

# Deep Learning Technology for Retinal Disease Classification

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**Abstract**—This paper reviews techniques for automated retinal disease detection, which is important due to the increasing prevalence of eye diseases. These techniques include deep learning, machine learning, and transfer learning. The paper analyzes their strengths, weaknesses, and challenges and suggests research directions for improving accuracy. The goal is to help ophthalmologists diagnose and treat retinal diseases promptly, thus reducing the rate of sight loss.

**Index Terms**— Deep Learning, Image Processing, Machine Learning, Neural Network, Transfer Learning, Automated diagnosis.

## I. INTRODUCTION

The prevalence of retinal diseases has risen dramatically because of aging and increased screen time. Detecting eye diseases early can save the fundus from permanent damage.

The following are some common retinal diseases:

1. Age-related macular degeneration (AMD) - This is the most common danger to vision, mostly seen in people older than 50, and it is critical to classify.
2. Diabetic Retinopathy - Associated with diabetes, it is one of the diseases affecting the retina. Diabetic retinopathy lacks externally visible symptoms at the initial stage or relatively minimal vision issues. However, it has the potential to cause blindness.
3. Glaucoma (GI) - One of the major factors contributing to blindness in people above the age of 60 is glaucoma.
4. Cataract - Cataracts don't show any symptoms in earlier stages, but as they grow, it causes differences in vision. These infections can cause partial or total blindness if they are not detected in time. Conventionally, ophthalmologists use specialized tools and lenses to detect these illnesses. These procedures take a lot of time and money.

Recently, a lot of research has been done in developing an automated system for detecting and classifying ailments related to the retina. Traditional Machine learning (ML) and Deep learning (DL) based models can be utilized extensively. The use of Traditional Machine Learning algorithms is limited due to the lower accuracy achieved by these models. With the advancement of image processing, processor architectures, artificial intelligence, etc., Deep Learning is considered to be an effective technique for improving automated methods to obtain better performance and real-time illness detection.

This review paper focuses on the collective study of existing Deep Learning, Machine Learning, and transfer learning approaches that could be useful in detecting retinal diseases. The linked work is examined in section 2

for various retinal disease classifications and predictions. Section 3 shows the proposed work, and section 4 consists of a discussion that includes limitations and challenges for the proposed work. Section 5 infers the conclusion.

## II. RELATED WORK

Researchers have been working on numerous technologies and have discovered that the procedures are effective to a certain extent for the early detection of retinal diseases. For extracting features from images, pre-processing is needed before applying any algorithm. Once an image is clear, extracting information is easier, and the accuracy surges. A green channel is used in most techniques to extract the salient features. Instead of performing conversion from the entire RGB type of image to grayscale, the green channel is an inexpensive alternative. Currently, convolutional filters are being used that allow feature extraction and learning, reducing computation load as only the filters' weights are trained. This approach also escalates the model performance. Contrast enhancing, resizing the image, and image augmentation are some techniques used for image pre-processing. When the dataset is unbalanced, image augmentation can be used. When the dataset is smaller, it produces various iterations of the same data to expose the model to a broad variety of training samples.

### A. Dataset

Several datasets for iris diseases are publicly available. The Kaggle dataset [1] has five types of disease classes - Bulging eyes (30 images), Cataracts (47 images), Crossed eyes (174 images), Glaucoma (82 images), and Uveitis (50 images). The Ocular Disease (OD) dataset [2] is a structured database with information on age, left and right fundus images, and medical professionals' diagnosis terminology. It contains information on 5,000 cases. It has eight classification labels for different retinal disorders. The Ocular Illness(OI) dataset [3] included 5000 photos with labels that either indicated whether or not the image contained a cataract or normal eyes.

Digital Retinal Images for Vessel Extraction (DRIVE) dataset [4] allows for the division of blood vessels from 40 eye images of a Diabetic Retinopathy(DR) patient. Structured Analysis of the Retina (STARE) dataset [5] contains 400 images having one or more than one retinal disorder. The labeled classes are - Histoplasmosis(HT), Choroidal Neovascularization(CN), Arteriosclerotic Retinopathy(AR), Central Retinal Artery Occlusion(CRAO), Central Retinal Vein Occlusion(CRVO), Drusen(D), and Diabetic Retinopathy(DR).

Intending to detect DR, Diabetic Retinopathy Database Calibration level 0(DIARETDB0) [6] contains 130 images of the retina from a digital fundus camera ( 20 normal eyes and 110 infected), and DIARETDB1 [7] dataset has 89 color fundus photographs ( 5 normal eyes and 84 infected).

The Messidor project dataset [8] has 1200 fundus images with a medical diagnosis of two parameters - retinopathy grade and risk of macular edema. The retinal Fundus Glaucoma Challenge (REFUGE) dataset [9] contains 1200 fundus images for Gl detection. It contains 1080 photos of normal and 120 infected images. A dataset for diagnosing Gl called G1020 [10] has 1020 photos of the fundus (724 normal eyes and 296 Gl infected). Online Retinal Fundus Image Database for Glaucoma Analysis(ORIGA) [11] consists of 168 photos of Gl patients and 482 photographs of the normal fundus. One hundred one fundus images are in Drishti-GS [12] for glaucoma assessment (31 normal eyes and 70 infected). The Retinal Fundus Multi-Disease Image Dataset(RFMID) [13] is a collection of 3200 colored fundus images for binary classification - normal and infected (comprising 45 different diseases), out of which 1920 were used for training, 640 each was reserved for testing and validation.

Table 1 summarizes the publicly available datasets, the number of images, and a number of classes in the dataset. It also distinguishes between class types.

### B. Detection of Retinal Disease using Deep Learning

With the current development in image processing, a vital improvement has been made in retinal disease detection using deep learning techniques. One DL algorithm that gives high performance is the Convolutional Neural Network(CNN). For feature extraction and classification, CNN is used. Fig. 1 depicts the superficial working of the Deep Learning model. It takes a fundus image as an input and applies image pre-processing and image augmentation followed by Deep Learning mode. The model can classify the fundus image into various classes.

GoogLeNet architecture was used by Cerentinia et al. [14] to detect the presence of Glaucoma. The model's accuracy for the High-Resolution Fundus(HRF) database was 90%, for RIM-ONE(r1), RIM-ONE(r2), and RIM-ONE(r3) was 94.2%, 86.2%, 86.4% respectively, and was 87.6% for the combined databases. Al-Bander et al.

TABLE I: THE PUBLICLY ACCESSIBLE DATASETS ARE DETAILED

| Ref No. | Dataset        | No of images | Number of classes | Class Type                     |
|---------|----------------|--------------|-------------------|--------------------------------|
| [10]    | OI             | 5,000        | 2                 | Binary classification          |
| [11]    | DRIVE          | 40           | 2                 |                                |
| [13]    | DIARETDB0      | 130          | 2                 |                                |
| [14]    | DIARETDB1      | 89           | 2                 |                                |
| [15]    | Messidor       | 1200         | 2                 |                                |
| [16]    | REFUGE         | 1200         | 2                 |                                |
| [17]    | G1020          | 1020         | 2                 |                                |
| [18]    | ORIGA          | 650          | 2                 |                                |
| [19]    | Drishti-GS     | 101          | 2                 |                                |
| [20]    | RFMID          | 3200         | 2                 |                                |
| [8]     | Kaggle dataset | 383          | 5                 | Multi - disease classification |
| [9]     | ODR            | 5,000        | 8                 |                                |
| [12]    | STARE          | 400          | 9                 |                                |

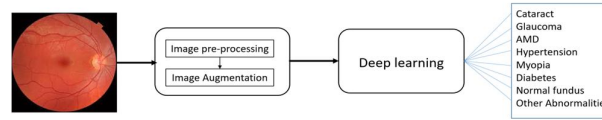


Figure 1: Working of Deep Learning Model

[15] employed CNN to extract features and SVM for Gl or non-Gl classification, achieving accuracy-88.2%, specificity-90.8%, and sensitivity-85%.

For better outcomes, Hemanth et al. [16] presented a hybrid model implemented by combining DL and image processing for diagnosing DR. 400 photos from the MESSIDOR [17] database was used in this model. The performance measures achieved were precision at 94%, specificity at 98%, recall at 94%, accuracy at 97%, F-Score was found to be 94%, and geometric mean (GMean) was 95%

Hu et al. [18] developed a technique for doing intraretinal fluid detection based on the CNN technique. The training on the CNN model was done using 1,289 OCT scans and segmented images, which gave a 0.911 dice score after cross-validation.

A 17-layer feature extractor DCNN that used a residual network to understand further specific properties of fundus images was used by Ran et al. [19]. Three modules make up the DCNN: shallow, residual, and pooling. The pooling module produced the final feature vectors for Random Forests after the external and residual modules extracted features on different levels like deep, medium, and shallow. The accuracy for six kinds of cataracts was 90.69%.

Using a 29-layered CNN model, Doshi et al. [20] identified the five phases of Diabetic Retinopathy(DR) and the severity of the illness. Three CNN layered models had an accuracy of 39.96% in identifying the stages of DR. However, adding more layers can increase the accuracy. Using a deep learning model, Gargeya and Leng [21] recognized DR with 87% specificity, 94% accuracy, and 93% sensitivity. Ghosh et al. [22] proposed 28-layered architecture and achieved 95% accuracy using the softmax function. Jiang et al. [23] employed 17 layers of deep CNN using the Caffe framework for fundus pictures; they achieved 75.7% accuracy. Pratt et al. [24] obtained

accuracy-75%, specificity -30%, and sensitivity-95%. Xu et al. [25] used a 16-layer model with the softmax classifier to identify this disease early with an accuracy of 94.50%.

Using the DRiDB dataset [26], Prentasi and Loncari [27] presented a CNN-based exudate identification technique for fundus. The network, composed of 10 alternately placed convolutional and max pooling layers achieved 78% Positive Predictive Value and 78% sensitivity. Detecting one disease at a time is a relatively easier task, but the multi-disease classification is complex. Work in multi-disease classification is minimal, and new techniques should be implied as the proposed work has inferior results. From the above discussion, we can deduce that CNN is widely used as it has the potential to yield high performance. The evaluation matrix enhances the number of layers in CNN. The combination of two or more strategies directs a good accuracy of the model, which ensures the detection reliably.

Table II explains the various work done in fundus disease classification using Deep Learning technologies. It summarizes the architecture used, the predicted diseases, and the result's evaluation metrics.

TABLE II (AC-ACCURACY, SP-SPECIFICITY, SE- SENSITIVITY)

| Reference No. | Model/ Architecture | Disease              | Evaluation metrics |
|---------------|---------------------|----------------------|--------------------|
| 21            | GoogLeNet           | Glaucoma             | Ac- 87.6%          |
| 23            | Hybrid model        | Diabetic Retinopathy | Ac- 97% Sp-98%     |
| 26            | DCNN                | Cataracts            | Ac-90.69%          |
| 32            | CNN                 | Diabetic Retinopathy | Ac- 95%            |

### C. Amalgamation of Deep Learning and Machine Learning Techniques

Researchers have found that combining DL with ML could yield better results for disease classification. The improved result parameters would help ophthalmologists with early disorder detection. Using a hybrid feature set that presented a combinational technique of structural (cup-to-disc ratio) and nonstructural (texture and intensity) information, Salam et al. [28] were able to boost the accuracy of automated GI analysis; The author designed a system to diagnose GI from digital fundus pictures. Two local datasets were employed, one containing 100 fundus photos and the other containing 50 fundus images (15 glaucoma images and 35 normal images) (26 glaucoma and 74 normal eye images). A specificity 98%, sensitivity 92%, and accuracy of 97% were achieved. Rachana Devanaboina et al. [29] proposed a cataract prediction using the CNN algorithm with TensorFlow. The dataset consisted of 4500 images which provided 94% of accuracy. A Deep Belief Network (DBN) was used by Arunkumar et al. [30] to classify DR images. Initially, the author used three hidden layers. DBN was used to extract the features, followed by the Generalized Regression Neural Network (GRNN) method and then used the SVM. The model obtained an accuracy, specificity, and sensitivity of 96.73%, 97.89%, and 79.32%, respectively. Using SVM with CNN, Al-Bander et al. [31] classified glaucoma with an accuracy 88.2%, specificity 90.8%, and sensitivity 85%.

The article proposed by Feng Li et al. [32] focused on 4 class classifiers detecting choroidal neovascularization(CNV), diabetic macular edema(DME), DRUSEN, and normal eyes. The model proposed was an ensemble of 4 classification model instances, each of them an enhanced residual neural network. 10-fold cross-validation was employed on the OCT images of the patient. The author achieved 97.3% of accuracy and a sensitivity of 96.3%. A major challenge to this problem was that OCT images require significant clinical training and clinically well-experienced ophthalmologists, an agreement that was limited. Also, it is unfeasible to manually inspect OCT datasets of huge size in highly engaged clinics and prone to errors.

Deep convolutional neural networks (DCNN) and SVM techniques were used by Ashrafi et al.[33] to build a technique for developing an automated system for diagnosing eye illnesses based on visually discernible symptoms. The work uses stochastic neighbor embedding with t-distribution and principal component analysis to improve feature selection. The suggested technique separated the eye part and components of the face taken from the front side facial image. The suggested approach evaluated and categorized seven eye illnesses, including Bitot's spot of deficiency of vitamin A, trachoma, conjunctivitis, corneal ulcer, ectropion, and periorbital cellulitis. Based on the experimental findings, the authors discovered that the DCNN model beats the SVM models. The DCNN model has an average accuracy 98.79%, sensitivity 97%, and specificity 99%. Orlando et al. [34] implemented a model to detect lesions using three publicly available datasets: Messidor, e-

ophtha, and DIARETDB1. The work used ten-layered LeNet architecture to extract the characteristics of intensity and form. The experimentation gave an accuracy 93.47%, and a sensitivity 97.21%.

Table III explains various works in fundus disease classification using Machine Learning with Deep Learning Techniques. It summarizes the Model/ Architecture, predicted diseases, and evaluation metrics. It can be noticed that the amalgamation of ML with DL strategies produces better performance results.

TABLE III. (AC-ACCURACY, SP-SPECIFICITY, SE- SENSITIVITY)

| Ref No. | Model/ Architecture              | Diseases             | Evaluation metrics             |
|---------|----------------------------------|----------------------|--------------------------------|
| [38]    | Random forest                    | Glaucoma             | Ac - 97%, Sp - 98%, Se - 92%   |
| [39]    | CNN                              | Cataract             | Ac - 94%                       |
| [40]    | DBN + GRNN + SVM                 | Diabetic Retinopathy | Ac-96.73%, Sp-97.89%, Se-79.3% |
| [42]    | Enhanced Residual Neural Network | Multiple disorders   | Ac - 97.3%, Se - 96.3%         |
| [43]    | SVM + DCNN                       | Multiple disorders   | Ac-98.79%, Sp-97%, Se-99%      |
| [44]    | LeNet                            | Lesions              | Ac- 93.47%, Se- 97.21%         |

#### D. Transfer Learning Techniques

To get the speedy results and to make the optimal performance achievable, Transfer Learning techniques can be widely used. MobileNetV2 was used by Chen Guo et al. [35] in Tensorflow and was trained on the platform of Google Colab having GPU runtime. The images used were from a portion of a publicly available dataset on Kaggle, having 1000 fundus images[36]. The work proposed a lightweight DL architecture using transfer learning(TL) to decide between four eye disorders: Gl, Maculopathy, Pathological Myopia, and Retinitis Pigmentosa. The model had one full convolution layer with 32 filters and gave 99.0% specificity, 95.8% sensitivity, and 98% accuracy. The model was trained into two steps: transfer learning and fine-tuning steps. The limitation was the lesser value of the layer as it focuses on reducing the network size and maintaining accuracy. Choi et al. [37] employed an ensemble DL algorithm to classify multiple retinal disorders on a limited dataset. Still, they only managed to reach 31% accuracy while considering ten categories and an accuracy of 73% with three categories. Even with the transfer learning technique(TL), the trial with ten categories gave a 5% improvement in performance.

Following Table IV talks specifies the work done using Transfer Learning Techniques.

TABLE IV: (AC-ACCURACY, SP-SPECIFICITY, SE- SENSITIVITY)

| Ref No. | Model/ Architecture | Disease                                                              | Evaluation metrics        |
|---------|---------------------|----------------------------------------------------------------------|---------------------------|
| 42      | MobileNetV2         | Glaucoma, Maculopathy, Pathological Myopia, and Retinitis Pigmentosa | Ac-98%, Sp-99.0%, Se-95.8 |

### III. PROPOSED WORK

The literature survey inferred that multi-disease classification is a comparatively complex task compared to binary classification. To overcome these gaps, we proposed an 8-layered Convolutional Neural Network (CNN) model to classify retinal diseases, which supports two-level classification. In the proposed system, an input image of the fundus will be classified into four classes - Age-related macular degeneration(AMD), Diabetic retinopathy(DR), Glaucoma(GL), and normal eye.

Fig. 2 shows the proposed work. Its 8-layered CNN model has four convolutional 2D layers with 64 and 128 neurons. This layer gets 2D input to which convolutional filters are being slid. The filters are moved in horizontal and vertical directions to compute the input and weight's dot product, after which a bias term is added. 2 max-pooling 2D layers are present. This layer performs downsampling work for the input given. The two dense, fully connected layers connect each input to each output in the layer. Activation functions reLU and softmax are being used to perform non-linear transformations.

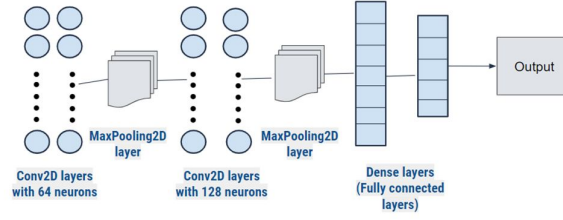


Figure 2: 8- Layered Convolutional Neural Network model

The reLU activation function can be defined as  $f(x)=\max(0,x)$ . Here,  $x$  is the input value and  $f(x)$  returns the reLU output. This function returns 0 if the input is negative or returns the input back.

The softmax function  $\sigma$  is defined by the following formula:

$$\sigma(o_i) = \frac{e^{o_i}}{\sum_{j=1}^n e^{o_j}}$$

where the index  $i$  is in  $(0, \dots, n-1)$  and  $o$  is the output vector of the network

$$o = (o_0, o_1, \dots, o_{n-1})$$

Table V shows the hyperparameters used in the proposed model.

Table V

| Hyperparameters | Values |
|-----------------|--------|
| Optimizer       | Adam   |
| Epochs          | 30     |
| Batch size      | 32     |

The above model obtained a test accuracy of 80.9%. The accuracy can be increased to a certain level by adding more layers to the CNN model, which requires more processing power.

#### IV. RESULTS

Above proposed model results in considerable accuracy. On changing the hyperparameters such as batch size or epochs, there occurs variation in accuracy. For a batch size of 32, if the number of epochs is 30 then accuracy comes out to be 80% and for the same batch size, if the number of epochs is increased to 64, accuracy comes out to be 85.2%. If the batch size is increased to 64, for 32 epochs accuracy obtained is 80.70%, and for 64 epochs accuracy of 86.6% is obtained. This conclusion can be made that in an increasing number of epochs, there is considerable improvement in accuracy. It is also observed that increasing the batch size improves the accuracy.

#### V. DISCUSSION

Developing an automated retinal disease detection system will help ophthalmologists with the faster diagnosis of diseases at the genesis stage. A lot of research has been done in this direction since the last decade. Most of the work is done using various CNN models for the extraction of features and classification to improve accuracy. The outcomes show that models using DL and ML techniques yield better results. However, the primary concern while using deep learning techniques is acquiring huge datasets.

Slit lamps, Retro lumination imaging, Ultrasonic imaging, Anterior Segment OCT imaging, spectroscopy, and many more tools are used to capture the eye images, which are then diagnosed by ophthalmologists. However, all these tools are costly and need accurate calibrations reducing their availability in many places. Other challenges include unfocused images of the fundus due to the distortion of pixels in the image leading to information loss, and thus classification task becomes difficult. If the eye image has multiple infections, they share common pixel information, which can lead to misclassification. Much work has been done in binary disease classification, but the multi-disease classification is still less explored due to the similarity in symptoms,

scarcity of multi-diseased datasets, and implementation complexities. Thus, a huge scope is there in multi-disease classification.

The proposed system aims for the user to capture an eye image in real-time with a lens having good magnifying power (to reduce information loss) and then run a classifier on the input image to predict the result. This classifier consists of 8 layered sequential models. This model works on the dataset to train itself. Upon giving a fundus image of the infected eye, the model predicts its output class (here each class indicates an eye disease). Our proposed system can be used in health checkup camps in the outback, which will be time-saving. Our technology will serve as the first filter for ophthalmologists in the health check-up camps, reducing the waiting time when there are a large number of patients. Thus this could act as a first filter that could filter out the crowd and only the people who were diagnosed with any of the diseases will be needing to consult doctors. The proposed system will notify the diagnosis of the patient immediately.

## VI. CONCLUSION

The paper presented the current work done in retinal disease classification that uses Deep Learning, the amalgamation of Deep Learning with Machine Learning, and Transfer Learning techniques. The work proposed an 8-layered Convolutional Neural Network model with an accuracy of 80% to perform multi-disease classification of retinal disorders. We can conclude from the discussion section that multi-disease classification is a comparatively complex task compared to binary classification. Advancements in multi-disease classification are still in progress; datasets are not widely available for multi-disease classification. Hence, there is scope for work achieving higher accuracy.

DL models like CNN and DCNN are widely used to categorize disorders. They give higher accuracy than classical ML algorithms because of their feature extraction capabilities. Accuracy can be further improvised using a combination of DL and ML approaches. Using DL techniques with shallow classifiers like SVM, accuracy can be increased up to 98.79%. On the other hand, DL necessitates a large dataset. Due to the difficulty in finding large public datasets, data augmentation techniques can be applied. Nowadays, the rise in retinal disorders and existing technological gaps is inspiring the community to work in automated retinal disease classification. Such systems can assist ophthalmologists by acting as a first filter to diagnose eye infections. It can prevent and control damage or vision loss by early-stage detection. This system will be useful in rural areas, various health check-up camps, and developed areas to expedite the process. Giving society a better vision is the vision of this endeavor.

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