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Cataract Detection and Classification Using Deep Learning Techniques

Abdullah A. Jabber[1], Ahmed Hassan Hadi[2], Salim Muhsin Wadi[3] and Ghada A. shaded[4]

[1]*Avionics Techniques Engineering Department, Technical Engineering College-Najaf, Al-Furat Al-Awsat Technical University, Najaf, Iraq*
[2,3]*Communication Tech. Eng. Dept., Technical Engineering College-Najaf, Al-Furat Al-Awsat Technical University, Najaf, Iraq*
[4]*Department of Medical Instrumentation Techniques Engineering, Hilla University, Babylon, Iraq*

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Abstract: Reduced eye damage and the possibility of treatment are outcomes of early detection of ocular illnesses. Deep learning models using color photographs of the eye allow artificial intelligence systems to diagnose and categorize ocular disorders. This paper showcases the use of Convolutional Neural Network (CNN) deep learning models on color pictures of the retinal fundus to detect, identify, and classify cataracts. Three hundred normal photos and one hundred cataract images make up a set of four hundred color photographs. Histogram equalization (HE) and contrast limited adaptive histogram equalization (CLAHE) were used for automatic pre-processing of the datasets before segmentation. In this study, three different models were used: Densenet201, GoogleNet, and ResNet-101. In the first case, raw source photographs were used; in the second, photos that had been histogram equalized (HE) were used; and in the third, a combination of HE and CLAHE was used. In tests, the Densenet201 model achieved an accuracy of more than 98%, whereas the GoogleNet model achieved 90% accuracy in classification. For both the cataract detection and classification tasks, the experimental findings are assessed using standard performance measures like as accuracy, precision, sensitivity, specificity, and F1-score. Accuracy, early identification, training, and promotion of future education all contribute to improved ocular health, and the proposed model represents a significant step forward in the automated detection and classification of cataract treatments for detection and performance support.

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. The most common factors that cause cataracts are indicated in research such as advanced age, diabetes, hypertension, and radiation exposure [1]. There are several types of cataracts, and their reasons and risks are summarized as follows [2]:

1) 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.
2) 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.
3) 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.
4) Complicated: Complications of some chronic inflammatory and degenerative eye disorders Patients with skin conditions, allergies, uveitis, glaucoma, diabetes, emphysema, and asthma.
5) 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.
6) Radiation and Electrical: Infrared, X-rays, UV rays, and a strong electric current. Individuals face excessive sunlight, artificial radiation, and high voltage.

This is generally transparent, and the refractive lens undergoes degenerative alterations that lead to a reduction in transparency and a decline in optical performance. These

E-mail address: abdullah.ali@atu.edu.iq, coj.ahd5@atu.edu.iq, coj.sal@atu.edu.iq, ghada.shadeed@gmail.com

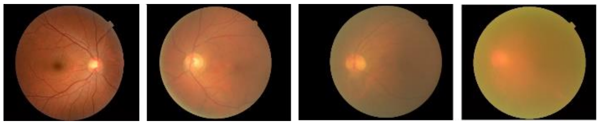

Figure 1. Retinal Fundus Images (a) non-cataract, (b) mild-cataract, (c) moderate-cataract, (d) severe-cataract

alterations eventually give rise to cataracts. 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. Cataracts can cause increased light sensitivity, leading to glare and halos around light sources, particularly in dim or bright settings. Moreover, individuals with cataracts frequently express discomfort about their eyesight, characterized by the perception of dim or dark objects. 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, 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 [3]. The World Health Organization defines a cataract as an ocular cloud [3]. The staggering number of persons affected by visual impairment is 285 million. 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 [4]. The two main types of eye cataracts are nuclear cataracts and cataracts in the cortex [5], [6]. Every day the cataract gets worse. There has been a 43.6% increase in recent cataract cases. Of all cataracts, 23.1% are nuclear, 13.1% are posterior subcapsular (PSC), and 22% are cortical. Merely 26.8% of patients had cataract surgery. Recent studies suggest that the incidence of cataract operations performed on girls surpasses that of males [7]. A nuclear cataract (NC), cortical cataract (CC), or posterior subcapsular cataract is characterized by the location of the opacity in the crystalline lens. NC signifies a hardening and gradual opacification of the nuclear area. CC is defined by white, wedge-shaped, radially arranged opacities that expand in a spoke-like configuration from the periphery of the lens toward the center [8], [9]. PSC is characterized by granular opacities and symptoms such as little breadcrumbs or sand particles distributed behind the lens capsule [10].

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 disorders, COVID-19 detection, gender detection, eye disease (glaucoma and cataracts), and others in ophthalmology [11], [12], [13], [14]. 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. One kind of neural network that is extensively used in picture processing is the Convolutional Neural Network (CNN). This network architecture comprises singular or multiple convolutional layers [13], [14]. Deep learning networks automatically extract characteristics from pictures, texts, and signals by simulating the human brain's physiological activity using artificial neurons with several layers. The ability of CNN to automatically extract features from pictures without human involvement is a major benefit compared to other feature extraction methods [11].

This paper presents several objectives such as developing a deep-learning model aimed at the early detection and classification of various eye ailments. in addition to introducing support for ophthalmologists in overcoming the difficulties in examining and treating visual impairment problems that directly affect a 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) Several enhancements have been applied to the dataset including HE, CLAHE, and segmentation to improve image quality and by extension, performance.
2) Three CNN models (GoogleNet, ResNet-101, and Densenet201) have been used to compare their performance and determine the optimal model for cataract detection.
3) The results from the detection section are applied to the classification section for calculating cataract severity using the same CNN models.
4) Calculate the performance evaluation for detection and classification cases.

2. LITERATURE WORK

Several recent studies have integrated DL pre-trained models with detection and classification models from computer-aided diagnostic (CAD) systems. A lot of people in the medical imaging field are interested in finding ways to automatically detect and classify cataracts from retinal pictures. Various research articles in this discipline highlight that the process typically involves three main stages: preprocessing, feature extraction, and classification.

A recent study attained 95.00% accuracy with an active shape model that used over 5,000 training examples [15]. In their presentation, Li et al. established a ResNet-based DST system. They achieved a 94.00% accuracy rate in diagnosing cataracts after surmounting the vanishing gradient challenges.

In [16], 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 [17], they used Slit-lamp lens images to evaluate a novel computer-aided design (CAD) imaging software for assessing nuclear lens opacity. A correlation coefficient of 0.96 was generated for the CAD approach by the experimental findings. They developed a computer-aided design (CAD) method based on fundus image analysis to grade and classify cataracts automatically [18]. To extract features from the fundus pictures, approaches based on sketches and wavelet transformations are employed. Compared to techniques based on sketches, wavelet produces superior results (accuracy approaches 90.9%).

They evaluated CNN's ability to automatically detect and classify nuclear cataracts using slit-lamp pictures [19]. With a success rate of 88.4%, they used a Support Vector Machine (SVM) to grade cataracts and get high-level characteristics.

In [20], 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. They presented a CNN-RF hybrid approach to cataract grading using fundus images in [21]. With an average accuracy of 90.69%, the trial findings are impressive.

In [22], 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%.

To address issues like categorization and imbalanced datasets, which lead to performance deterioration, they developed a new CNN architecture called Tournament-based Ranking CNN [23]. 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 [24], 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 [25], the author proposed an automatic detection of eye cataracts using CNN and retinal fundus images. They achieved an accuracy of 95.77%.

The optimal CNN network selection in the presence of additive white Gaussian noise (AWGN) was evaluated in the context of a computer-aided cataract diagnostic system [26]. Applying this strategy ensures that the pre-trained CNN maintains its optimal performance even when exposed to varying levels of noise.

The CNN employing the VGG-19 cataract detection technique proposed in [27] attained an overall accuracy of 97.47%, a precision of 97.47%, and a loss of 5.2.

In [28], 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%.

The authors of [29] introduced a CNN deep learning system that uses images taken with slit lamps and retro illumination lenses to automatically diagnose and grade cataracts according to the Lens Opacities Classification System (LOCS). The suggested approach achieves a 91.22% success rate using pre-trained, up-to-date convolutional neural network (CNN) models.

According to their proposal in [11], utilizing convolutional neural networks (CNNs) and discrete Fourier transform (2D-DFT) on fundus pictures, they could automatically identify and classify early-stage cataracts. The top color picture quality algorithm yields a maximum accuracy of 93.10%.

In [30], the authors primarily dealt with the topic of cataract anomaly detection by the use of machine learning and image processing methods for digital camera photos. They achieved a 96% success rate by utilizing the LeNet-CNN model.

The automatic assessment of nuclear cataracts utilizing slit-lamp images and a Support Vector Machine (SVM) grading model was illustrated in [31]. A 95% success rate in feature extraction and a mean grade difference of 0.36 was attained by utilizing over 5,000 clinical photographs for training.

In [32], they used a non-contact capturing of cataract opacity using AS-OCT images for the nucleus region to detect nuclear cataracts automatically. The MRA-Net and SENet models are used as the proposed method for NC severity level classification based on AS-OCT images. They achieved an accuracy of 87.78%.

In [33] more than 25000 retinal images are used with an automated deep learning algorithm for cataract detection with an accuracy approach of 96.6%.

In [5], they used ocular pictures (smartphone slit-lamp images) to apply deep learning algorithms to the problem of automated nuclear cataract severity. Cataract grading and assessment make use of a mix of ShuffleNet and SVM models, while YOLOv3 is employed for nuclear area detection. They were able to attain an F1-score of 92.3% and an accuracy of 93.5%. In this article, the presented work differs from previous works by the enhancement algorithms especially the segmentation process of the dataset. Also, the utilization of detection and classification algorithms may have different strategies to achieve results at each stage.

3. METHODOLOGY

Automatic cataract identification and categorization is made more effective and exact by utilizing the techniques and approaches that have been provided in this part. The primary framework of the suggested project is shown in Figure 2. It produces the complete vision of how the cataract can be detected and classified automatically. This section

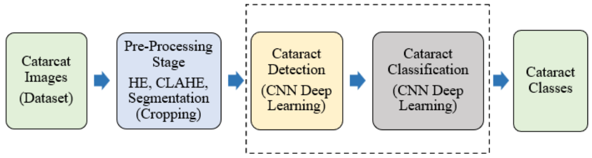

Figure 2. The proposed structure of the automatic cataract detection/classification system

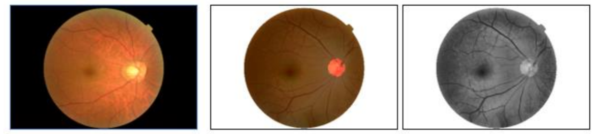

Figure 3. The image processing enhancement before applying CNN algorithms, a) Original image, b) Segmented image, c) Image after HE and CLAHE

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. The tools that are utilized in this study are a PC laptop, Matlab2022a, and retinal fundus images (dataset).

A. Dataset

TThe 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 [34]. The dataset consists of 400 images that are divided into 300 normal images and 100 cataract images. The datasets in this study are chosen for the highest resolution, diversity of conditions, and other aspects.

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. Image segmentation is the final stage before the use of image improvement techniques such as histogram equalization (HE) and contrast-limited adaptive histogram equalization (CLAHE). For a more accurate diagnosis, HE and CLAHE improve contrast and disclose essential, minute information. Certain segments of the image have been modified using adaptive enhancement, preserving local details. To enhance image quality, it is essential to minimize artifacts, particularly in noisy environments. the identification of anatomical characteristics and abnormalities can be accomplished by Improved visibility and retention of image information are crucial for guaranteeing clinical accuracy.

C. Cataract Detection and Classification using the CNN model

Automatic cataract diagnosis and categorization using deep learning pre-trained models follows the development of methods for pre-processing retinal fundus pictures. This article utilizes three pre-trained convolutional neural network (CNN) models: GoogleNet, ResNet-101, and Densenet-201.

In addition to its three fundamental layers—the convolutional, pooling, and inception layers—GoogleNet, one of the most popular CNN variants, has 22 complicated layers. An alternative model is ResNet-101, which has 101 layers total and includes pooling, batch regularization, and convolutional layers. Layers for batch normalization, activation, and pooling are among the 201 that make up the final model, DenseNet-201. These convolutional neural network (CNN) models are trained and tested using 224 × 224 x 3 input pictures.

Feature extraction and classification are the two main steps in diagnosing and categorizing cataracts. Because of the vital role it plays in the diagnostic and classification processes, the feature extraction step is considered an essential and basic part of the process. 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 [35], [36]. 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 the exponential of each output and dividing 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) [37]:

$$SoftMax(Zj) = \frac{Exp(Zj)}{\sum_{k=1}^{k} Exp(ZK)}, for j = 1..., K \quad (1)$$

In this context, Zj 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. 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.

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

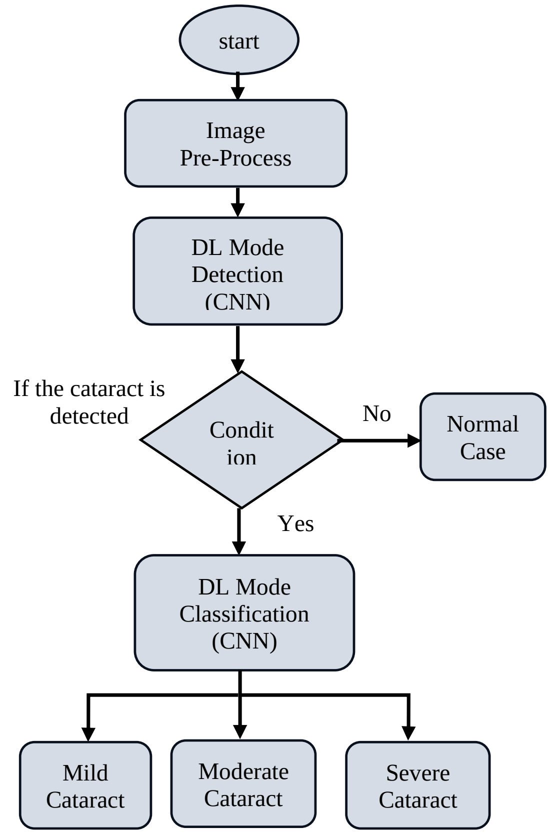

Figure 4. The proposed algorithm for automatic cataract detection and classification

4. RESULTS AND DISCUSSIONS

Here we present the experimental findings obtained by using pre-processing methods and CNN pre-trained models to the retinal fundus pictures to automatically detect and classify cataracts. Accuracy, sensitivity, and F1-score are only a few of the performance criteria measured by the outcomes. This section is divided into three parts, performance evaluation metrics, experimental results of detection, and classification results.

A. *Performance Evaluation Criteria*

Here you may find the important metrics that were used to measure how well the pre-trained convolutional neural network (CNN) models performed in the detection and classification tasks. Standard criteria including F1 score, specificity, accuracy, and sensitivity form the basis of these models' performance evaluations [11]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$F1 - score = 2 * \frac{(Precision * Sensitivity)}{(Precision + Sensitivity)} \quad (6)$$

It is common practice to classify test pictures as either true positive (TP), true negative (TN), false positive (FP), or false negative (FN) to ascertain the assessment. The F1 score gained popularity as a result of how easy it is to calculate accuracy and sensitivity, which are often the most utilized metrics for evaluation in this area of study.

B. Results of Detection

The dataset shown in Table II is used to accurately identify ocular cataracts. Training, validation, and test subsets make up 80%, 10%, and 10% of the dataset, respectively. After running three deep-learning models—GoogleNet, RestNet-101, and DenseNet-201—on the dataset, the test set is utilized to evaluate the outcomes. Table III shows the outcomes of the accuracy tests conducted using the three CNN models before and after picture pre-processing. The outcomes acquired from just using the three CNN models, devoid of any picture modifications, are displayed in the second column of Table III. 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 summarizes the accuracy of further image enhancements with HE, 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. Looking at Table III, it's clear that the DenseNet-201 model is the top performer. Table IV displays the best model's performance results for test, validation, training, and total accuracy. For the detection example, Table V summarizes the performance assessment metrics for the top model. The DenseNet-201 model's high-level detection is provided via the performance assessment metrics. The eye is a crucial organ, thus getting a quick and precise diagnosis of cataracts is crucial. Twenty seconds following picture input, the suggested approach enables rapid and accurate cataract identification. From the results of the detection tables, it can be seen that even though the dataset size (no. of images) is considered to be small but achieved higher accuracy than previous works.

TABLE II. THE DATASET USED FOR THE CATARACT DETECTION

Dataset type	Normal	Cataract	Total images
PNG	100	300	400

TABLE III. THE RESULTING TEST ACCURACY OF DETECTING 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 and 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 Models	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 Models	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
Densenet-201	98.33	98	98	100	98

C. Results of Classification

Upon establishing a precise cataract diagnosis, the subsequent phase entails the categorization of cataracts into three tiers: Mild, Moderate, and Severe. Table VI presents the dataset of cataract classifications. The CNN models utilized for cataract identification are also employed for cataract grading. The categorization performance results are displayed in Table VII. Table VII indicates that the predominant model is the GoogLeNet model, which attained an accuracy of 82.23%, surpassing DenseNet-201 and ResNet-101 by 7% and 6%, respectively. Subsequently, data processing and picture enhancement utilizing HE were performed, leading to improved data quality. The accuracy of the GoogLeNet model rose to 86.40%, exceeding DenseNet-201 by 8% and ResNet-101 by 7%. Finally, an additional improvement process, CLAHE, was performed, 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 offers fast and accurate results in a time not exceeding 40 seconds. In Table VIII, we can see the training set, validation set, test set, and overall data assessment findings, all demonstrating the GoogLeNet model's superior performance. Table IX shows the test set assessment metrics based on the model findings. Finally, the proposed work has been compared with previous works to show the effectiveness of the presented work over the rest of the work, as shown in Table X.

TABLE VI. THE DATASET USED FOR THE CATARACT CLASSIFICATION

Cataract Classes	Total images
mild	35
moderate	45
Severe	20

TABLE VII. THE RESULTING TEST ACCURACY OF CLASSIFICATION 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 and 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 Models	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 Test./Classif.(%)	Precision Test./Classif.(%)	Sensitivity Test/Classif.(%)	Specificity Test/Classif. (%)	F1-Score Test/Classif.(%)
[11]	SVM AlexNet VGGNet ResNet	2D-DFT Transformation Augmentation	93.10	93.13	93.09	97.71	93.08
[16]	Vanilla-ResNet DST-ResNet EDST-ResNet	Improved Haar Wavelet Features	91.43	80.5	—	—-	—-
[20]	SVM SOFTMAX	HE transform function	94.01	—	—-	—-	—-
[21]	DCNN-RF M-SVM	Desensitization nonlinearity brightness adjustments	90.69	97.26	96.92	97.04	—-
[22]	AlexNet, SVM	G-channel R-channel	92.91	96.24	—-	—-	—-
[24]	CC identification models	—-	81	—-	79	82	—-
[25]	Res-Net50	—-	95.77	94.43	94.43	98.07	—-
Proposed Work	GoogleNet, ReseNet-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

This research uses a dataset of fundus retinal images to autonomously identify and categorize cataracts utilizing pre-trained deep learning models. The challenge has two components: one focused on cataract detection and the other on their classification. The output of the convolutional neural network (CNN) is integrated into the cataract classification method, enabling the two algorithms to function collaboratively. In both sections of this study, CNN pre-trained models like Densenet-201, ReseNet-101, and GoogleNet are utilized. With a 98.33% success rate, Densenet-201 is the top model for cataract detection, while GoogleNet is the top model for cataract classification with a 90% success rate. The experimental findings demonstrate that the suggested work can hold its own against prior studies using assessment measures like F1 score (96%), specificity (100%), accuracy (98.33%), and precision (98%). Not only may the suggested study make it easier to identify and classify cataract disorders, but it can also lower the expense of doing so. This is particularly helpful in remote regions without equipment or supplies to detect eye problems. Until equipment is fully automated and the IoT is utilized for remote diagnosis, categorization, and result retrieval, the suggested work can be developed in the future by using an optimization process for enhanced feature extraction or classification of the used pre-trained DL models. In addition, the proposed algorithm can be used as an application that works remotely, especially in rural areas.

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