International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307 OPEN ACCESS

Available Online at : www.ijsrcseit.com

doi : https://doi.org/10.32628/CSEIT2410137

Eye Disease Detection using CNN

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ARTICLEINFO

Article History:

Accepted: 10 Feb 2024

Published: 24 Feb 2024

Publication Issue

Volume 10, Issue 1

January-February-2024

Page Number

193-200

ABSTRACT

Medical professionals such as ophthalmologists frequently use fundus images, which are particularly useful in detecting different retinal problems. They used this to diagnose many eye conditions, including pathological myopia, glaucoma, cataracts, hypertension, and age-related macular degeneration. These fundus pictures can also be utilized to anticipate how severe a disease would be and to identify early warning indicators. In the field of medical science, machine learning algorithms have become increasingly important in recent times. This is also the case in the field of ophthalmology. Our goal in this work is to use deep neural networks to automatically classify retinal fundus images into healthy and pathological categories. Due to the fact that deep learning is a superb machine learning method that has shown to be incredibly accurate when applied to computer vision difficulties. Convolutional neural networks (CNNs) were employed in our study to categorize retinal pictures according to their level of health.

Keywords : CNN, Deep Learning, Machine Learning, Fundus Images, Retinal Diagnosis

I. INTRODUCTION

The eyes are like our body's built-in cameras, helps us to capture the pictures of the world around us. They help us to see, avoid dangers, read, and recognize people's faces. But they're not just for looking; they also give us clues about our health. Sometimes, changes in our eyes can signal problems in other parts of our body, like diabetes or high blood pressure. So, taking care of our eyes is not just about seeing better; it's about staying healthy and safe in our daily lives.

Ocular disorders are a major global health concern that require precise detection techniques for diseases such as pathological myopia, age-related macular degeneration (AMD), cataract, glaucoma, and ocular problems connected to hypertension.

In 2020, there were 1.1 billion visually impaired people in the world; 43 million of them are blind (crude prevalence: 0.5%).

- The crude prevalence of moderate to severe visual impairment is 3.7%, affecting 295 million individuals.
- The crude prevalence of mild vision impairment is 3.3%, affecting 258 million individuals.

- Nearsightedness affects 510 million individuals (crude prevalence: 6.5%).

By utilizing the VGG16 Convolutional Neural Network (CNN) to deal with the complexities of ocular disease detection, this effort leads a groundbreaking project. Beyond improved diagnostic accuracy, the focus also embraces the possibility of creative early interventions. Human vision quality compromises have a negative impact on one's overall quality of life and productivity. Retinal abnormalities impact millions of individuals globally and can cause blindness if they are not identified and treated in a timely manner. [1,2]

In this context, leveraging advanced technologies in the field of artificial intelligence, particularly Convolutional Neural Networks (CNNs), holds promise for accurate and efficient diagnosis.

This project focuses on the development of a CNN-based model to detect and classify common eye diseases, including Glaucoma, Cataract, Hypertension, Age-related Macular Degeneration, and Pathological Myopia. The model utilizes a dataset of preprocessed eye images, where each image corresponds to a specific disease category or a healthy state. By learning intricate patterns and features from the provided images, the CNN aims to distinguish between various eye conditions, aiding in the early identification of diseases.

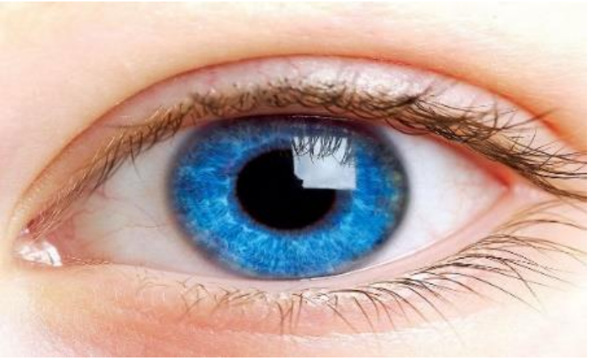
Popular deep learning frameworks TensorFlow and Keras are used in the implementation for model building and training. Because of the CNN architecture's ability to capture hierarchical representations, the model is able to identify minute characteristics that could be signs of various eye conditions. The model is trained using binary cross entropy loss and the Adam optimizer once the dataset is divided into training and validation sets. Dropout layers ensure robust generalization to fresh, unseen data by mitigating overfitting.

The significance of this project lies in its potential to offer a non-invasive, automated, and scalable solution for eye disease diagnosis. If successful, the model could serve as a valuable tool for healthcare practitioners, providing a faster and more accessible means of screening and early detection. As we delve into the details of the project, the subsequent sections will outline the methodology, architecture, and outcomes of the CNN-based eye disease detection system.

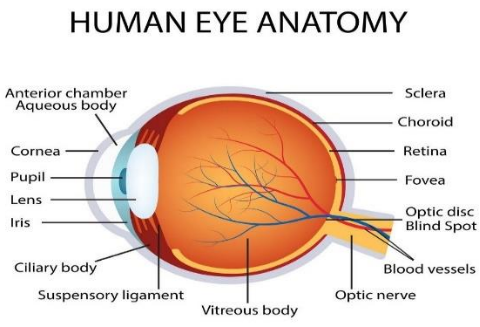
II. COMMON OCULAR DISORDERS

A. Structure of the Eye

Vision is a function of the sensitive organ known as the eye. To gather visual information and send it to the brain, it is made up of a number of interconnected components.



An outline of the eye's principal parts is provided below.



Structure of the Eye

This image shows normal retina taken by a fundus camera.

B. Systemic Diseases Manifesting in the Retina

a) Cataract

A kind of eye condition that causes foggy vision is a cataract. Vision that is foggy or icy is experienced by those who have cataracts. Reading, driving, and even just recognizing faces can be challenging for someone with cataracts in their eyes. [3]

The WHO estimates that there are about 285 million visually impaired persons around the world, of whom 39 million are blind and 246 million have moderate to severe blindness. [4]

Age-related cataracts cause 19.34 million people to be bilaterally blind (less than 3/60 in the better eye), according to the 1998 World Health Report. This was responsible for 43% of all occurrences of blindness. [5]

Cataract

b) Glaucoma

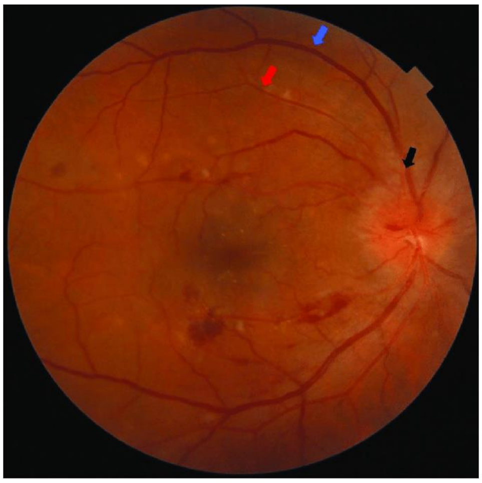
The term "glaucoma" describes a disorder in which damage to the optic nerve in the human eye results in loss of vision or blindness. This disorder manifests as different degrees of visual impairment that, if left untreated, could eventually lead to permanent blindness. The World Health Organization states that, following cataracts, glaucoma is the leading cause of blindness worldwide.[6]

Clinical analysis of glaucoma by using the evaluation of CDR by using an opthalmologist is time ingesting and subjective. Moreover, the supply of the medical device to perform this system is constrained. Therefore, Digital retinal fundus images show to be of excessive capacity to be utilized to locate and examine the progression of glaucoma. Computer aided analysis of these photos facilitates to diagnose this situation the usage of diverse computational algorithms while not having to worry approximately inter and intra observer variability that is generally visible in clinical analysis.

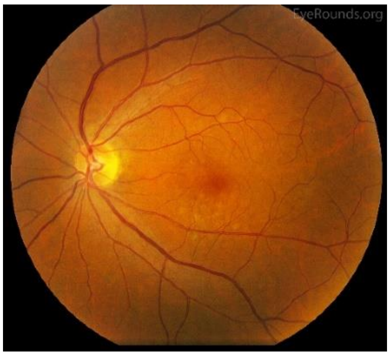
Glaucoma

c) Hypertension

The greatest risk factor in the world for heart disease (CVD), stroke, disability, and mortality is hypertension. A significant percentage of hypertensive adults still fail to meet their recommended blood pressure (BP) treatment targets on three antihypertensive medications or require more than four medications to do so, despite a steady improvement in hypertension awareness, treatment, and control rates over the past thirty years. Despite receiving continuous antihypertensive medication therapy, these people—who are classified as having treatment-resistant hypertension (RH)—remain at risk for target organ damage, morbidity, and mortality.[6]



Hypertension



Age Related Macular Detection

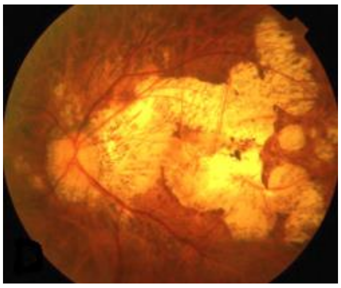
d) Age related Macular Degeneration

Age-related macular degeneration is a commonplace, chronic, modern degenerative disease of the macula that influences older individuals and functions loss of important vision due to abnormalities in the photoreceptor/retinal pigment epithelium/Bruch's membrane/choroidal complicated regularly resulting in geographic atrophy and/or neovascularization. Advanced AMD may be categorised extensively into two sorts: dry and moist. Although dry AMD debts for the majority of all recognized instances, moist AMD is answerable for the bulk of the severe vision loss and it usually occurs over weeks to months. Although neovascularization has been the maximum commonplace cause of severe vision loss, geographic atrophy, the maximum superior shape of dry AMD, can cause a sizeable lack of imaginative and prescient as properly.

e) Pathological Myopia

Myopia has been a common health problem around the world, and during the coming decades, more people are predicted to develop the condition. Refractive error known as myopia is characterized by an image entering the eye that focuses in front of the retina rather than on it. Its development is thought to be significantly influenced by both environmental and genetic factors. Visual acuity (VA) may deteriorate as a result of pathologic myopia, sometimes referred to as "myopic macular degeneration," "myopic maculopathy," or "degenerative myopia," which can happen in high myopic eyes. One of the main causes of impaired vision and blindness globally, pathologic myopia affects 1-3% of the general population. Moreover, pathologic myopia is regarded as such since it frequently affects people in their productive years. It is considered to be a social and economic burden.[5]

Myopic macular degeneration was the main cause of bilateral or monocular blindness (22.4%) and the third most prevalent cause of impaired vision (9.2%) among persons with high myopia (< 5.0 D), according to a 2006 report on the Tajimi Study, which included subjects 40 years of age or older.[6]

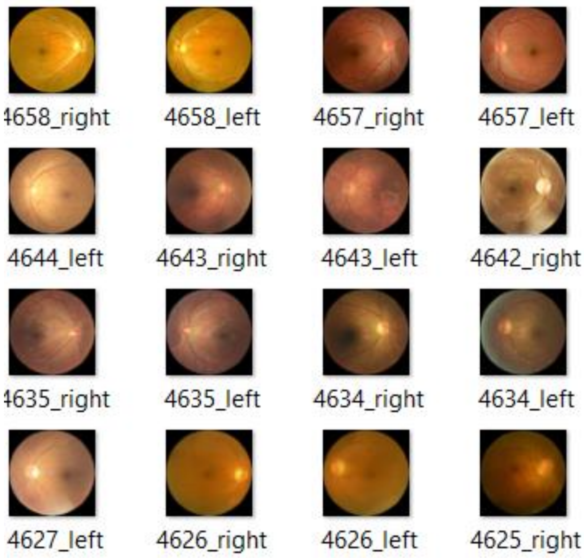


Pathological Myopia

Convolutional Neural Networks (CNNs) are a promising and significant use of deep learning in healthcare for the diagnosis of eye problems. CNNs are useful for analysing medical images, like as retinal scans, for the diagnosis of various eye illnesses since they perform exceptionally well in image recognition tasks. This is a broad guidance on how to go about utilizing CNN to develop an eye illness detection system.

III. Dataset

Based on the ocular diseases, the dataset consisting of 6392 fundus images consists of right and left fundus images. They are categorized into normal and diseased eye.



Fundus Images

The Comma Separated Value(.csv) file consisting of 6398 rows and 18 columns.

ID	Patient Age	Patient Sex	Left-Fundus	Right-Fundus
0	69	Female	0_left.jpg	0_right.jpg
1	57	Male	1_left.jpg	1_right.jpg
2	42	Male	2_left.jpg	2_right.jpg
4	53	Male	4_left.jpg	4_right.jpg
5	50	Female	5_left.jpg	5_right.jpg
6	60	Male	6_left.jpg	6_right.jpg
7	60	Female	7_left.jpg	7_right.jpg
8	59	Male	8_left.jpg	8_right.jpg
9	54	Male	9_left.jpg	9_right.jpg
10	70	Male	10_left.jpg	10_right.jpg

Table-1

A	B	C	D
ID	filename	class_name	target
0	0_right.jpg	Normal	[1, 0, 0, 0, 0, 0, 0, 0]
1	1_right.jpg	Normal	[1, 0, 0, 0, 0, 0, 0, 0]
2	2_right.jpg	Diabetes	[0, 1, 0, 0, 0, 0, 0, 0]
4	4_right.jpg	Diabetes	[0, 1, 0, 0, 0, 0, 0, 0]
5	5_right.jpg	Diabetes	[0, 1, 0, 0, 0, 0, 0, 0]
6	6_right.jpg	Diabetes	[0, 1, 0, 0, 0, 0, 0, 0]
7	7_right.jpg	Diabetes	[0, 1, 0, 0, 0, 0, 0, 0]
8	8_right.jpg	Normal	[1, 0, 0, 0, 0, 0, 0, 0]
9	9_right.jpg	Other diseases/	[0, 0, 0, 0, 0, 0, 0, 1]
10	10_right.jpg	Normal	[1, 0, 0, 0, 0, 0, 0, 0]

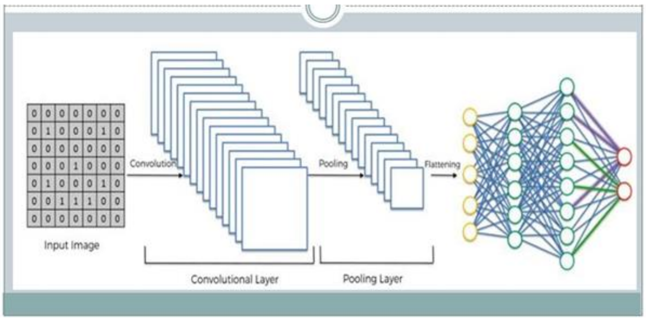
Table-2

Table-1 consists of patient information and the Table-2 consisting of the information regarding fundus images along with classes.

IV. METHODS AND METHODOLOGY

A. Convolutional neural networks (CNN)

CNN is a kind of deep learning model that is used to analyse grid-patterned data, such photographs. It is inspired by the way the animal visual cortex is organized and is made to learn spatial hierarchies of characteristics, from low-level patterns to high-level patterns, automatically and adaptively. Three different types of layers, or building blocks, make up a CNN, which is a mathematical construct. These include convolution, pooling, and fully connected layers. The first three layers—convolution, pooling, and fully connected—perform feature extraction, whereas the third layer—completely connected—transforms the features into a final output, such categorization. CNN is made up of a series of mathematical operations, including convolution, a particular kind of linear operation, which is why a convolution layer is so important.



To improve categorization, CNN trains the model using the raw pixel data from the image and then automatically extracts the features.

CNNs are very effective for processing images because features can appear anywhere in the image. In digital images, pixel values are stored in a two-dimensional (2D) grid, or an array of numbers, and a small grid of parameters called a kernel, an optimizable feature extractor, is applied at each image position. Extracted features can grow increasingly sophisticated in a hierarchical fashion as one layer feeds its output into the one below it. Training is the process of fine-tuning parameters like kernels in order to minimize the discrepancy between outputs and ground truth labels. This is done using a variety of optimization algorithms, including gradient descent and backpropagation.

Layer Type	Input Shape	Output Shape
Conv2D layer 1	Input Image	(256, 256, 32)
MaxPool2D layer 1	(256, 256, 32)	(128, 128, 32)
Conv2D layer 2	(128, 128, 32)	(128, 128, 64)
MaxPool2D layer 2	(128, 128, 64)	(64, 64, 64)
Conv2D layer 3	(64, 64, 64)	(64, 64, 128)
MaxPool2D layer 3	(64, 64, 128)	(21, 21, 128)
Conv2D layer 4	(21, 21, 128)	(21, 21, 256)
MaxPool2D layer 4	(21, 21, 256)	(7, 7, 256)
Flatten	(7, 7, 256)	12544
Dense	12544	120

This table shows the Max Pooling

B. VGG16

VGG-16 is a convolutional neural network (CNN) model that is 16 layers deep and is used for image recognition. It is considered one of the best computer vision models to date.

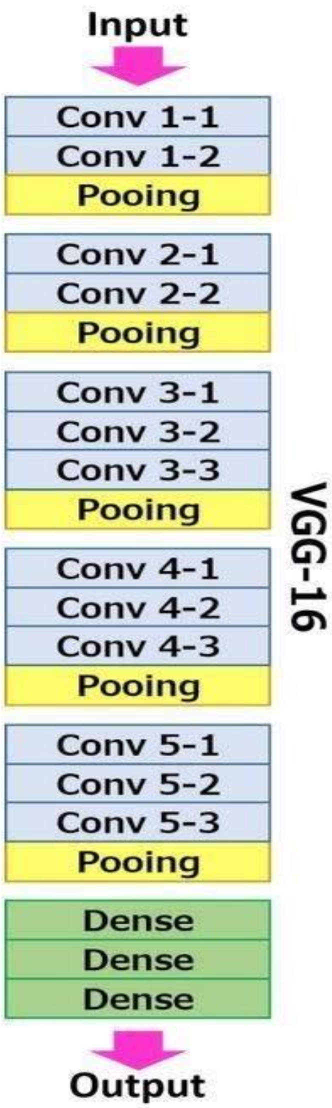
Here's a breakdown of the VGG16 architecture:

a) **Input Layer:** The model takes retinal fundus images as input. These images are typically pre-processed to ensure standard size and proper normalization.
b) **Feature Extraction:** The core of the model lies in its feature extraction capabilities. RetinalNet-500 employs a series of convolutional and pooling layers to extract relevant features from the input

image. These features capture crucial data about the retinal structures, textures, and abnormalities.

c) **Classification:** The extracted features are then fed into a classification network that determines the presence or absence of eye disease. This network typically consists of fully connected layers that learn to discriminate between healthy and diseased patterns.

d) **Output Layer:** Finally, the model outputs a prediction – whether the retinal image is classified as healthy or diseased.



VGG-16

The image indicates the steps in which the fundus undergoes.

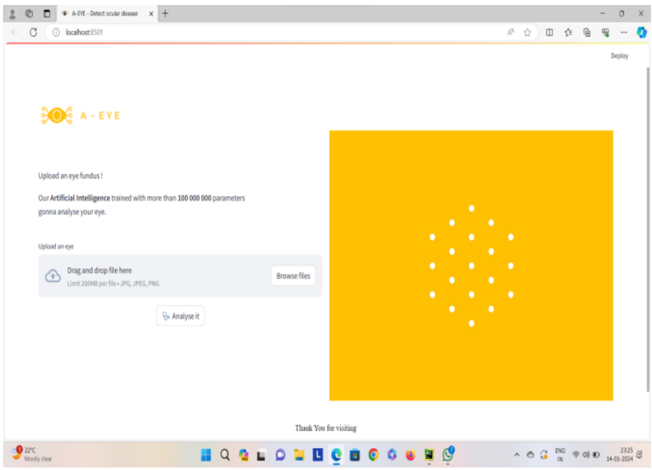
In addition, VGG-16 attained state-of-the-art performance at the time of its launch in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), marking a significant advancement in deep learning for image recognition tasks.

V. RESULTS AND DISCUSSIONS

This is the User Interface which can be the first page when the user runs the code using the below command.

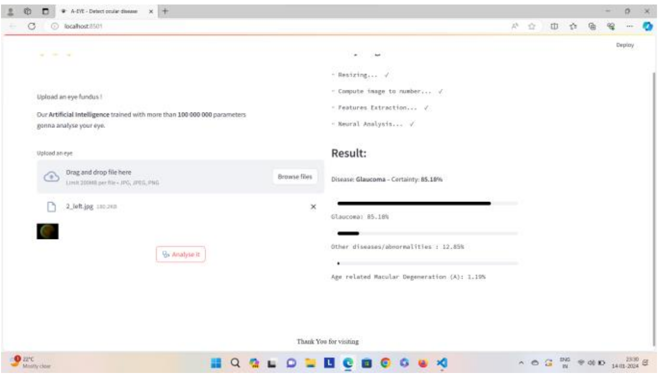
Streamlit run app.py

The user can select the input image by clicking Drag and Browse files. The supported extensions are .jpg,.jpeg,.png.



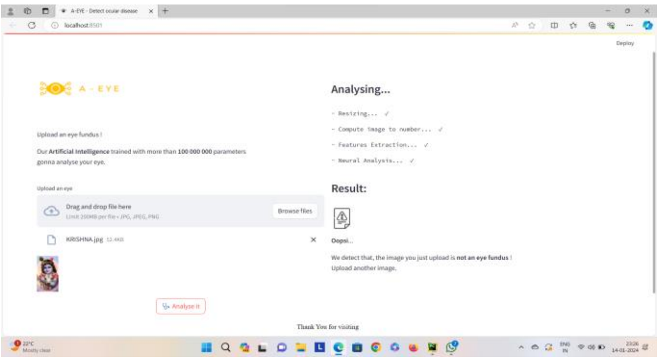
User Interface

Whenever the user selects the fundus image, the disease name with the affected percentage will be generated.



Affected Percentage of Eye

Whenever the user selects the image which is not a fundus image, then "please provide the fundus image" will be generated as error message.



Error Message

VI. CONCLUSION

Eye Disease Detection is taking lot of time in the clinics, when compared to the Eye Hospitals. The results are lacking in accuracy. This project helps the patients for the early detection of eye diseases so that the affective percentage will get decreased.

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Cite this article as :

B. Guna Indumathi, B. Harika, M. Vijay Raj, G. Sharmila, U. V. S. S. S. Kumar, S. Swaroop, "Eye Disease Detection using CNN", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 10, Issue 1, pp.193-200, January-February-2024. Available at doi : https://doi.org/10.32628/CSEIT2410137

Journal URL : https://ijsrcseit.com/CSEIT2410137