

Eye Disease Detection and Classification from Retinal Images using Convolutional Neural Networks

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Abstract

1 billion people worldwide are affected by blindness or moderate to severe distance vision impairment brought on by untreated cataract, glaucoma, and diabetic retinopathy. This vision damage might have been avoided or is still unaddressed. The research aim of the present study is at creating a deep learning (DL) tool that can classify retinal images into four categories: 1) normal, 2) cataract, 3) glaucoma, 4) retinal disease using a convolutional neural network (CNN). The dataset used was obtained from Kaggle and had 601 images, which were randomly divided into training and testing data. 70% i.e. 421 images were used for training and 30% i.e. 180 images were used for testing. The images were resized to 150*150 pixels, flipped horizontally randomly, converted to grayscale and normalized color range to [0,1] to reduce skewness and improve performance of CNN. The CNN model was then created using pytorch and torch vision libraries of python. 3 convolutional layers and 3 pooling layers were used. The ReLU function was used for activation. The CNN model was tested using 50 epochs but the pytorch chooses the number of epochs with best testing accuracy. The output label is compared to the actual label of the image. Our model showed a training accuracy of 0.96 and a testing accuracy of 0.78 Even though, as the number of epochs increased, the training accuracy went as close to 1.00, the model became prone to overfitting. Our research hopes that this tool can be employed by doctors to automate the process of eye disease detection. This can potentially help save time and also promote early diagnosis.

Keywords: Eye diseases detection, Classification, Retina image, Deep Learning, Convolutional neural network,

1. Introduction

Eye disease recognition is a challenging task, which usually requires years of medical experience. In this work, we would conduct research that can be a start for the most versatile solution - Detection of various eye diseases (such as cataract, glaucoma, and retinal diseases) using retinal images and classifying them with the help of convolutional neural networks. Figure 1 shows a label diagram of the retinal image of the normal eye.

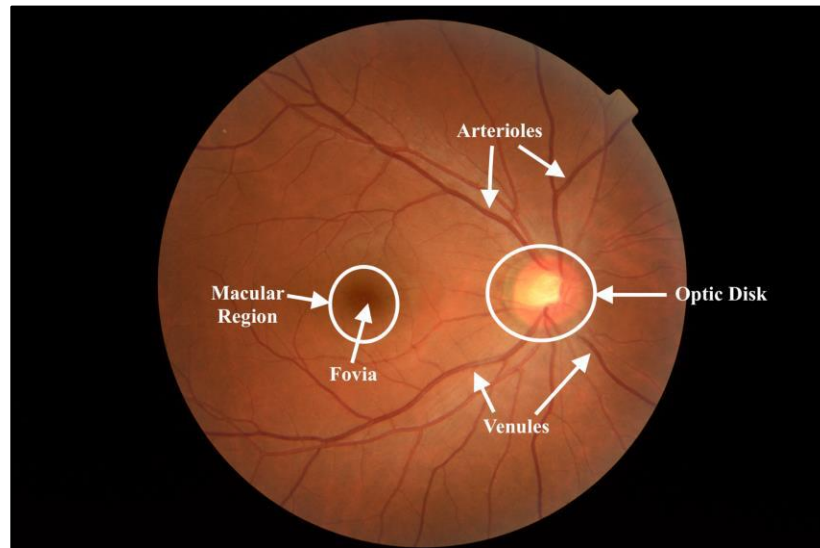


Figure 1: Labeled retinal image

According to the World Health Organization, at least 2.2 billion people all over the world face vision impairment [1] and in at least one billion of these, vision impairment could have been prevented through early detection [2]. With such a huge number, one can only expect doctors to face an influx of retinal images to diagnose the problem. This task being automated through Deep Learning (DL) can potentially save a lot of time.

The application of DL to eye disease detection and treatment is significant. Medical science has advanced thanks to the application of cutting-edge Artificial Intelligence (AI) approaches to image identification and medical diagnostics. Automated retinal illness identification requires preprocessing using picture quantization, segmentation and sampling techniques, training neural networks with massive amounts of data, and statistical analysis. To increase the effectiveness of deep learning-based algorithms, methods based on "deep extraction of information from the available images," such as "affine transformation" and "rotation of the images," have been developed. The present research priorities are to increase the precision of disease classification and diagnosis, decrease computational time and memory usage, segment the ocular layers correctly, and reduce computational complexity.

The research will help save doctor's time by self-diagnosis of the problem. The patient can simply put their retinal image through the classifier and receive their diagnosis with a particular accuracy, upon which they can consult a doctor. Early detection of the problem will of course prove beneficial to the affected. The aim of the research is to create a deep learning-based tool which can classify images of the retina into eyes with cataract, glaucoma, retinal diseases or simply a normal eye with a certain accuracy, which can inform the person whether they need to consult a doctor or not.

1.1. Motivation and Novelties

Eyes are one of the most essential parts of the human body but still a vast majority of people are deeply affected by eye diseases. Late detection continues to be the number one cause for the aggravation of such diseases and leading to complications as extreme as blindness. This particular research topic, therefore, addresses the early detection and how it potentially can help detect blindness. To achieve this aim, the paper implements the innovation of being able to put an eye image through a CNN which will further formulate whether the particular eye has a disease or not. Through our literature review, we believe there still does not exist a classifier accessible to people through which they can self-diagnose eye disease. It takes years of practice in the medical profession to be able to detect eye disease. A classifier doing that for a doctor is a relatively new idea.

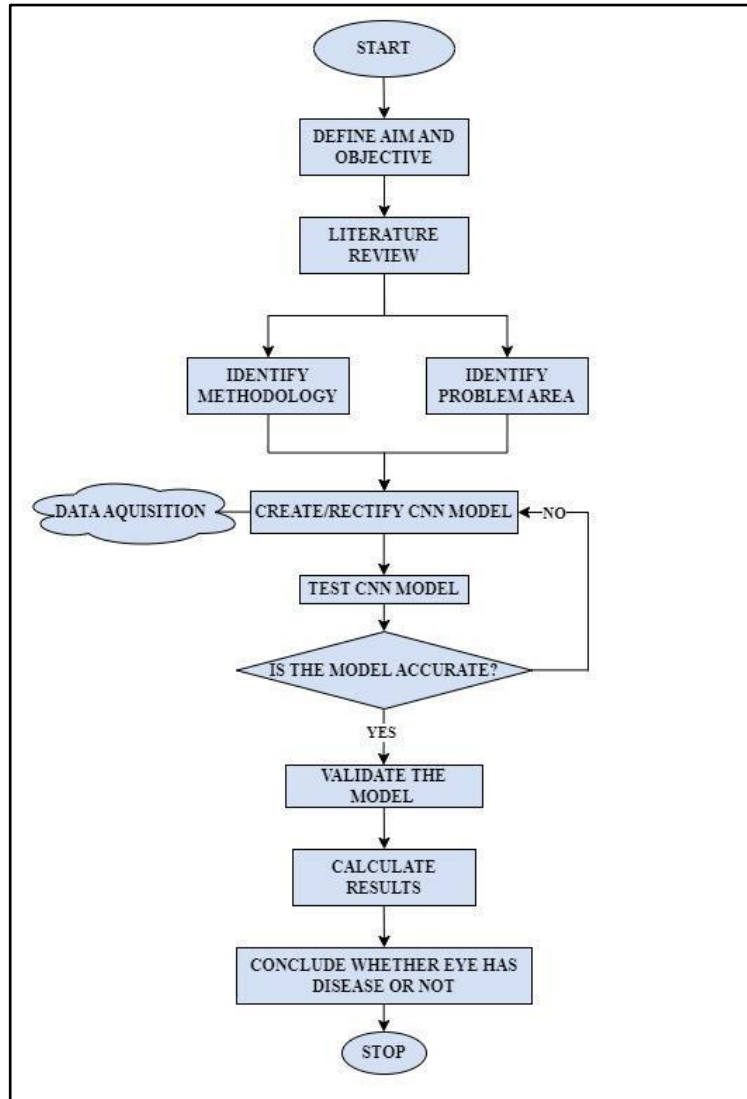


Figure 2: Schematic diagram of organization of research paper

The organization of the paper is as such:

Section 2 of the paper reviews the contemporary literatures and summarizes them which is followed by section 3 describing the dataset and methodology employed to fulfill the aim of the study. Section 4 describes the results and discussions and finally section 5 concludes the paper and suggests some future application of the present study.

2. Literature review

This section of the paper summarizes some of the significant contemporary literature. In the paper [3], the authors developed a novel method to extract the main features in color retinal images that have been developed in this paper. Principal component analysis (PCA), modified active shape model and fundus coordinate system are respectively used for locating optic disk, detecting shape of optic disk and providing a better description of features in the retinal images. The success rates of these three tasks are 99%, 94%, and 100%, respectively. The article [4] aimed to determine the sensitivity and specificity of the Iowa Detection Program (IDP) to detect referable diabetic retinopathy (RDR). 874 people with diabetes at risk for DR were included in the research. The paper concluded that the IDP had high sensitivity (96.8%) and specificity (59.4%) to detect RDR. In paper [5], the author establishes a professional structure to familiarize an individual with up-to-date vessel segmentation techniques. Formulated that the average accuracy of deep learning methods is reaching around 98% and that is strong evidence that the employment of these algorithms can help prevent victims at an early stage. In paper [6], the authors proposed the use of a back propagation neural network (BPNN) classifier for automatic cataract detection based on the classification of retinal images. The BPNN model classifies images into normal, mild, medium or severe cataract. In the research paper [7], the authors surveyed literature about the automatic extraction of anatomical features from retinal images to assist early diagnosis of the Glaucoma. Performed critical evaluation of the existing automatic extraction methods based on features including Optic Cup to Disc Ratio (CDR), Retinal Nerve Fiber Layer (RNFL), Neuroretina Rim Notching etc. The academicians assessed the algorithms proposed by different groups and described the preeminent steps in the development of an automated diagnosis system. Studies from 2014-19 were chosen and out of those the ones that used segmented optic disk method were excluded. The systematic analysis of such studies was performed and results summarized in the paper [8]. The aim of paper [9] is to assess the role of artificial intelligence (AI)-based automated software for detection of diabetic retinopathy (DR) and sight-threatening DR (STDR) by fundus photography taken using a smartphone-based device and validate it against ophthalmologist's grading. 296 retinal images were graded, and the software showed 95.8% sensitivity and 80.4% specificity. The intention of the study [10] is to detect glaucoma, which is established on principal components analysis (PCA) and Bayes classifier. 95.3% and 89.9% were the respective success rates of optic disk localization for normal set and glaucoma set. Over 300 retinal images were tested and a success rate of 78% was shown. In [11], puts forward image processing techniques for the early detection of glaucoma. Uses two features, namely, Cup to Disk ratio and Ratio of Neuroretinal Rim in ISNT quadrants. 50 retinal images were used, and a 94% accuracy level was achieved. The main aim of paper [12] is to develop an efficient diagnosis system for screening the Glaucoma disorder using retinal images. Features such as Gray Level Co Occurrence Matrix (GLCM), Effective Local Binary Pattern (ELBP), and Optic Band features are extracted from this neuro retinal rim region. These are then trained and classified using the Support Vector Machine classifier. The proposed methodology achieves an average accuracy of 99.3%. In [13], the authors developed an automated disease segmentation approach based on Fast Region-based Convolutional Neural Network (FRCNN) algorithm with fuzzy k-means (FKM) clustering. The efficacy of the approach in terms of both disease detection and segmentation is confirmed through a rigorous comparison against the latest methods. In paper [14], the authors aim to automatically classify images with retinal problems without performing any explicit segmentation or feature extraction. Two datasets were used, one being a real patient retinal fundus obtained from a local hospital. The range of accuracy was 96.5% to 99.7%. In article [15], the authors identified age-related eye diseases at an early stage using retinal fundus images taken from an online dataset. The pre-processed images, transformed using maximum entropy, were fed into a convolutional neural network to yield an accuracy of 95.27%. In paper [16], the authors applied various image processing and machine learning techniques for detection of eye diseases. A survey on review of medical image processing and machine learning techniques for detecting and classifying eye disease images for disease recognition was also defined. In paper [17], the authors surveyed different machine learning (ML) and deep learning (DL) techniques to detect eye diseases namely ARMD, cataract, DR and glaucoma were reviewed in this paper. The key observation was that the accuracy of AI based techniques outperformed manual feature extraction and classification techniques in all four disease detection areas. In article [18], the authors proposed a novel approach to provide an automated eye disease recognition system

using visually observable symptoms applying digital image processing techniques and machine learning techniques such as deep convolutional neural network (DCNN) and support vector machine (SVM). The DCNN model was seen to outperform the SVM models. The average accuracy rate of the DCNN model was 98.79% with sensitivity of 97% and specificity of 99%. In [19], the authors proposed a multi-level deep convolutional neural network (ML-DCNN) architecture on retinal fundus images to diagnose glaucoma. 1338 retinal glaucoma images were used to test the proposed model. Specificity, sensitivity, accuracy, and precision were respectively 97.04%, 98.99%, 99.39%, and 98.2%. The article [20] aims in developing a general framework for recording diagnostic data in an international standard format to facilitate prediction of disease diagnosis based on symptoms using machine learning algorithms was developed in this paper. The random forest and decision tree algorithms' prediction rate is more than 90% as compared to more complex methods such as neural networks and the naïve Bayes algorithm owing to a structured data arrangement. In paper [21], the authors detect human eye infections of Glaucoma disease by firstly using different machine learning (ML) classifiers. The obtained results showed that the RF and MLP classifiers achieved the highest accuracy of 77% while the deep learning model provides an even better accuracy of 84% for the same task and dataset. In [22], the authors proposed a deep learning method for extracting features and classification using a support vector machine. The proposed method is tested using 77 and 70 retinal images of base 12 and base 13 respectively. The highest accuracy values are 95.83% and 95.24% for base 12 and base 13 respectively.

Many other papers are reviewed for compiling the present research paper. However, limiting the research to the most significant and the recent papers.

3. Materials and Methods

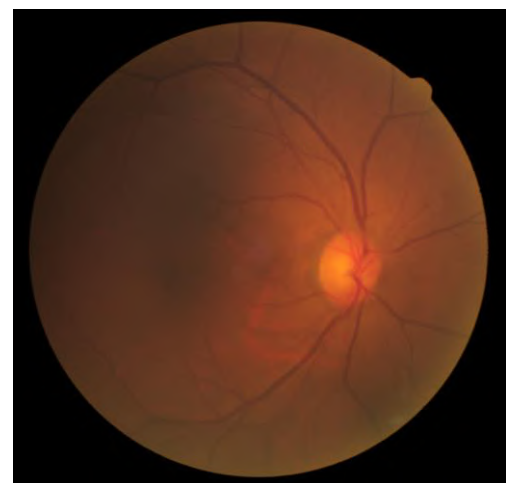
In this section of the paper, a brief description of the methodology and the dataset used for developing the classification model is given.

3.1. Dataset

The dataset, "retina dataset", was from Kaggle [23]. It is a retina dataset containing four categories: 1) normal 2) cataract 3) glaucoma 4) retina disease. The retinal images show certain visual differences for each category. An eye with cataract has a clouded lens, a glaucomatous eye differs in its optic disc and retinal images have wool spots or differ in optic nerves. The total number of images are 601, and 70% i.e. 421 images are randomly selected for training and the remaining 30% i.e. 180 images are used for testing. Figure 3 shows the one retinal image from each class.



(a)



(b)

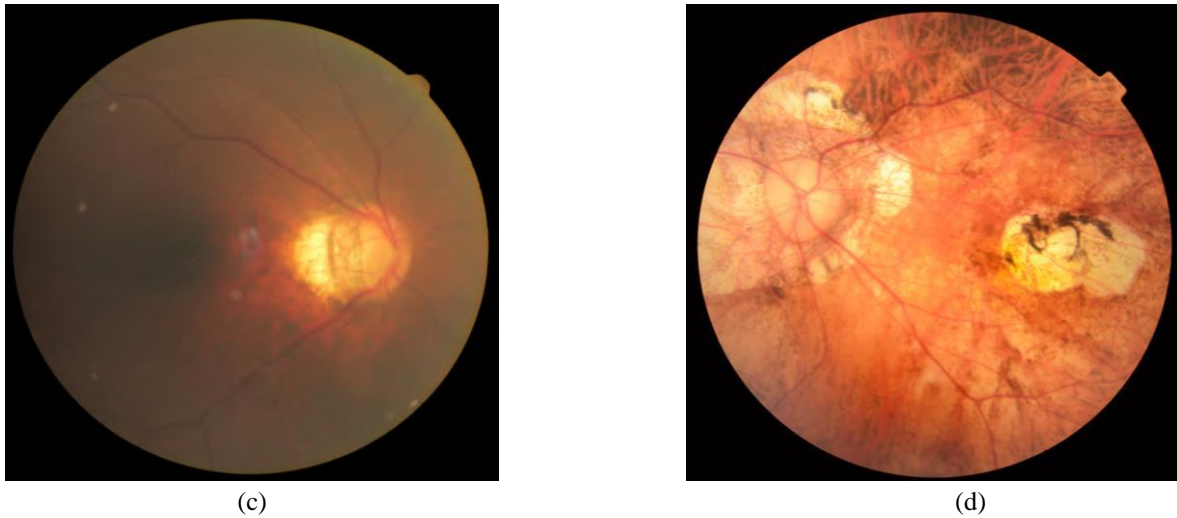


Figure 3: Retina images of (a) Normal Eye, (b) Cataract, (c) Glaucoma and (d) Retinal Disease

3.1.1. Preprocessing of the dataset

All the pictures have different aspect ratio, size, shape and format. The images were resized to 150*150 pixels, flipped horizontally randomly, converted to grayscale and normalized color range to [0,1] in order to reduce skewness and improve performance of convolutional neural networks.

3.2. Methodology

The Convolutional Neural Network (CNN) classification model employed for detecting and categorizing eye diseases from retina images. The CNN is a potent deep learning (DL) algorithm, mostly used for classifying the image datasets. At present scenario, these are the best algorithms available for automatically processing and classifying photos. CNN's fundamental advantage over its forerunners is that it uses machine learning to identify key elements without human intervention. Figure 4 shows the flowchart for developing the CNN model.

3.2.1. Training the CNN model

In DL, model training procedure involves providing the DL algorithm which is CNN in the present paper with data in order to help it recognise and learn the best values for all relevant variables [24]. In order to compare the processed output to the sample output, the training model is used to run the input data through the algorithm. The correlation's outcome is utilized to change the model. Model fitting is the term for this iterative procedure. For the model to be precise, the training dataset or validation dataset must be accurate. The steps for training a CNN model is as follows:

Convolution layer

In the CNN model, the convolutional layer extracts features from the image while removing noise. A mathematical procedure known as convolution combines two functions, usually denoted by the letters f and g , to create a third function (φ) that describes how the shape of one is changed by the other. The dot product of f and g , which is given in Eq (1), is the expression for calculating the value of in the proposed CNN model. The visual representation of the convolution layer is shown in figure (5).

$$\varphi = f.g \tag{1}$$

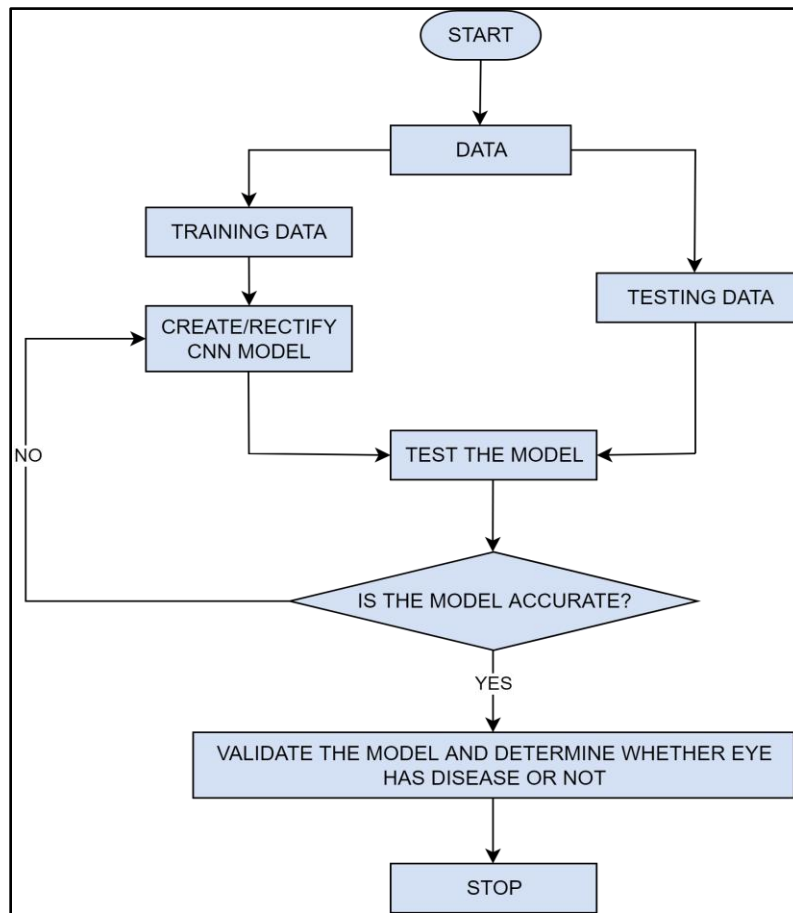


Figure 4: Flowchart of the CNN model

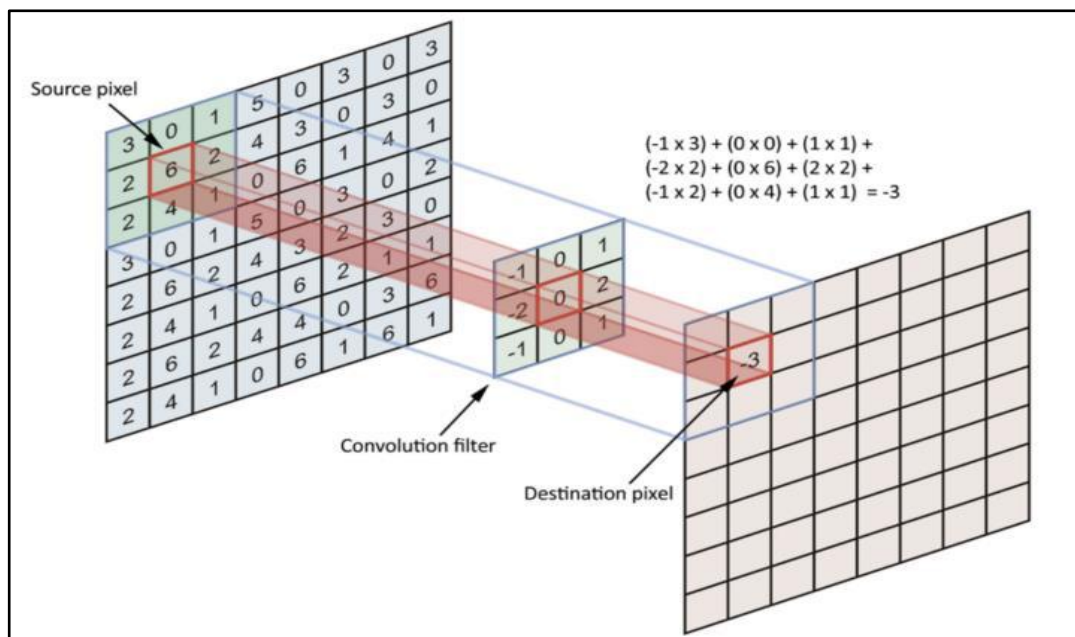


Figure 5: Visual representation of a convolution layer

Activation function

In neural network models, activation function transfers the weighted sum of the input of the node to the output of the node in the layer of the network. The activation function used in this CNN model is called a rectified linear unit (ReLU). It is mathematically expressed as:

$$f(x) = 0, \text{ if } x \leq 0 \tag{2}$$

$$f(x) = x, \text{ if } x > 0 \tag{3}$$

Figure 6 shows the graph for ReLU.

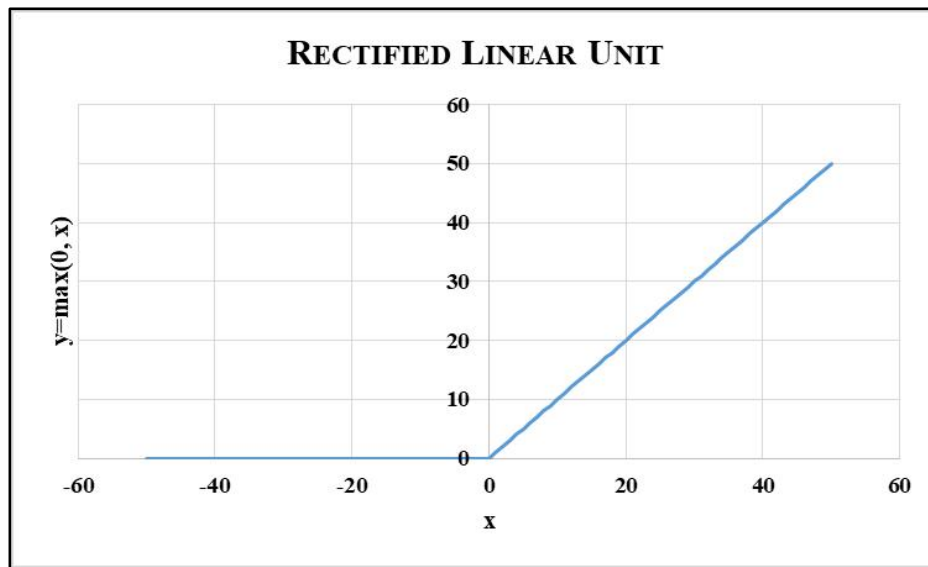


Figure 6: Graph for Rectified Linear Unit (ReLU)

Pooling operations

The feature maps' dimension is decreased as a result of the pooling procedure, which also reduces the number of parameters that must be learned, and the amount of network computation required. The pooling layer is crucial because it provides a summary of the features that are present in a particular area of the feature map created by the convolution layer. We can either use max pooling or average pooling. In the present research paper, max pooling has been used because we are interested in the lighter pixels of the image.

Layer stacking operations

Convolution, activation, and pooling operations are repeatedly used in layer stacking until the output is a reduced matrix of the input picture. We have used 3 layers to decrease the loss values and to increase the accuracy. Time taken is very high but accuracy is increased. If we used more layers, our model would have been prone to overfitting.

Fully connected layer

Neurons from the previous layers are fully coupled to one another in the Fully Connected (FC) Layer. The output or label of the input class is predicted by the FC layer. Different activation functions are used to categorize the label of the inputs in multi-class problems.

Classification

Classification is a process related to categorization. In the study, the CNN model classifies the images of eyes into four categories: 1) normal eye, 2) cataract, 3) glaucoma, 4) retinal disease. The diagrammatic representation of the proposed CNN model is shown in figure 7.

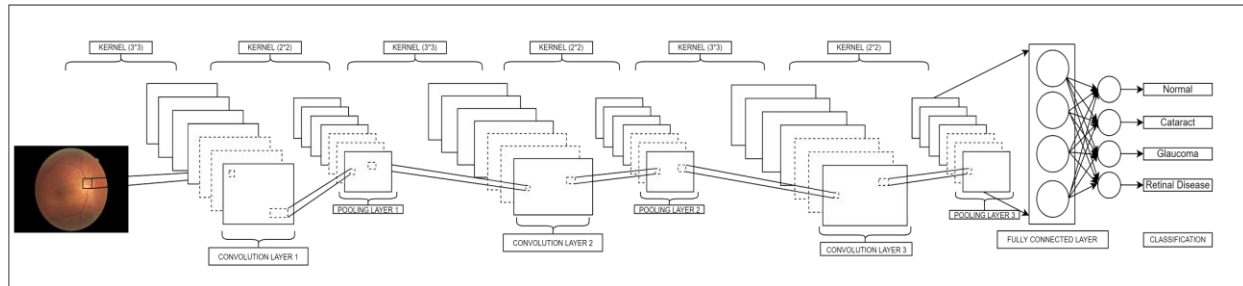


Figure 7: The CNN network

3.2.2. Testing the CNN model

The model is tested using the 180 images. The number of epochs is initially defined as 50 but the pytorch chooses the number of epochs with best testing accuracy. The output label is compared to the actual label of the image.

4. Results and Discussions

In this study a CNN model is using the torchvision DL library. The CNN algorithm is coded on MacBook Air (13-inch, 2017), Memory 8 GB 1600 MHz DDR3, and Processor 1.8 GHz Dual-Core Intel Core i5. The different python libraries used for the coding of the CNN algorithm are shown in table 1.

Table 1: The libraries used for developing the CNN model

Sl. No.	Library Imported	Usefulness	Sl. No.	Library Imported	Usefulness
1	os	For using OS dependent	5	torchvision	Used for machine learning framework
2	numpy	Used for array operations	6	pathlib	Provides an object API for working with files and directories
3	torch	Used for scientific computing framework	7	opencv	Image and video processing
4	glob	Used for finding pathnames			

4.1. Results

The CNN model that is developed with the aim of classifying Glaucoma, Cataract, Retinal diseases and Normal class from the images of retina is executed for 50 epochs with 15 iterations per epoch and 1 iteration per epoch for validation. The performance of the CNN model is scrutinized with the help of plotting the accuracy graphs for the testing and training data. The parameter settings for the CNN with the epoch that showed the highest test accuracy is saved and later used for predicting and categorizing the diseases from the images of retina.

The training and testing accuracy graphs of the CNN model is shown in figure 7 and 8 respectively. From the training and testing accuracy graphs, it is observed that the training accuracy of the CNN model was 0.665 in the first epoch which increased to 1 in the 50th epoch. On the other hand, the testing accuracy of the CNN model was 0.097 in the first epoch and increased to 0.62 in the 50th epoch. However, the highest testing accuracy is shown in the 21st epoch of 0.7622. Hence the CNN parameter settings of the 21st epoch are saved. The training and testing accuracy graph for the developed CNN model is shown in figure 8 and 9 respectively.

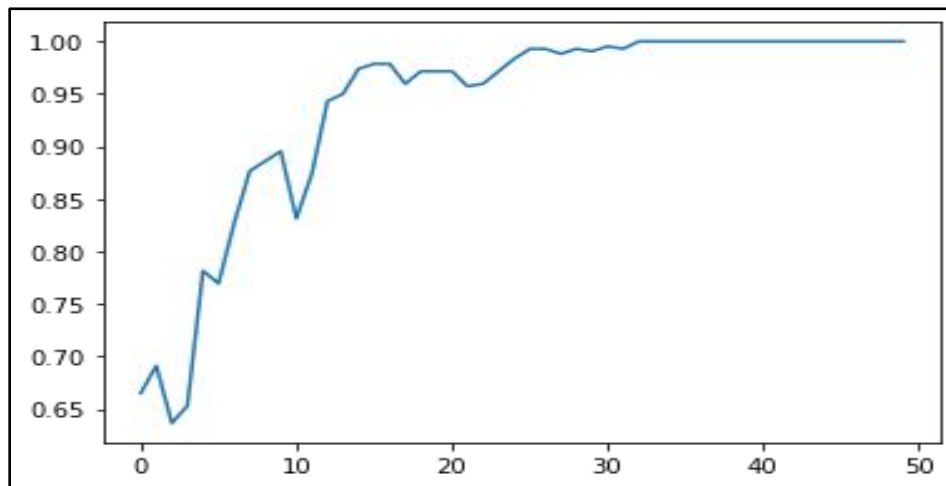


Figure 8: Training accuracy of the CNN model

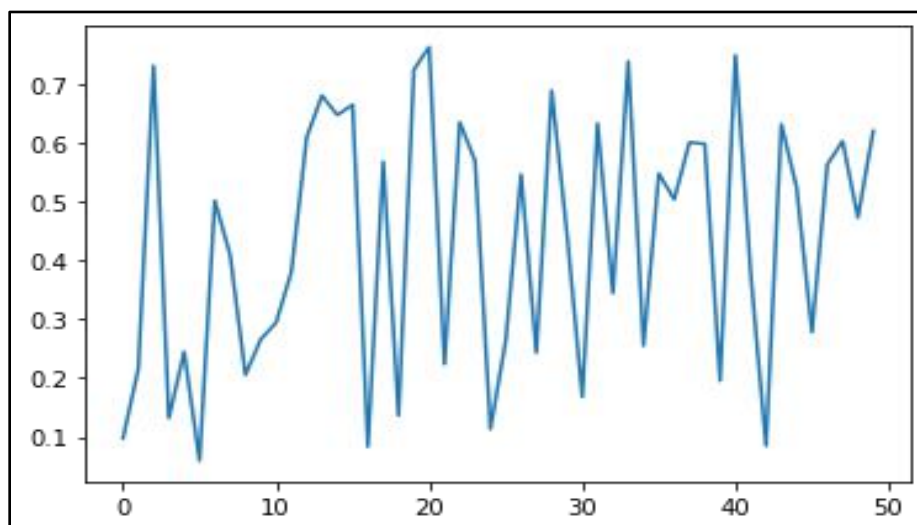


Figure 9: Testing accuracy of the CNN model

4.2. Validation of CNN model

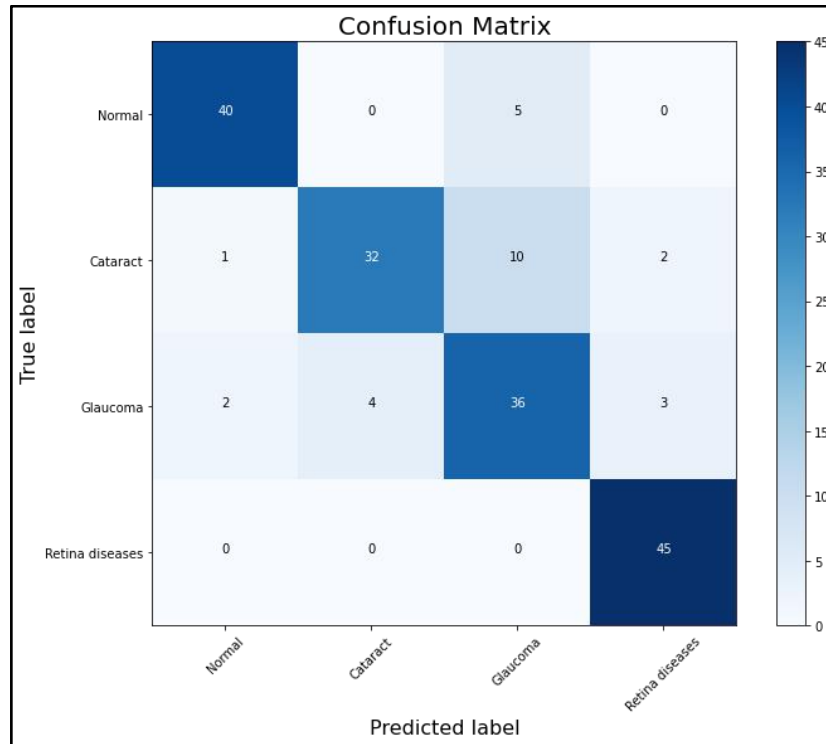


Figure 10: Heatmap of the confusion matrix

Figure 10, shows the heat map representation of the confusion matrix for validating the model. The model is validated by predicting the labels of the 180 test images 45 images from each label. The proposed model is able to correctly classify 153 images. The proposed model correctly classifies the 40 out of 45 images belonging to the Normal label, 32 out of 45 images belonging to the Cataract label, 36 out of 45 images belonging to the Glaucoma label and 45 out of 45 images belonging to the Retina diseases label. From the confusion matrix, it is observed that the develop model is capable of Retina diseases with absolute accuracy, whereas the model showed lower accuracy for identifying Cataract and Glaucoma. From the validation done, it could be concluded that the model developed can be used for practical applications and can be used for identifying and categorizing the retina diseases.

4.3. Discussions

During our research we have come across the following points:

- Near- or far-vision impairment affects 2.2 billion individuals globally. One billion of these cases entailed vision loss that was either preventable or went untreated.
- There are 1 billion people worldwide who are blind or have moderate to severe distant vision impairment due to untreated cataract (94 million people), glaucoma (7.7 million people), or diabetic retinopathy (diabetic retinopathy) (3.9 million).
- In this paper, the retina images are trained using CNN model to detect the eye diseases and classify them as Glaucoma, Cataract, Other Retina diseases or Normal.
- For developing the CNN model, 601 retina images are used. Out of the 601 images, 421 images are used for training and the remaining are used for testing the model.

- e. The CNN model is trained for 50 epochs and the parameter settings are saved for the epoch with the best test accuracy value.
- f. The model is validated with 45 random images from each class. 40 out of 45 photos with the Normal label, 32 out of 45 images with the Cataract label, 36 out of 45 images with the Glaucoma label, and 45 out of 45 images with the Retina disorders label are accurately classified by the proposed model.

From the overall observation it can be concluded that the model is suitable for detecting and classifying eye diseases using the retina images.

5. Conclusion

This research was done with the intention to create a deep learning tool that can classify retinal images into four categories: 1) normal, 2) cataract, 3) glaucoma, 4) retinal disease. This was done by creating a convolutional neural network using the torchvision library in python. The CNN had 3 convolutional layers and 3 pooling layers, which were activated using ReLU function. A dataset of 601 retinal images was used; this was randomly divided into training and testing data. 70% i.e. 421 images were used for training and 30% i.e. 180 images were used for testing. This model showed a training accuracy of 0.96 and a testing accuracy of 0.78. The strength of a proposed model is its practical applicability. There the proposed model is validated with 180 test images with 45 images from each class. The proposed model can correctly classify 40 out of 45 images that have the label "Normal", 32 out of 45 images that have the label "Cataract", 36 out of 45 images that have the label "Glaucoma" and 45 out of 45 images that have the label "Retinal diseases". After looking at the accuracy and precision, it can be concluded that the proposed model can be used for eye diseases detection and classification.

5.1. Future Scope

In the future, this tool can be extended to other eye diseases such as Amblyopia or Strabismus. This software can also be embedded in hardware to make it a handy tool for optometrists and also can be used by people for self diagnosis.

Ethical standards:

The authors would like to declare that no funding or monetary help is received in any form from any governmental or non-governmental organization for carrying out this project. The authors would also like to declare that all ethical standards are maintained in carrying out execution of this project.

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