An Efficient Deep Learning Model for Eye Disease Classification

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***Abstract*— Early detection of eye diseases is crucial, particularly for individuals with a family history of eye diseases, people over 60 years of age, individuals with diabetes, and those who have a history of eye injuries or surgeries, as they are at a higher risk of developing eye diseases. Early detection and timely treatment are crucial in treating eye diseases and preventing permanent vision loss. Detecting eye diseases early on is crucial in preventing or slowing down the progression of vision loss and blindness. Unfortunately, many eye diseases, including diabetic retinopathy, glaucoma, and cataracts, do not have early warning signs or symptoms. Therefore, regular eye checkups and early detection of these diseases can be essential in preventing vision loss and improving the quality of life for those affected. Retinal fundus image screening is a commonly used technique for diagnosing eye disorders, but manual detection is time-consuming and labour-intensive. To address this issue, various researchers have turned to deep learning methods for the automated detection of retinal eye diseases. In this work, a convolutional neural network model has been developed for classifying eye diseases, demonstrating an impressive accuracy rate of 99.85%. This suggests that the model can correctly classify eye diseases in nearly 4 out of 5 cases. These findings have the potential to significantly improve the accuracy and efficiency of diagnosing eye diseases using retinal fundus images.**

Keywords*— *Eye disease, deep learning, multi-class classification, image processing.

I. Introduction

Among the five senses, the human body's eyes are the most often used sensory organs. One million or so, nerve fibres make up the retina layer, which organizes into the optic nerves [1]. Diseases of the retina, a thin layer of tissue on the inner back wall of the eye, are referred to as retinal diseases. The retina contains tens of millions of rods, cones, and other nerve cells that receive and organise visual information [2]. Because the retina sends this information to the brain via the optic nerve, we can see it. A wide range of conditions, including direct trauma to retinal tissue, a detached retina, and diseases like diabetic retinopathy and age-related macular degeneration, can lead to issues with the retina [3]. Blind spots, loss of night vision, and blurred or distorted vision are just a few of the symptoms that retinal diseases can produce. Diabetic retinopathy, retinal tears, retinal detachment, glaucoma, retinitis pigmentosa, and vein occlusion are a few eye conditions that harm the retina [4].

The blood vessels in the retina are harmed by DR, which emerges as a result of the increase in blood sugar. The eye's lens seems to become clouded, which leads to cataract development. Glaucoma results from fluid buildup in the front of the eyes, which in turn causes the pressure inside the eyes to rise and damage the optic nerve [5]. To prevent blindness and improve quality of life, eye diseases must be identified early and properly treated [6]. Conventional diagnosis techniques rely on the experience and training of the doctor, who is frequently known for making incorrect diagnoses. Deep learning algorithms have transformed the field of computer vision over the past few years and are now affecting our daily lives [7].

There are numerous and widely used computer-aided diagnosis systems for eye diseases [8]. Deep learning has demonstrated its abilities in ophthalmology and other areas of public health [9]. To find, recognize, and quantify pathological features in retinal disease diagnosis, a method based on DL and convolutional neural networks is used. The effectiveness of this strategy keeps improving [10].

II. Related Work

In [11] Ophthalmologists and skilled technicians diagnose and treat eye diseases. Ophthalmoscopy, ultrasound imaging, fundus photography, tomography, ultrasound imaging, and Heidelberg retinal tomography are the imaging systems required for the detection of abnormalities. In rural and remote areas of developing nations like India, ophthalmologists are frequently unavailable and there aren't any eye care facilities. This issue can be greatly resolved by early detection of various eye diseases, followed by appropriate medical treatment. A more effective alternative for the prompt diagnosis and treatment of eye diseases is the automated detection of eye diseases through the analysis of various types of medical images. In general, image acquisition, pre-processing, and extraction of the region of interest are the steps involved in image processing-based automated diagnostic techniques. [12] conducts a methodical analysis of the importance of image processing for DED classification. The steps in developing the suggested automated classification framework for DED include image quality enhancement, picture segmentation (area of interest), image augmentation (geometric alteration), and classification. The best outcomes were produced by combining conventional image processing techniques with a recently created convolution neural network (CNN) architecture. In [13] fuzzy k-means clustering algorithm and the fast region-based convolutional neural network algorithm presents a computerized method for disease localization and segmentation. They created bounding-box annotations using ground truths because datasets were missing them. These annotations are necessary for the FRCNN, an object detection method. After separating the annotated images using FKM clustering, localization is further trained on the FRCNN over the segmented images. By intersection-over-union processes, the segmented regions are then contrasted with the ground facts. In [14], the objective of this study is to intelligently distinguish between photos with retinal abnormalities and images of healthy retinas without undertaking any intentional segmentation or feature extraction. Alternatively, they made use of a deep learning algorithm to identify any retinal fundus image either healthy or ill. The network's architecture is basic and quick. Two datasets, including individual patient retinal fundus images obtained from a nearby hospital, were used to evaluate the model. In [15], This study utilizes retinal fundus photos from an online dataset whose images have been pre-processed, and early detection of age-related eye disorders was achieved by using the maximum entropy transformation. To locate, recognize, and quantify pathological features in the retina, a method based on DL and convolutional neural networks is used. A convolution neural network (CNN) that was improved using a flower pollination optimization technique (FPOA) for feature extraction was fed to the pre-processed images. FPOA was used to modify the hyperparameters before training the CNN. This boosted the network's accuracy and speed. A Multiclass SVM (MSVM) classifier was employed in order to identify the category of sickness out from CNN output. The online dataset known as Ocular Disease Intelligent Recognition was utilized in order to assess the suggestion for CNN-based multiple disease detection (CNN-MDD) (ODIR).

III. MATERIAL & METHODS

The dataset and the method used to identify the eye disease are discussed in this section.

A. *Dataset*

The dataset used to make the eye disease prediction was obtained from the Kaggle Open Repository. Images of different eye conditions as well as images of healthy eyes are included in the dataset to train and test the model [16].

Fig. 1. depicts images of various classes of eye diseases as well as images of healthy eyes. The first image depicts a healthy eye, the second one is glaucoma, the third, is diabetic_retinopathy, and the fourth, is cataract disease.

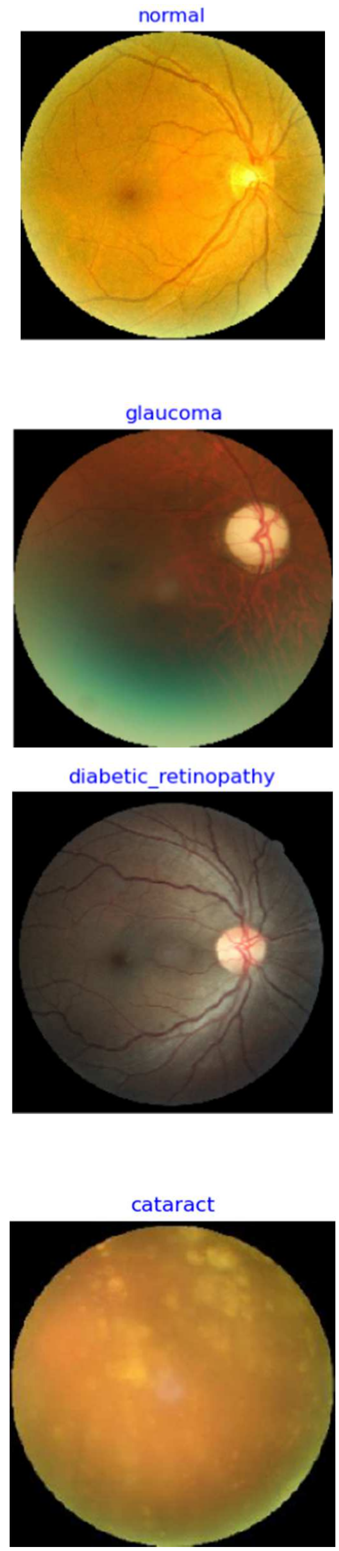

Fig. 1. Different classes to predict eye disease[16]

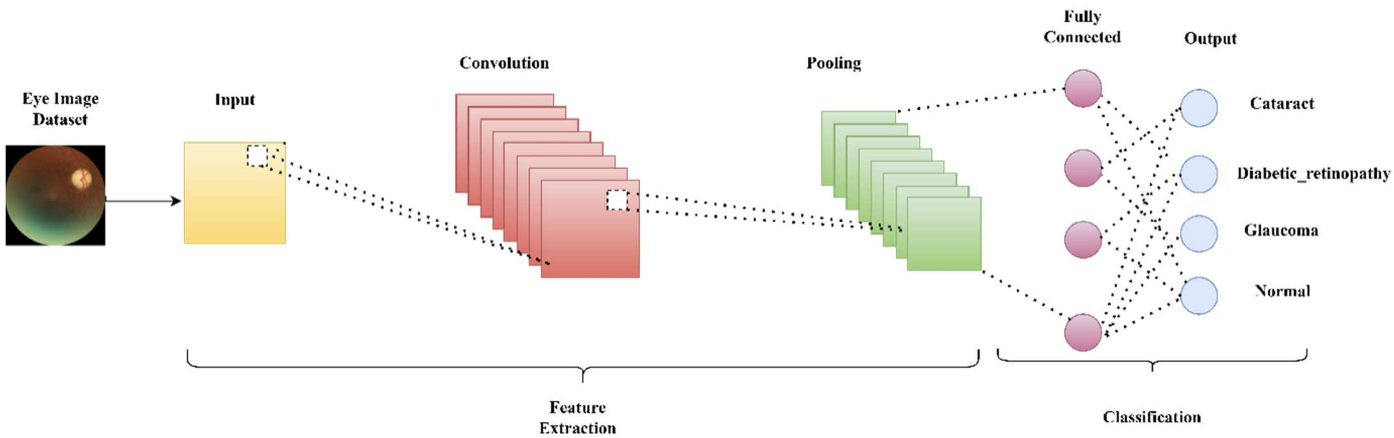

Fig. 2. Proposed methodology to predict eye disease

Fig. 2. illustrates the suggested methodology for forecasting eye disease. The dataset is first used to extract the eye image, which is then sent to the input layer, input layer, convolutional layer, and image pooling layer in order to reduce the dimensionality of the dataset and produce a pooled feature map. The data is then sent to a fully connected layer, which classifies the image and sends it to the output layer, following this feature extraction.

B. Methodology

The natural lens of the eye, which is situated behind the iris and the pupil, becomes clouded as a result of the eye condition known as cataracts. Aside from other vision-related problems, this clouding can make it difficult to see at night, make you sensitive to light, and cause blurry vision. Although cataracts are frequently linked to ageing, they can also be brought on by genetics, trauma, or other medical conditions. People with diabetes are susceptible to a specific type of eye disease called diabetic retinopathy. When blood vessels in the retina, the area of the eye that senses light and transmits visual signals to the brain, are harmed by high blood sugar levels, this condition develops. Vision that is hazy or distorted, spots or floaters in the visual field, and difficulty seeing in low light are all signs of diabetic retinopathy. Diabetic retinopathy can, in extreme cases, cause blindness. A group of eye conditions collectively referred to as glaucoma cause damage to the optic nerve, which transmits visual information from the eye to the brain. If left untreated, this damage may result in vision loss, beginning with peripheral vision and eventually leading to total blindness. There are numerous types of glaucoma, such as open-angle and angle-closure glaucoma, and the condition is frequently accompanied by an increase in eye pressure. The best method for avoiding glaucoma-related vision loss is early detection and treatment. When there is no disease present, the eye is healthy or normal.

In the proposed work, a common DL model for image processing, classification, and recognition is the convolutional neural network (CNN). It draws its structure and operation from the human visual system, which is capable of quickly and accurately identifying objects and patterns in visual data [17]. A CNN is made up of various layers, each of which has a specific job to do when analyzing and categorizing image data. The input layer is the one that takes raw image data as input. It typically consists of a grid of pixels, where each pixel's colour or intensity is represented by a numeric value. The convolutional layer performs a convolution, which is a mathematical operation, on the input image by applying a number of filters to it. The filters make it easier to spot particular elements or patterns in the image, like edges, lines, or textures. The convolutional layer's output is subjected to an activation function in the activation layer [18]. The model can learn more intricate patterns and relationships in the image data thanks to the activation function's assistance in introducing non-linearity. The pooling layer down samples the image to reduce its size, typically using a method known as max pooling. This makes the model more effective by lowering the amount of computation it needs to perform. During training, the dropout layer randomly removes some of the neurons from the model, preventing overfitting and enhancing generalization. The fully connected layer completes a final classification or regression task using the features the model has learned by connecting all the neurons in the previous layer to all the neurons in the following layer. The model's final output, which may be a class label or a numerical value, is produced by the output layer. To transform the model's output into a probability distribution over all possible classes or values, the output layer typically uses a softmax function [19].

A deep neural network with the EfficientNetB3 model architecture was created for image classification tasks. It belongs to the family of EfficientNet models, which have been enhanced for both precision and effectiveness, making them suitable for use in practical applications. Convolutional layers that extract features from the input image make up the EfficientNetB3 model architecture [20]. The final classification output is then created by passing these features through a number of pooling layers and fully connected layers. The EfficientNetB3 model's architecture is based on a compound scaling technique that simultaneously optimizes the model's depth, width, and resolution. It enables the model to achieve high accuracy while requiring fewer parameters and shorter computation times. In order to extract features from the input image, a series of filters make up the convolutional layers. The pooling layers reduce the spatial dimensions of the feature maps while the fully connected layers aggregate the features and generate the final classification output. Overall, the EfficientNetB3 model architecture performs exceptionally well at image classification tasks because of its effective layout and superior scaling technique whereas the hyperparameters such as epochs, activation function, and batch size have been kept as 20, ReLU, and (40,32), respectively.

IV. Result & Discussion

A table called a confusion matrix is used to assess how well a machine-learning model is working. It lists a set of data points' actual and anticipated classifications. True positives, false positives, true negatives and false negatives are the four entries in the matrix. True positives are instances where the model correctly predicted the positive class, false positives are instances where the model incorrectly predicted the positive class and true negatives are instances where the model correctly predicted the negative class.

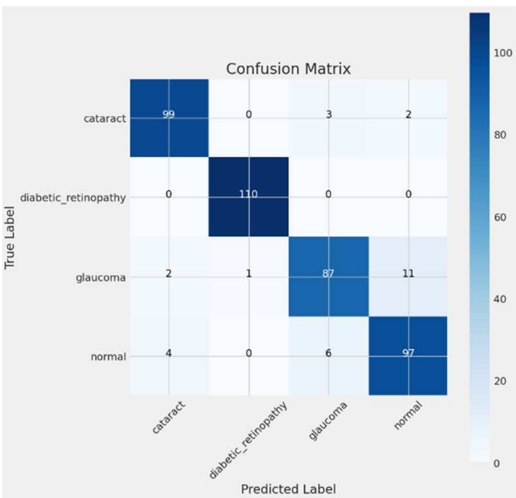

Fig. 3. Confusion Matrix to predict eye disease with batch size 40

The obtained confusion matrix with batch size 40 is shown in Fig. 3. According to this matrix, the accuracy for categorizing cataracts correctly is 95.19%, for categorizing diabetic retinopathy it is 100%, for categorizing glaucoma it is 86.13%, and for categorizing "normal" it is 90.65%. This confusion matrix shows the wrongly predicted classes, overall accuracy, and the accuracy of each eye disease class predicted in the proposed CNN model.

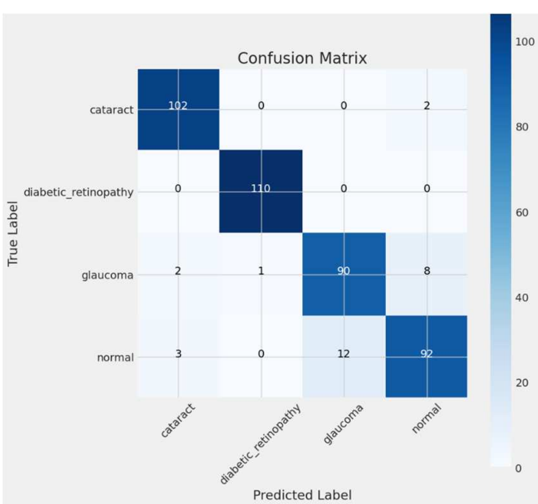

Fig. 4. Confusion Matrix to predict eye disease with batch size 32

The obtained confusion matrix with batch size 32 is shown in Fig. 4. According to this matrix, the accuracy for correctly categorizing cataracts is 98.07%, for diabetic retinopathy it is 100%, for glaucoma it is 89.10%, and for categorizing "normal" class is 85.98%. This confusion matrix results in the wrongly classified classes, and achieved accuracy for each class along with overall accuracy with the batch size value of 32.

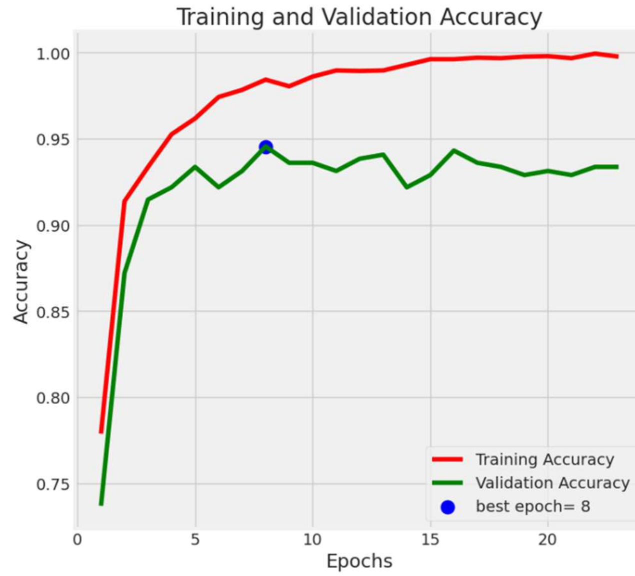

Fig. 5. Training and validation accuracy analysis with batch size 40

Using a batch size of 40, Fig. 5 shows the accuracy analysis based on training and validation. For the training accuracy, the figure shows that with the increase in epoch value, the training accuracy also increases whereas validation accuracy increases till epoch value 5 and decreased at epoch 6. The model's accuracy has been achieved highest at epoch 8. Afterward, when the model was validated with a higher epoch value the accuracy started fluctuating.

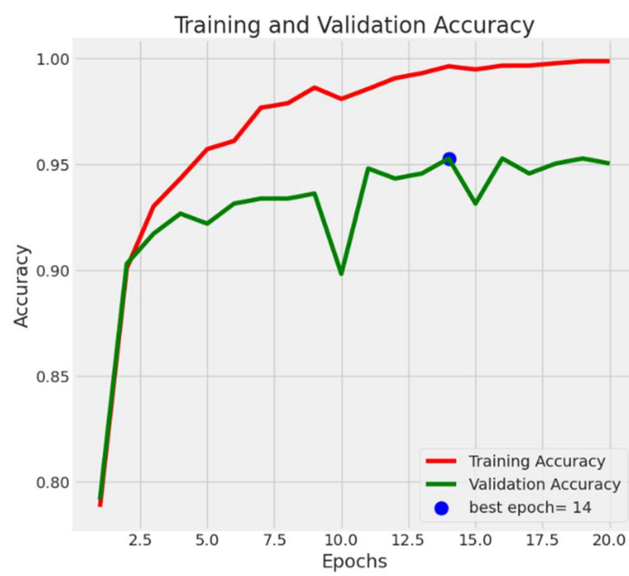

Fig. 6. Training and validation accuracy analysis with batch size 32

By implementing the proposed CNN model with a batch size of 32, training accuracy and validation accuracy have been shown in Fig. 6. The model's accuracy has been achieved highest at epoch 14. However, the least training accuracy and validation accuracy were achieved at epochs 3 and 5, respectively.

Table. I display the accuracy analysis of various eye disease categories using various batch sizes. The batch sizes in use are 40 and 32.

TABLE I. ACCURACY ANALYSIS OF DIFFERENT EYE DISEASES OBTAINED FROM THE DIFFERENT BATCH SIZE

Eye Disease	Batch Size (40)	Batch Size (32)
Cataract	95.19	98.07
Diabetic_Retinopathy	100	100
Glaucoma	86.13	89.10
Normal	90.65	85.98

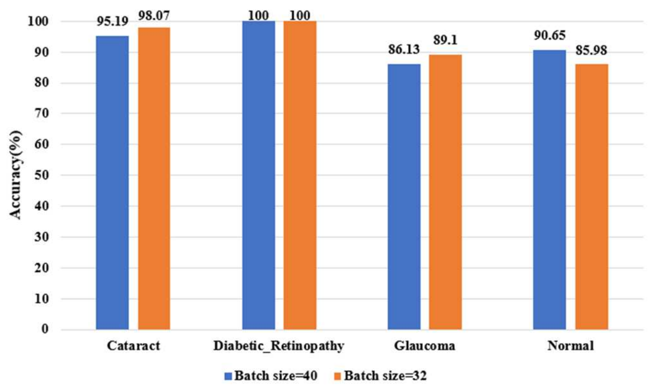

Fig. 7. Class-wise accuracy analysis with different batch sizes

Fig. 7. displays the accuracy analysis of various eye disease categories using various batch sizes. The batch sizes in use are 40 and 32. With batch size 40 cataracts achieved an accuracy of 95.19%, diabetic_retinopathy 100%, glaucoma 86.13%, and normal 90.65% whereas with batch size 32 the achieved accuracy for cataracts is 98.07%, diabetic_retinopathy 100%, glaucoma 89.10%, and normal 85.98%.

TABLE II. OVERALL ACCURACY ANALYSIS OF DIFFERENT EYE DISEASES OBTAINED FROM THE DIFFERENT BATCH SIZE AND EPOCHS

Sr.No.	Batch Size	No. of epochs	Accuracy (%)
1.	40	40	93.12
2.	32	20	99.85

Table. II depicts the overall accuracy comparison of the model along with the different batch sizes and different no of epochs. With batch size 40 and epoch 40 the accuracy is 93.12% and with batch size 32 and epoch 20 the achieved accuracy is 99.85%.

Fig. 8. compares the model's overall accuracy while also showing the various batch sizes and epoch counts. The accuracy is 93.12% with batch size 40 and epoch 40, and it is 99.85% with batch size 32 and epoch 20.

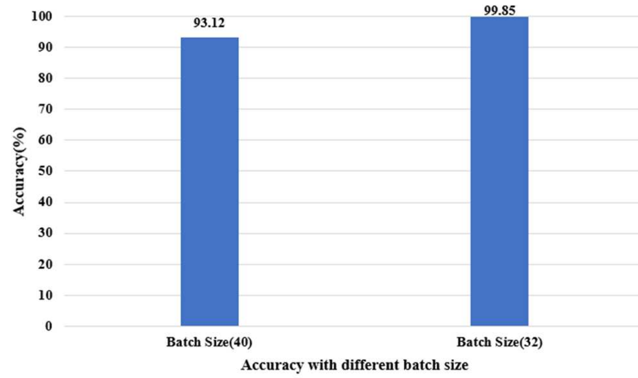

Fig.8. Overall accuracy analysis with different batch sizes and epochs

V. CONCLUSION AND FUTURE SCOPE

Eye disease is a broad term used to describe various conditions that impact the well-being of the eyes and can lead to visual impairment or blindness when not properly addressed. There are several types of eye diseases, each with distinct symptoms, causes, and treatments. To avoid visual impairment conditions, it is required to early detect eye diseases. Nowadays, DL-based models have attracted a lot of attention internationally recently. Although DL has been widely used in speech and image recognition, along with natural language processing, its influence on healthcare is still developing. DL has been utilized in ophthalmology to detect various eye diseases, such as diabetic retinopathy, glaucoma-like disc, macular edema, and age-related macular degeneration, through fundus photographs, optical coherence tomography, and visual fields. DL in ocular imaging can be beneficial for diagnosing, and monitoring serious eye diseases for patients in primary care and community settings, in combination with telemedicine. Similarly, in the proposed work, a CNN model has been developed for the classification of eye diseases which has resulted in an accuracy of 99.85%, indicating that the model can correctly classify eye diseases in nearly 4 cases out of 5. In addition, the work can further be extended by enhancing the dataset with the utilization of the augmentation methods.

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