics provide high-level detection produced using the DenseNet-201 model. It is significant to make an accurate and fast diagnosis of cataracts because it is an important vital organ of the human body. The proposed work provides precise and high-speed cataract detection in 20 seconds after the image input to the process.

TABLE II. THE DATASET USED FOR THE CATARACT DETECTION

Dataset type	Normal	Cataract	Total images
PNG	300	100	400

TABLE III. THE RESULTING TEST ACCURACY OF VARIOUS DEEP LEARNING MODELS WITH DIFFERENT CASES OF IMAGE PROCESSING

Deep learning Models	Dataset without Pre-Processing (Original) (%)	Dataset with Pre-Processing (HE and Segmentation) (%)	Dataset with Pre-Processing (HE & CLAHE and Segmentation) (%)
GoogleNet	85.67	87.35	88.69
ResNet-101	90	95.67	96.56
Densenet-201	93.33	96.83	98.33

TABLE IV. THE PERFORMANCE RESULTS OF THE BEST DL MODEL

Deep learning Model	Testing Accuracy %	Validation Accuracy %	Training Accuracy %	Overall Accuracy %
Densenet-201	98.33	98.89	100	99.67

TABLE V. THE PERFORMANCE RESULTS AND EVALUATION METRICS OF THE BEST DL MODEL

Deep learning Model	Accuracy %	Precision %	Sensitivity %	Specificity %	F1-Score %
Densenet-201	98.33	98%	98%	100%	98%

C. Results of classification

After making an accurate cataract diagnosis, the successive stage involves the classification grading of cataracts into three categories: Mild, Moderate, and Severe. Table VI produces the dataset of cataract categories. As presented in the section on cataract detection the same CNN models are used for cataract grading. the performance results of the classification are presented in Table VII. From Table VII it can be seen that the dominant model is the GoogLeNet model which achieved an accuracy of 82.23% greater than the DenseNet-201 and RestNet-101 by 7% and 6%

respectively. Subsequently, data processing operations and image enhancement using HE were conducted, resulting in an enhancement of data quality. The accuracy of the GoogLeNet model increased to 86.40%, surpassing DenseNet-201 by 8% and RestNet-101 by 7%. Finally, an additional improvement process was performed, which is CLAHE, which raised the accuracy result to 90%, which outperformed DenseNet-201 by 7%, and RestNet-101 by 5%. The classification process is essential because knowing the extent of the deterioration of the patient's condition is one of the basics of diagnosis, and also determining the type of classification makes the process of giving appropriate treatment easier and faster. Entering the image of the eye lens into the automatic diagnosis and classification model is a quick process that gives fast and accurate results in a time not exceeding 40 seconds. The superior performance of the GoogLeNet model is presented in detail to illustrate the results of the training set, validation set, and test set, as well as the evaluation of the data as a whole in Table VIII. The evaluation metrics for the test set, according to the model results, are shown in Table IX. Finally, the proposed work has been compared with previous works in order to show the effectiveness of the presented work over the rest of the work, as shown in Table X.

TABLE VI. THE CATARACT DATASET USED FOR THE CLASSIFICATION

Dataset type	Cataract		Total images
PNG	Mild	35	100
	Moderate	45	
	Severe	20	

TABLE VII. THE PERFORMANCE OF TEST ACCURACY OF VARIOUS DEEP LEARNING MODELS WITH DIFFERENT CASES OF IMAGE PROCESSING

Deep learning Models	Dataset without Pre-Processing (Original) (%)	Dataset with Pre-Processing (HE and Segmentation) (%)	Dataset with Pre-Processing (HE & CLAHE and Segmentation) (%)
GoogleNet	82.23	86.40	90
ResNet-101	76.64	79.30	85.20
Densenet-201	75.72	78.60	83.40

TABLE VIII. THE PERFORMANCE RESULTS OF THE BEST DL MODEL

Deep learning Model	Testing Accuracy %	Validation Accuracy %	Training Accuracy %	Overall Accuracy %
GoogleNet	90	91.67	96	93.33

TABLE IX. THE PERFORMANCE RESULTS AND EVALUATION METRICS OF THE BEST DL MODEL

Deep learning Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
GoogleNet	90	82	82	95	82

TABLE X. THE PERFORMANCE COMPARISON OF THE PROPOSED WORK WITH PREVIOUS WORKS

Refs	Deep Learning Models	Pre-Processing Type	Accuracy Testing/Classific. (%)	Precision Testing/Classific. (%)	Sensitivity Testing/Classific. (%)	Specificity Testing/Classific. %	F1-Score Testing/Classifi %
[12]	SVM, AlexNet, VGGNet, ResNet	2D-DFT Transformation, and Augmentation	93.10	93.13	93.09	97.71	93.08
[17]	Vanilla-ResNet, DST-ResNet, EDST-ResNet,	Improved Haar Wavelet Features	91.43/ 80.5	---	----	----	----
[21]	SVM, SOFTMAX	HE and transform function	94.01	---	----	----	----
[22]	DCNN-RF, M-SVM	Desensitization and nonlinearity brightness adjustments	90.69	97.26	96.92	97.04	----
[23]	AlexNet, SVM	G-channel, R-channel	92.91	96.24	----	----	----

[25]	CC identification models	----	81	----	79	82	----
[26]	Res-Net50	------	95.77	94.43	94.43	98.07	-----
Proposed Work	GoogleNet ResNet-101 Densenet-201	Segmentation, HE, & CLAHE	88.69/90 96.56/85.2 98.33/82.4	98/82	98/82	100/95	98/82

5. Conclusions

In this work, automatic detection and classification of cataracts using pre-trained deep-learning models are applied to the fundus retinal images dataset. The work is divided into two parts, the first part for cataract detection and the second is for cataract classification. The algorithm of cataract detection and classification match each other where the results of detection obtained from the CNN are used as an input for the cataract classification. CNN pre-trained models are used for the two parts of this work such as GoogleNet, ReseNet-101, and Densenet-201. The best model for cataract detection is Densenet-201 which produces an accuracy of 98.33%, while the best model for cataract classification is GoogleNet which produces an accuracy of 90%. The experimental results show that the proposed work can compete with the previous works with the evaluation metrics such as accuracy (98.33%), precision (98%), sensitivity (98%), specificity (100%), and F1 score (96%). The proposed work can reduce the cost of detecting and diagnosing cataract diseases, in addition to the benefit of ease of detection and classification, especially in rural areas where sufficient equipment and supplies are not available for detecting eye diseases. The proposed work can be developed in the future until the devices are automated and the Internet of Things IoT is used for diagnosis, classification, and obtaining results remotely.

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