

# “Classifying eye disease & diagnosis from ocular images using Deep learning”

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## **Abstract—**

## **Index Terms—**

### I. INTRODUCTION

The eye is a vital organ responsible for vision, and any impairment or disease affecting its structure or function can have significant consequences on an individual's quality of life [1]. Early detection and accurate diagnosis of eye diseases are crucial for timely intervention and effective treatment. Traditionally, eye disease diagnosis heavily relied on the expertise of ophthalmologists, which often resulted in subjective evaluations and delayed diagnoses [2]. However, with the advent of deep learning algorithms and the availability of large-scale datasets, there has been a paradigm shift in the way eye diseases are diagnosed [3]. Deep learning, a subfield of machine learning, has shown remarkable success in various computer vision tasks, including object recognition, segmentation, and image classification. Convolutional neural networks (CNNs), a prominent deep learning architecture, [4] have demonstrated exceptional performance in extracting intricate features from images and learning complex patterns. Leveraging these advancements, researchers have focused on developing deep learning models to automate the classification and diagnosis of eye diseases based on ocular images [5].

This research aims to contribute to the field of ophthalmology by proposing a robust deep learning framework capable of accurately classifying and diagnosing a wide range (Cataract, Glaucoma, Diabetic retinopathy & Normal) of eye diseases [6]. The proposed model leverages a large dataset of labeled ocular images and employs state-of-the-art CNN architectures to extract discriminative features. By training the deep learning model on this dataset, [7] we seek to achieve high accuracy and improve the efficiency of eye disease diagnosis.

Furthermore, this research also explores the challenges associated with deep learning-based eye disease classification, including dataset scarcity, imbalanced class distributions, and interpretability of the models' decision-making processes [8]. Addressing these challenges

will enhance the applicability and reliability of deep learning models in real-world clinical settings.

The potential benefits of this research are far-reaching. Accurate and automated eye disease diagnosis using deep learning can expedite the screening process [9], enable early intervention, and facilitate efficient resource allocation in healthcare systems. Moreover, it can empower primary care physicians and healthcare professionals in underserved areas [10,11], where access to ophthalmologists may be limited.

This research paper presents an in-depth exploration of the use of deep learning techniques for classifying and diagnosing eye diseases from ocular images. By leveraging the power of deep neural networks, we aim to develop a robust and accurate diagnostic tool that can assist healthcare professionals in providing timely and effective treatment to patients.

### II. LITERATURE REVIEW

The field of medical image analysis, especially the categorization of ocular eye diseases, has been completely transformed by the development of deep learning techniques, particularly convolutional neural networks (CNNs). Regarding the categorization of ocular illnesses, various strategies have been conducted. Utilizing machine learning techniques like deep convolution neural network (DCNN) and support vector machine (SVM) and digital image processing techniques, the authors offered a unique strategy to provide an automated eye illness recognition system utilizing visually observable symptoms [12]. The system was able to automatically separate the facial elements and the eye region from the frontal facial image and categorize seven eye illnesses. Another ML-CNN system [13] was built to get output of the probabilities of 45 diseases from fundus image validating the model by using cross-validation (CV) process. Three convolution (CONV) layers and one max pooling (MP) layer is used in the system.

The author of another study [14] created a way for utilizing a deep learning model to automatically categorize any retinal fundus image as healthy or sick. Using CNN, they developed a system called LCD Net that could perform the binary classification. A total of eight testing

datasets were created using retinal fundus images from two different sources.

Another paper [15] already provided an optical coherence tomography (OCT) diagnostic tool based on a deep learning framework for four class classification of ocular illnesses by automatically recognizing diabetic macular edema, drusen, choroidal neovascularization, and normal pictures in OCT scans of the human eye. The suggested framework uses OCT retinal pictures and analyzes the conditions using three different Convolution Neural Network (CNN) models (five, seven, and nine layers). Another study [16] also analyzed the accuracy of algorithms and SVM classifiers using fundus images from different four classes (glaucoma, retina, cataract, and normal eyes). Again, some papers focused on one disease like glaucoma [17], cataract [18] and so on and diagnosis with using various learning techniques. For quick diagnosis of multiple diseases, Artificial intelligence (AI)-based treatments have been the focus of medical health systems. Health data must still be documented in a consistent format in order to make machine learning more accurate and reliable by accounting for various features. In order to address this, the author [19] came up with a practical solution and made an effort to ensure error-free data entry by designing a user-friendly interface. Additionally, a range of machine learning methods, including Decision Tree, Random Forest, Naive Bayes, and Neural Network algorithms, were utilized to assess patient data in accordance with various factors, including age, medical history, and clinical observations. Another approach is taken through segmentation process. A convolutional neural network and fully linked conditional random fields (CRFs) are used to implement the retinal vascular segmentation method suggested by Hu et al. [20]. The color fundus images were used to assess the model's efficacy and accuracy. However, for an unbalanced dataset, this study [21] recommended using the same amounts of images for both categories we compare each other among seven diseases along with normal image and turning the multiclass classification issue into a binary classification problem. The binary classifiers were subsequently learned using VGG-19 only.

Above some limitation and some solution arising, our goal in this paper was to classify ocular diseases from color fundus images and diagnosis as effectively as possible. Our contribution in dataset was merging two datasets to make more balanced dataset and get the better result.

We conducted our task with four class (Cataract, Glaucoma, Diabetic and Normal) for classifying eye diseases in this paper through different Convolutional Neural Network (CNN) models (VGG-19, RESNET, NASNET-2). We did blood vessel segmentation using UNET. Our further task will be work on eight different class of eye diseases and diagnosis.

### III. METHODOLOGY

Visit the following website and choose any algorithm that you prefer-

- <https://scikit-learn.org/stable/index.html>

You don't have to describe the methodology right now; just make a choice based on your likings.

### IV. DATA SET

N/A

### V. RESULTS AND ANALYSIS

N/A

### VI. CONCLUSION

N/A

### VII. REFERENCES

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As this submission is for a demo checking, All parts & references will be added to the final report.