

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

MULTIPLE EYE DISEASE PREDICTION IN OPHTHALMIC IMAGERY USING DEEP LEARNING

Dr.Harihara Santosh Dadi (Associate Professor)¹, Vanapalli Devi Alekhya², Patnana Ram Sai³, Kallepalli Charan Santosh⁴, Thotapalli Vinod Kumar⁵

(Students)

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING ADITYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT, TEKKALI

ABSTARCT :

This project uses deep learning techniques on ocular pictures to predict various eye disorders at the same time. Our model analyzes and extracts complex patterns from the images using a convolutional neural network (CNN) architecture, which enables precise detection of different ocular diseases. After undergoing comprehensive training and validation on a variety of datasets, our system has strong predictive capabilities for ailments like cataract, diabetic retinopathy, and glaucoma. In order to train using a medical image dataset and identify the colors and textures of lesions unique to individual diseases, the proposed work makes use of a range of pre- trained architectures. The suggested multi- model CNN classification of eye diseases is similar to human decision-making and the outcomes of testing various eye disease features as convolutional neural network inputs.

KEYWORDS Multiple eye diseases - prediction - ocular images - deep learning - glaucoma - diabetic retinopathy - cataract - efficientnet

INTRODUCTION

This project employs deep learning on ocular images to predict multiple eye problems simultaneously. By employing a convolutional neural network (CNN) architecture, our model examines and extracts intricate patterns from the images, facilitating accurate identification of various eye conditions. Following extensive validation and training on many datasets, our approach demonstrates robust predictive abilities for conditions such as glaucoma, diabetic retinopathy, and cataracts. The proposed research uses a variety of pre-trained architectures to train using a medical image dataset and detect the colors and textures of lesions specific to various diseases. The proposed multimodel CNN classification of ocular disorders is comparable to human decision-making, and the results of evaluating several ocular disease characteristics as convolutional neural network inputs.

Deep learning approaches in medical image analysis have led to some amazing advances in the area of ophthalmology in recent years. Deep learning methods provide promise for the early identification and prediction of various eye illnesses, particularly with the growing availability of high-resolution ophthalmic imaging. This introduction will provide an overview of the importance and problems of using deep learning to predict various eye disorders using ophthalmic images.

Significance of Early Disease Prediction:

Preventing the irreversible vision loss and ensuring prompt action are dependent on the early detection of eye illnesses such as age-related macular degeneration (AMD), glaucoma, and diabetic retinopathy. Conventional diagnosis techniques frequently depend on the subjective and time-consuming manual interpretation of skilled professionals. Deep learning-based methods present a viable way to automate this procedure and generate predictions that are precise, effective, and scalable.

Challenges in Ophthalmic Image Analysis:

Because of their complexity, changing picture quality, and the existence of subtle illness signs, ophthalmic images pose special challenges. The analysis task is further complicated by factors such as anatomical variances among individuals, occlusions, and variable illumination. Furthermore, complex algorithms that can extract pertinent features are needed for theinterpretation of multi-modal imaging data,



EFFICIENTNET

EfficientNet is a convolutional neural network design and scaling technique that uses a compound coefficient to scale all dimensions of depth, breadth, and resolution evenly. The EfficientNet scaling approach evenly increases network breadth, depth, and resolution using a set of preset scaling coefficients, in contrast to standard practice, which scales these elements arbitrarily. For instance, we may easily raise the network depth by α^{N} , the breadth by β^{N} , and the picture size by γ^{N} if we wish to employ 2^N times more computational resources. Here, α , β , and γ are constant coefficients that were found via a small grid search on the initial small model. EfficientNet applies a principled uniform scaling of network breadth, depth, and resolution through the application of a compound coefficient Π .

fig 1: Efficient Net Architecture

CATARACT:

Many people experience eye disorders, as the eyes are the only vision glands in the human body. Convolutional neural networks like EfficientNet are based on the idea of "compound scaling." The long- standing trade-off between model size, accuracy, and computational efficiency is addressed by this idea. Compound scaling is based on scaling the breadth, depth, and resolution—the three key dimensions of a neural network.

- 1. Width: The number of channels in each neural network layer is referred to as width scaling. The model's accuracy increases when the breadth is increased because it can capture more intricate patterns and characteristics. On the other hand, a model with less width is lighter and better suited for low-resource settings.
- 2. **Depth**: Depth scaling pertains to the totalnumber of layers in the network. Deeper models can capture more intricate representations of data, but they also demand more computational resources. On the other hand, shallower models are computationally efficient but may sacrifice accuracy.
- 3. Resolution: Resolution scaling involves adjusting the input image's size. Higher- resolution images provide more detailed
- information, potentially leading to better performance. However, they also require more memory and computational power.

One of the most common eye conditions that frequently results in blindness is cataract illness. A retinal fundus image that depicts the typical retinal fundus image with visible capillaries and vascular cells is shown in Figure 2 (Fig. 2a). A cataract image is displayed in Fig. 2b, where the blurriness obscures the view of capillaries and vascular structures. Most people have lost their vision at this point.





Fig 2 : Retinal Fundus Image (a).non-Cataract (b).Cataract

A cataract is a clouded spot in your eye's lens, which is the clear portion of the eye that aids with light focus. As you age, cataracts become more and more common. In actuality, over half of all Americans whoare 80 years of age or older either have cataracts or have undergone cataract surgery. At first, you may not notice that you have a cataract. But over time, cataracts can make your vision blurry, hazy, or less colourful. You may have trouble reading ordoing other everyday activities. Over time, cataracts can lead to vision loss.

Symptoms of Cataract:

You might not have any symptoms at first, when cataracts are mild. But as they grow, cataracts can cause changes in your vision. For example, you may notice that:

- Your vision is cloudy or blurry
- Colours look faded
- You can't see well at night
- Lamps, sunlight, or headlights seemtoo bright
- You see a halo around lights
- You see double (this sometimes goes away as the cataract gets bigger)
- You have to change the prescription for your glasses or contact lenses often

GLAUCOMA:

All over the world, glaucoma is the primary cause of vision impairment, and there is currently no treatment for it. If it is not identified in the early stages, it may be the cause of irreversible blindness. If the yesight loss is detected early on, there are treatments available to stop it from happening. Given that it is a prominentlong-term eye condition that leads to

permanent blindness.

Consequently, it is critical to perform eye screening in order to identify glaucoma.Because each patient must be examined individually, which takes a lot of time, the eye screening procedure is anticipated to be laborious and time-consuming process. Aclass of eye conditions known as glaucomacan result in blindness and visual loss by harming the optic nerve, which is located in back of the eye.



Fig 3: An Example of Visually Presented Glaucoma (a). Normal retinal Image (b).Glaucoma

You might not notice the symptoms at first because they can appear so slowly. Getting a thorough dilated eye exam is the only method to determine if you have glaucoma. While there is no known cure for glaucoma, vision protection and damage can frequently be stopped with early intervention.

DIABETIC RETINOPATHY:

Diabetic Retinopathy (DR) is the primary cause of blindness in people of working age

and is a dangerous condition. In addition, diabetic retinopathy (DR) is the most dreaded consequence of diabetes mellitus and raises the risk of developing other illnesses, including renal problems, cardiovascular disease, and death. The threerisk factors that are most strongly linked to the initiation and progression of diabetic ketoacidosis (DR) are elevated blood pressure, inadequate glycemic control, and prolonged diabetes. Figure 3 shows the eye structure of a healthy person and that of a DR patient.



fig 4. (a) Eye structure of Non-DR patient; (b) Eye structure of DR patient.

Diabetes patients may develop diabetic retinopathy, an eye disorder that can lead toblindness and vision loss. The retina, which is the light-sensitive layer of tissue in the rear of your eye, is affected by blood vessels. It's crucial to undergo a thorough dilated eye exam at least once a year if you have diabetes. Even though diabetic retinopathy may not show any symptoms at first, identifying it early on can enable you to take protective measures for your eyesight.

Maintaining an active lifestyle, eating well, and taking your medication can help you avoid or postpone vision loss as a result of diabetes.

Symptoms of Diabetic Retinopathy

Diabetic retinopathy typically shows no symptoms in its early stages. Some experience visual changes, such as difficulty reading or seeing objects that arefar away. There may be sporadic updates tothem.

Blood vessels in the retina begin to leak into the vitreous, the gel-like fluid that fills the eye, as the condition progresses. If this occurs, you can notice streaks or dark, cobweb-like areas that float. Although the spots may occasionally go away on their own, it's crucial to seek treatment as soon aspossible. The back of the eye may develop scars if treatment is not received. Additionally, blood vessels may begin to bleed once again or may bleed more severely.

PROPOSED METHODOLOGY



fig 5: Proposed Methodolgy

Step-1: The raw ophthalmic images are undergone for preprocessing. In Data Pre- Processing the images are cropped to 224x224 and the image contrast and brightness are enhanced.

Step-2: After Data Pre-Processing the images are classified as Train & Test images which are 90% and 10% respectively.

Step-3: The training dataset is undergone for data augmentation.

Step-4: Now the train dataset is undergone for training in different neural networkssuch as simple EfficientNet.

Step-5: Finally these neural networks are compared and selected one best neural network for the ophthalmic diseases

detection by observing the test accuracies, f1 scores, precisions and Confusionmatrices of each and every neural networks. This entire process isrepresented as a flow chart.



Number of Epochs (s = 30):Each epoch involves one complete pass through the entire training dataset. Training for 30 epochs means the model goes through the entire training dataset 30 times. More epochs allow the model to further refine itsparameters and potentially improve its performance. Training Size (training =3373):Refers to the number of samples in the training dataset. With 3373 samples available for training, the EfficientNet model has a substantial amount of data to learn from. Larger training datasets can provide more diverse examples for the model to learn from, potentially improving its ability to generalize to unseen data.



fig 7: Final Output of Eye Dataset

Testing Size (testing = 422):Indicates the number of samples in the testing dataset used to evaluate the model's performance. With 422 samples available for testing, the model's performance is evaluated on a separate dataset that it hasn't seen during training. Evaluating on a separate testing dataset helps assess the model's ability to generalize to new, unseen data.

Accuracy (98%):Accuracy represents the proportion of correctly classified samples out of the total number of samples in the testing dataset. A model accuracy of 98% indicates that the EfficientNet model correctly classified approximately 98% of

the samples in the testing dataset as shown in confusion matrix. A higher accuracy indicates better performance in classifying the samples correctly.

In summary, training an EfficientNet-B0 model involves iterating through the training dataset for a specified number of epochs, utilizing a large training dataset to learn from, evaluating its performance on aseparate testing dataset, and assessing its accuracy as a measure of performance. Achieving a high accuracy indicates that the model has effectively learned to classify the samples in the testing dataset.

THE ACCURACY VS LOSS CURVES :



CONCLUSION:

The eye is one of the most important sense organs in human anatomy, and losing vision would significantly affect the quality of life. Besides, the eye could also indicate some serious health issues. Unfortunately, many people may not beware of these health problems due to the lack of ophthalmologists and access to eye care. Nevertheless, the advent of deep learning and image processing could immensely help in detecting and diagnosing these diseases. This study used EfficientNet in deep learning to detect three eye diseases: cataracts, diabetic retinopathy, and glaucoma.

For future research, we plan to investigate the efficacy of transfer learning on a more diverse dataset that includes other types of eye diseases. And explore other applications of transfer learning in disease detection tasks.

REFERENCE:

- 1. A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, Feb. 2017.
- Kanagasingam, A. Bhuiyan, M. D. Abràmoff, R. T. Smith, L. Gold schmidt, and T. Y. Wong, "Progress on retinal image analysis for age related macular degeneration," Prog. Retinal Eye Res., vol. 38, pp. 20–42, Jan. 2014.
- D. S. Kermany, "Identifying medical diagnoses and treatable diseases by image-based deep learning," Cell, vol. 172, no. 5, pp. 1122–1131, Feb. 2018.
- 4. M. M. M. S. Fathy and M. T. Mahmoudi, "A classified and comparative study of edge
- 5. detection algorithms," in Proc. Int. Conf. Inf. Technol., Coding Comput., Apr. 2002, pp. 117–120.
- C.-H. H. Yang, J.-H. Huang, F. Liu, F.-Y. Chiu, M. Gao, W. Lyu, M. D. I.-H. Lin, and J. Tegner, "A novel hybrid machine learning model for auto-classification of retinal diseases," 2018, arXiv:1806.06423.

- 7. M.B.Jabra, A.Koubaa, B.Benjdira, A. Ammar, and H.Hamam, "COVID 19 diagnosis in chest X-rays using deep learning and majority voting," Appl. Sci., vol. 11, no. 6, p. 2884, Mar. 2021.
- 8. S. Guefrechi, M. B. Jabra, A. Ammar, COVID-19 from chest X-ray images," Multi media Tools Appl., vol. 80, no. 2021, pp. 31803–31820.
- K. Shankar, A. R. W. Sait, D. Gupta,
 S. K. Lakshmanaprabu, A. Khanna, and H. M. Pandey, "Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model," Pattern Recognit. Lett., vol. 133, pp. 210–216, May 2020.
- 10. R.ArunkumarandP.Karthigaikumar, "Multi-retinal disease classification by reduced deep learning features," Neural Comput. Appl., vol. 28, no. 2, pp. 329–334, Feb. 2017.