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Classification and Grading of Cataracts Using a Deep Convolutional Neural Network

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ABSTRACT

Cataract, a leading cause of partial impairment and blindness worldwide, is characterized by the clumping of protein in the transparent lenses, resulting in a white-colored covering. This eye condition is attributed to various factors, including developmental abnormalities, trachoma, metabolic disorders, genetics, drug-induced changes, and aging. Among these causes, genetics and aging are the primary contributors to cataracts that lead to blindness. Cataracts can be classified into three types based on the location of lens opacities: nuclear, cortical, and posterior subcapsular. Additionally, ophthalmologists grade cataracts according to the severity of the disease. The grading system aids in early detection and timely treatment. Notably, previous research overlooked the influence of eye color, despite its impact on cataract development stages. Hence, this study aims to classify and grade cataracts while considering the effect of eye color, specifically within the Ethiopian population. This study encompasses various cataract classes, including normal, nuclear, cortical, and posterior subcapsular. Moreover, the severity of each cataract type is graded, encompassing cortical early, cortical advanced, nuclear early, nuclear advanced, posterior subcapsular early, and posterior subcapsular advanced stages. To achieve these objectives, an experimental research approach was employed, involving data collection, analysis, and processing. A model was designed to extract cataract features for effective classification and grading. The cataract classification and grading model demonstrated an accuracy of 74% using raw data, which significantly improved to 97% after implementing data preprocessing techniques. Furthermore, the model exhibited a 99% accuracy in grading cataract severity. Evaluation of the proposed model employed metrics such as accuracy, confusion matrix, precision, recall, and F1-score.

Keywords: Deep Learning, Cataract Severity, Cataract Classification and Grading Model

1. INTRODUCTION

The eye serves as a vital sense organ for vision, and any disorders affecting it can significantly impact various aspects of human life, including participation in and response to visual activities. Comprising components such as the pupil, retina, and lens, the eye works together to enable vision and comprehend object characteristics, similar to a camera capturing an object [3]. Cataract stands out as a leading cause of partial impairment and global blindness. It occurs when protein clumps within the transparent lenses of the eye, resulting in a white covering and eventual blindness [10]. Factors contributing to cataracts include developmental abnormalities, trachoma, metabolic disorders, genetics, drug-induced changes, and aging. Genetic factors and aging are the most common causes leading to cataract-related blindness. Ophthalmologists classify cataracts based on their causes and the affected location within the eye. Age-related cataracts are prevalent, and ophthalmologists often diagnose them by assessing the location of lens opacity. In Ethiopia, cataract disease accounts for 49.9% of blindness cases among 1.6% of the population [6]. Age-related cataracts are further categorized as pediatric cataracts (PC) and secondary cataracts. Based on the location of lens opacity, cataracts are grouped as nuclear cataracts (NC), cortical cataracts (CC), and posterior subcapsular cataracts (PSC). NC refers to the gradual clouding and hardening of the lens's nucleus area. CC manifests as spoke-like opacities developing from the outer edge of the lens toward the center. PSC involves granular cataracts resulting from protein clumping within the lens. Ophthalmologists grade cataracts based on disease severity, allowing for timely prevention and treatment [3].

Researchers have concentrated their efforts on developing classification and grading models for cataracts, employing machine learning and image processing algorithms. Early detection and treatment of cataracts are crucial due to limited treatment options, primarily surgical intervention. Various researchers have identified stages of cataracts, differentiating between early and advanced stages. Early-stage cataracts can be effectively treated, reducing risks and preventing blindness. Conversely, advanced-stage cataracts pose challenges for surgical intervention and may result in blindness. Consequently, early diagnosis and treatment of cataracts are imperative. Eye characteristics, including eye color and shape, vary across different populations. These variations can impact the early detection of cataracts, as the normal eye color among foreign individuals differs from that of Ethiopians. Extensive research has focused on cataract classification and grading to facilitate early detection and treatment. While these studies have considered the effects of color and patterns on the disease, the natural eye color also influences its severity. Hence, our primary focus is on developing a cataract classifying and grading (CCG) model. This model takes into account the impact of eye color to reduce the severity of the disease, utilizing a conventional neural network (CNN).

1.1 Report of world health organization

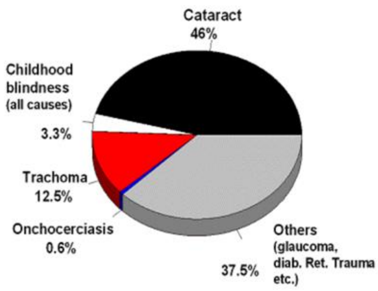

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Fig 1. Blindness report of WHO in 2018

According to a report by the World Health Organization (WHO), 2.2 billion people worldwide are visually impaired. The 2018 WHO report states that cataract accounts for 46% of global blindness. Figure 1 in the report highlights the prevalence of blindness, with cataract being the leading cause [7]. Various authors have undertaken the task of classifying and grading cataracts using machine learning techniques, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other image processing algorithms. These methods involve categorizing cataract diseases based on the location of lens opacity and age-related factors. According to the latest literature, cataracts are classified into pediatric cataracts and secondary cataracts, with a specific focus on age-related differences. Furthermore, cataracts can be categorized into nuclear cataracts, cortical cataracts, and posterior subcapsular cataracts, with each classification associated with different aspects of lens opacity. To assess the severity of cataracts, these authors utilized stages of the disease, including normal, early stage, and advanced stage severity grading. However, it is important to consider the natural color of the affected eye when analyzing the severity of cataract disease.

2. MATERIALS AND METHODS

2.1 Dataset preparation

Data was collected from various sources in image format, including Boru Meda Hospital and Kombolcha General Hospital during a cataract prevention campaign. With the assistance of hospital experts and ophthalmologists, the cataract dataset was classified into normal, cortical, nuclear, and posterior classes, with data graded as either early stage or advanced stage across all cataract types. To construct a cataract classification and grading model, the dataset was divided into training, validation, and testing sets. The proposed model, as illustrated in Figure 2, incorporates image acquisition, preprocessing techniques, feature extraction algorithms, and classification algorithms. Following these steps, a model was developed to classify cataract types based on a lens opacity classification system and grade their severity. Various image enhancement algorithms, feature extraction techniques, and classification methods were tested to improve the model's performance. Evaluation of the model was conducted using metrics such as accuracy, confusion matrix, precision, and F1-score. Based on the evaluation results, the best-performing model was selected.

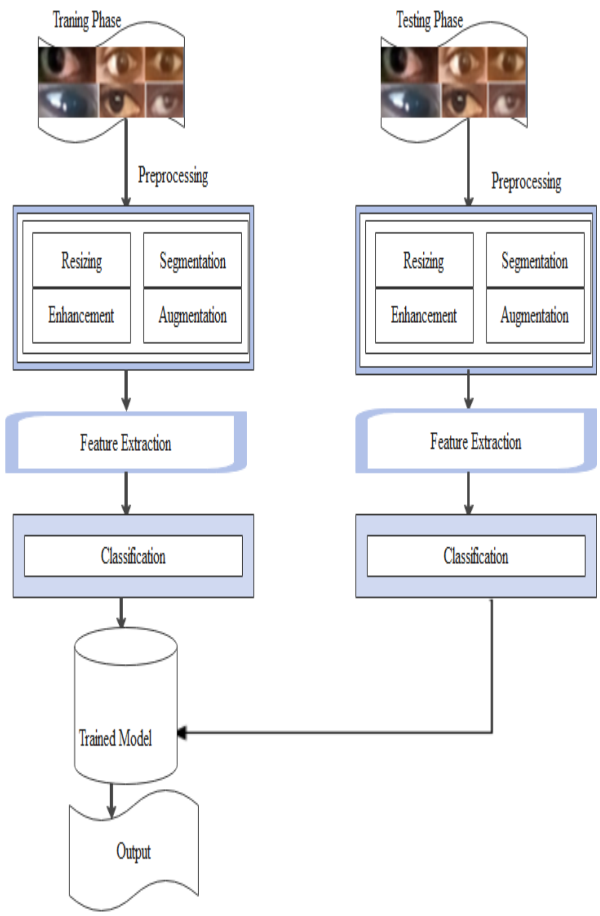

Fig 2. Proposed model for classification and grading of cataract

Preprocessing: Various preprocessing algorithms were tested to normalize image size and enhance quality. Improving dataset quality is crucial for enhancing the model's performance. Therefore, face and eye detection algorithms were employed to identify the region of interest (ROI) and extract a single image of the ROI. Additionally, image size normalization and image enhancement algorithms were applied.

Face and eye detection algorithms: Face detection algorithms were utilized to distinguish the face region from non-face areas within the dataset. This step is important as the eyes are located on the face, and selecting the face region enables accurate eye detection. Various face and eye detection algorithms have been proposed in literature. For this research, the Viola-Jones object recognition and detection algorithm was chosen due to its simplicity, use of rectangular Haar features, capability to detect objects across different scales, and wide range of translation [9]. The Ada Boost algorithm was employed to select the best features and improve the classification accuracy of weak classifiers. Since the relevant information for cataract classification and grading model is found in the eye region, it is crucial to accurately detect and select the eye region by calculating its location within the face. K. Vikram et al, have demonstrated the effectiveness of the Viola-Jones algorithm for facial part detection, including the eyes, nose, mouth, and others. Thus, in this research, the Viola-Jones algorithm was used for both face and eye detection, as depicted in Figure 3.

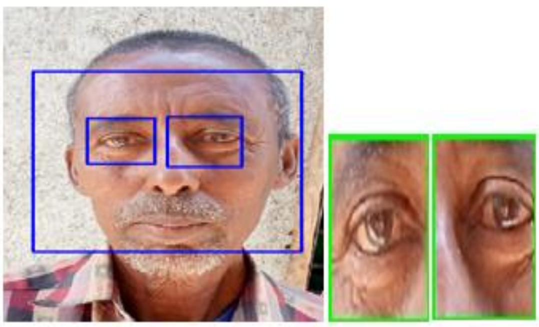

Fig 3. Faces and eyes through a process of analyzing patterns on images

Segmentation: Following the detection of the eye using the Viola-Jones algorithm, a segmentation algorithm was applied to select the region of interest (ROI), where crucial features for the cataract classification and grading model are found. The distance between the actual eye and the detected image's height and width, as identified by the Viola-Jones algorithm, was used in the segmentation process. By observing the images, we determined the maximum and minimum distances in all directions. These minimum and maximum values were then utilized to extract the ROI from all the images detected by the Viola-Jones eye detection algorithm, resulting in improved outcomes. The formula employed for this purpose is presented as follows. Figure 4a and Figure 4b illustrates the process of eye detection using the Viola-Jones algorithm (a) and the segmentation of the ROI by calculating approximate pixel values from the top, left, right, and bottom (b).

ROI Left = (Viola Left Max + Viola Left Min) / 2

ROI Right = (Viola Right Max + Viola Right Min) / 2

ROI Top = (Viola Top Max + Viola Top Min) / 2

ROI Bottom = (Viola Bottom Max + Viola Bottom Min) / 2

Where:ROI Left represents the distance traveled from the top left towards the positive x-direction.

ROI Right represents the distance traveled from the top right towards the negative x-direction.

ROI Top represents the distance traveled from the top left towards the negative y-direction.

ROI Bottom represents the distance traveled from the top left towards the negative y-direction.

Fig 4a. Detection of eyes using the Viola-Jones algorithm

Fig 4b. Process of identifying and delineating specific regions

Image size normalization: The dataset comprises images of varying sizes, which can impact the model's performance. Consequently, we tested our model using different image sizes, specifically (360x360), (256x256), and (224x224). Among these sizes, (224x224) yielded the highest accuracy in our model.

Image Enhancement: Various image enhancement techniques were employed to enhance the image quality and highlight relevant features. Adjusting the contrast and brightness of the raw eye image is crucial for visualizing texture features and improving the cataract classification and grading model. Figure 5a and 5b illustrate the image before and after applying the image enhancement techniques, respectively.

Fig 5a. Image before applying image processing algorithm

Fig 5b. Image after applying the image enhancement factor using image processing algorithm

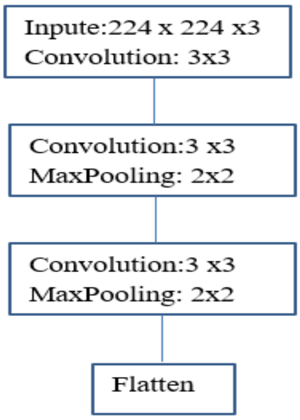

Fig 6. Convolutional neural network (CNN) model for extracting deep features

Classification: Feature vectors were extracted using the aforementioned algorithm. Subsequently, a SoftMax classifier was employed to develop the model and it was shown in Figure 6.

4. RESULTS AND DISCUSSION

4.1 Experimental setup regenerate response

For experimentation purposes, an HP Laptop with the specifications of an Intel Core ™ i5-6200 CPU and 8 GB of RAM was utilized. The experiments were conducted using Python programming, specifically based on Keras prototype development and TensorFlow as the backend. End-to-end CNN model (CCG) experiments were conducted using both raw and preprocessed data for cataract classification, and preprocessed data for cataract severity grading. Throughout the experiment, an 80/20 train/test split was employed. In each section, the conducted experiments are discussed. Ophthalmologists assisted in annotating the results of cataracts from slit-lamp instruments, utilizing 7680 images with 1280 images per class, as shown in the Table 1 below.

Table 1. Types and grade of cataract annotated by Ophthalmologist

S.No	type and grade cataract	Image Format	Image Resolution	Quantity
1	Cortical cataract Early Stage (CCER)	JPG	1728x3936	1000
2	Cortical Cataract Advanced Stage (CCAD)	JPG	1728x3936	1000
3	Nuclear Cataract Early Stage (NCER)	JPG	1728x3936	1000
4	Nuclear Cataract Advanced Stage (NCAD)	JPG	1728x3936	1000
5	Posterior subcapsular Early Stage (PSCER)	JPG	1728x3936	1000
6	Posterior subcapsular Advanced Stage (PSCAD)	JPG	1728x3936	1000

4.2 Experiments on CCG model using raw data

Figure 7 illustrates the model's accuracy of 74% when using raw data. However, there is a false positive rate of 35% when predicting CC, indicating instances where the image is CC, but the prediction is incorrect. Additionally, false positive rates of 24%, 3%, and 44% were observed when predicting NC, NT, and PSC, respectively. These findings suggest that the model made incorrect predictions for certain samples. Consequently, in the subsequent experiment, segmentation and image enhancement factors were applied to mitigate incorrect sample classification and improve the performance of the CCG model.

	precision	recall	f1-score
CC	0.65	0.55	0.60
NC	0.76	0.79	0.78
NR	0.97	0.99	0.98
PSC	0.56	0.62	0.58
accuracy			0.74
macro avg	0.74	0.74	0.73
weighted avg	0.74	0.74	0.74

Fig 7. Precision, recall, and F1-score of CCG using Raw data

The model was evaluated using a confusion matrix, as illustrated in Figure 8.

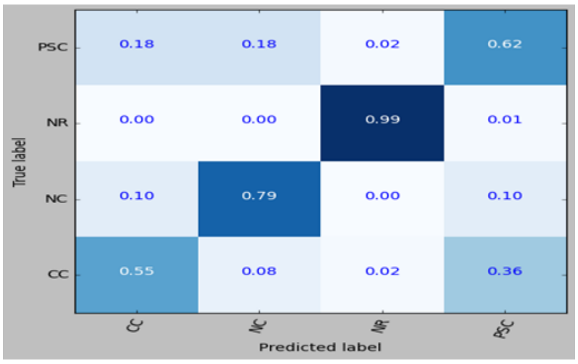

Fig 8. Confusion matrix of CCG model using Raw data

Figure 8 clearly illustrates the predictions made by the CCG model. It accurately predicted normal eyes with a rate of 99%, nuclear cataracts with a rate of 79%, posterior subcapsular cataracts with a rate of 62%, and cortical cataracts with a rate of 55%. However, there were some incorrect predictions: 1% of normal eyes were mistakenly classified as posterior subcapsular cataracts, 21% of nuclear cataracts were incorrectly classified as cortical cataracts and posterior subcapsular cataracts, 38% of posterior subcapsular cataracts were predicted as cortical cataracts and nuclear cataracts, and 45% of cortical cataracts were wrongly classified as posterior subcapsular cataracts and nuclear cataracts. The confusion matrix in Figure 8 reveals that certain samples of cataract diseases were incorrectly predicted as other types. This can be attributed to the similarity in texture among different cataract diseases. To address this issue, the next experiment involved the utilization of image enhancement factors and a segmentation algorithm to enhance the clarity of eye image textures and improve the performance of the CCG model.

4.3 Experiments on CCG model applying segmentation and enhancement

Image segmentation was employed to select the most crucial features for the CCG model, while image enhancement factors were applied to enhance the clarity of texture features. The accuracy, precision, recall, and F1-score values of the CCG model, after incorporating image segmentation and enhancement factors, are presented in Figure 9.

	precision	recall	f1-score
CC	0.99	0.99	0.99
NR	0.94	0.97	0.95
NC	0.97	0.94	0.96
PSC	1.00	1.00	1.00
accuracy			0.97
macro avg	0.97	0.97	0.97
weighted avg	0.97	0.97	0.97

Fig 9. Precision, recall and F1-score of CCG using segmentation

Figure 9 demonstrates that the accuracy of the CCG model significantly improved to 97% after implementing segmentation and image enhancement factors, representing a 23% increase compared to the previous end-to-end CCG model. The confusion matrix of the CCG model, following the application of segmentation and image enhancement factors, is presented in Figure 10.

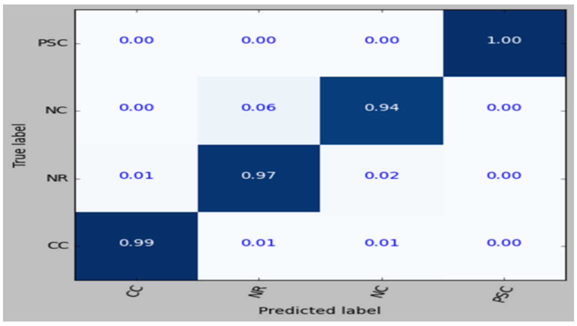

Fig 10. Confusion matrix of CCG model using segmentation

Figure 10 provides a clear illustration of the CCG model's predictions. The model achieved an accuracy of 97% for normal eyes, 94% for nuclear cataracts, 100% for posterior subcapsular cataracts, and 99% for cortical cataracts. These results demonstrate improved prediction accuracy for each class of the CCG model following the implementation of segmentation and enhancement techniques.

4.4 Experiments on grading the severity of cataract:

In the previous experiments (4.2 and 4.3), the attention is focused on classifying cataracts into different types, namely NR, CC, NC, and PSC. In this section, we conducted an experiment to grade the severity of each cataract type as either early or advanced stage. The severity grading includes cortical cataract early stage (CCE), cortical cataract advanced stage (CCA), nuclear cataract early stage (NCE), nuclear cataract advanced stage (NCA), posterior subcapsular early stage (PSCE), and posterior subcapsular advanced stage (PSCA). The model achieved an accuracy of 99% for this severity grading, as depicted in Figure 11.

	precision	recall	f1-score
CCA	1.00	0.97	0.98
CCE	1.00	0.98	0.99
NCA	0.99	1.00	0.99
NCE	0.98	1.00	0.99
PSCA	0.98	0.99	0.99
PSCE	1.00	1.00	1.00
accuracy			0.99
macro avg	0.99	0.99	0.99
weighted avg	0.99	0.99	0.99

Fig 11. Precision, recall, and F1-score of CCG model for cataract grading

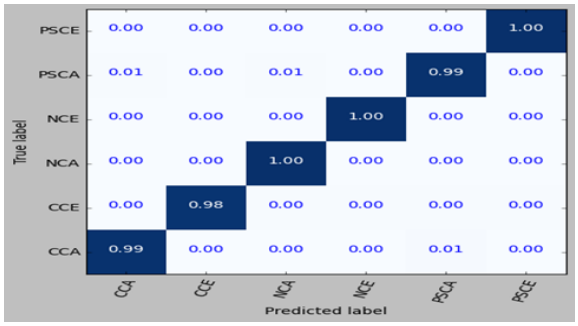

Fig 12. Confusion matrix of CCG model for cataract grading

The confusion matrix reveals that the severity samples of NCA, NCE, and PSCE were correctly predicted with a 100% accuracy. Additionally, 99% of CCA and PSCA samples were accurately predicted, while the CCE sample had a prediction accuracy of 98%. The Figure 12 below illustrates the training and validation accuracy.

4. CONCLUSION

One of the major causes of blindness in Ethiopia is cataract. Previous attempts to detect cataract disease at an early stage have failed due to differences in eye color among Ethiopians. Motivated by the goal of reducing blindness, we developed a model capable of identifying cataract types and assessing their severity. Data collection was initiated by gathering information from various hospitals in the Amhara regional state. To detect the eyes, we employed the Viola-Jones face and eye detection algorithm. However, this algorithm also captured unwanted regions surrounding the eyes. To address this, we calculated the average distance between the actual eye and the unwanted regions, allowing us to remove them effectively. Segmentation was performed using a contrast factor to enhance the quality of the segmented region of interest. For both classification and grading purposes, an end-to-end CNN model was utilized. A series of experiments were conducted based on the segmentation results, and improved outcomes were achieved when applying smoothing and segmentation compared to the raw data obtained from the Viola-Jones algorithm. The classification recognition rate for cataract disease reached 97%, while the grading recognition rate reached 99% when contrast enhancement and segmentation were applied. As a result, the cataract classification and grading (CCG) model has demonstrated promising results, offering a potential solution to prevent cataract disease in Ethiopia. Therefore, the proposed model plays a vital role in early identification of cataract type and severity. Diagnosing cataract before it reaches an advanced stage is crucial in reducing blindness rates.

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