Classification of Retinal Occlusion in Fundus Images

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***Abstract*—Convolutional Neural Networks (CNNs), a type of Artificial Neural Network is used for the detection of eye diseases in the field of ophthalmology. Eye diseases are a significant issue globally, especially in developing countries, but the use of pattern recognition techniques, such as CNNs, is helping to address the problem. The proposed algorithm is a novel intelligent pattern classification system that uses a CNN and will be tested using the K-Fold Cross Validation method.The performance of the classifier will be confirmed by high numerical metrics such as Accuracy, Recall, Specificity, Precision, and F1 score. Retinal occlusion is a disease that can lead to loss of vision. They are classified into 3 types : Central Retinal Vein Occlusion, Branch Retinal Vein Occlusion and Retinal Artery Occlusion. Detection of these diseases in the early stages can help the patient from permanent loss of vision. In early stages of retinal occlusion, detection of disease is very difficult, and, in some cases, there may be combined retinal vascular occlusion that make it difficult to classify. Detection and classification of this diseases during early stages may help the patient from cardio-vascular diseases. The use of automated diagnosis for retinal occlusion can streamline clinical procedures and optimize treatment plans. Unfortunately, patients with retinal conditions may experience severe vision loss due to limited awareness of these diseases and inadequate medical resources. The project can detect and classify retinal occlusion diseases. If a combination of retinal occlusion occurs, then the severity cannot be known in the early stages. This project checks for combination and predict the severity of the disease.**

***Index Terms*—Retinal Occlusion, Convolutional Neural Network, Medical Image Processing, Fundus images**

I. Introduction

A. General Background

Eye diseases are a range of conditions that can negatively impact the structure or function of the eye.Some of the prevalent eye conditions are cataracts, glaucoma, age-related macular degeneration, and diabetic retinopathy. These conditions can range from minor vision problems to serious conditions that result in permanent vision loss. Early detection and treatment are crucial to prevent or minimize vision loss.

Ophthalmologists, or eye doctors, use a variety of methods, including eye exams, imaging tests, and surgery, to diagnose and treat various eye diseases. The eye is composed of a lens at the front that focuses images onto the retina at the back. The retina is equipped with special nerve cells that transform light into signals that are sent to the brain and perceived as images. Any conditions affecting the retina also affect one's vision.

The optic disc is located at the back of the eye and is the point where the nerve fibers of the retina converge and leave the eye to travel to the brain. The optic disc is responsible for transmitting visual signals and is surrounded by a vascular bundle composed of the central retinal artery and vein. These vessels carry blood to and from the heart, but can become blocked and lead to an occlusion or stroke, causing macular edema and rapid loss of visual acuity. The optic disc is not sensitive to light and creates a small blind spot in the field of vision.

Retinal occlusion refers to a situation where the blood supply to the retina is cut off. There are two types of retinal occlusion, namely retinal vein occlusion (RVO) and retinal artery occlusion (RAO). RVO is caused by a blockage in the retinal vein, leading to bleeding and fluid leakage, while RAO is caused by a blockage in the retinal artery, reducing the supply of oxygen to the nerve cells in the retina. There are two subtypes of RVO and RAO: central and branch. Central refers to a blockage in the main blood vessel, while branch refers to a blockage in a smaller blood vessel.

Automated diagnosis of retinal occlusion can improve clinical workflow and facilitate early detection. Treatment options for retinal occlusion include medications to dissolve the clot, laser surgery, or injections of medications into the eye. Overall, eye diseases can range from minor to serious and early detection and treatment are essential to prevent or minimize vision loss.

B. Objectives

- Classification of the 3 types of retinal occlusion diseases.
- Detection of combined retinal vascular occlusion.
- Creation of a convolutional neural network (CNN) model for classification and detection of diseases with very high accuracy.

C. Scope

Medical image processing is a field that uses technology to manipulate and analyze medical images to extract useful information and improve the original image. The focus is on 3D datasets of the human body obtained through CT or MRI scans. In this project, the goal is to classify different types of retinal occlusion diseases which can cause vision loss if not detected early. These diseases are difficult to classify, especially when a combination of different types of retinal vascular occlusion is present. Early detection and accurate classification of these diseases can also aid in the prevention of cardiovascular diseases.

II. Literature Survey

The study aimed at developing a new Convolutional Neural Network (CNN) for the automatic recognition of retinal vascular occlusions, specifically central retinal vein occlusion (CRVO) and branch retinal vein occlusion (BRVO), using fundus images. A pre-processing step was applied to differentiate actual lesions from noisy data and to enhance the images. For this purpose, different image processing techniques such as histogram equalization, low/high pass filtering, and thresholding were used [10].

Two different CNN frameworks were used in the study: the first one was a simple two-layer CNN with 64 neurons in a single deep layer and the second one was a VGG-CAM network based on the VGG19 architecture but with modifications such as the reduction of fully connected layers, the use of general average pooling (GAP), and the introduction of class activation mapping (CAM) and CAM attention [2].

The recognition process was performed either on the whole image or on image patches. A voting method was proposed to make the image-based method more robust [9]. The recognition of BRVO was made by analyzing fundus images, which are non-invasive and inexpensive. The automatic recognition of fundus images can reduce the workload of the ophthalmologist, reduce the cost and time for patients, and help improve the diagnosis conditions in rural areas [11].

The CNN designed for recognizing CRVO comprised of 12 layers, including 3 convolution layers, 3 pooling layers, 4 ReLU activation functions, and 2 fully connected layers [14]. The performance was evaluated through 10-fold cross-validation and compared with the results from AlexNet and SIFT techniques. The images were then classified using the softmax activation method, and the accuracy was determined using a confusion matrix. [3].

The use of deep learning techniques and image processing techniques can help improve the accuracy of the diagnosis and reduce the workload of ophthalmologists.The Keras library was utilized to construct a new CNN model that includes two layers of convolution, which reduces the image dimensions through max-pooling and converts the maps into a vector [1].

III. Methodology

A. Data Collection

The project uses fundus images to diagnose retinal occlusion diseases, which can cause vision loss and increase the risk of cardio-vascular diseases. The dataset for the project includes colored fundus images of different types of retinal occlusion diseases such as Central Retinal Vein Occlusion, Branch Retinal Vein Occlusion, and Retinal Artery Occlusion, as well as normal images. These images are sourced from Kaggle and will be used to train and test a convolutional neural network (CNN) model. The goal of the project is to use the trained CNN to classify these images, potentially improving the accuracy and speed of detecting retinal occlusion diseases in their early stages and helping prevent vision loss.

B. Data Preprocessing

Preprocessing is an important step in diagnosing retinal diseases automatically. It involves improving the quality of retinal images, which are often of poor quality due to factors such as noise and low contrast. The goal of preprocessing is to remove this noise and enhance the contrast and quality of the images. This is usually achieved through color space conversion and image enhancement techniques.

Color space conversion involves converting the original color image into a grayscale model, which is more efficient and easier to work with than color images. The grayscale image quality is enhanced through the use of contrast-limited adaptive histogram equalization (CLAHE). This method improves the image's contrast by calculating histograms for various sections of the image and adjusting the lightness values.

CLAHE is a form of adaptive histogram equalization (AHE) that is particularly effective in enhancing the local contrast and sharpening the edges in various regions of an image. Unlike AHE, which can amplify noise in uniform areas of an image, CLAHE limits the amplification of noise by applying a contrast restriction for each neighborhood.

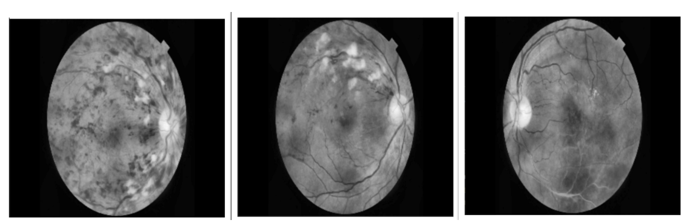

Fig. 1. Images after Preprocessing

C. VGG-19

The VGG-19 [17] is a convolutional neural network (CNN) that was developed by the Visual Geometry Group (VGG) at the University of Oxford. It is a 19-layer CNN that has been trained on the ImageNet dataset, a large database of

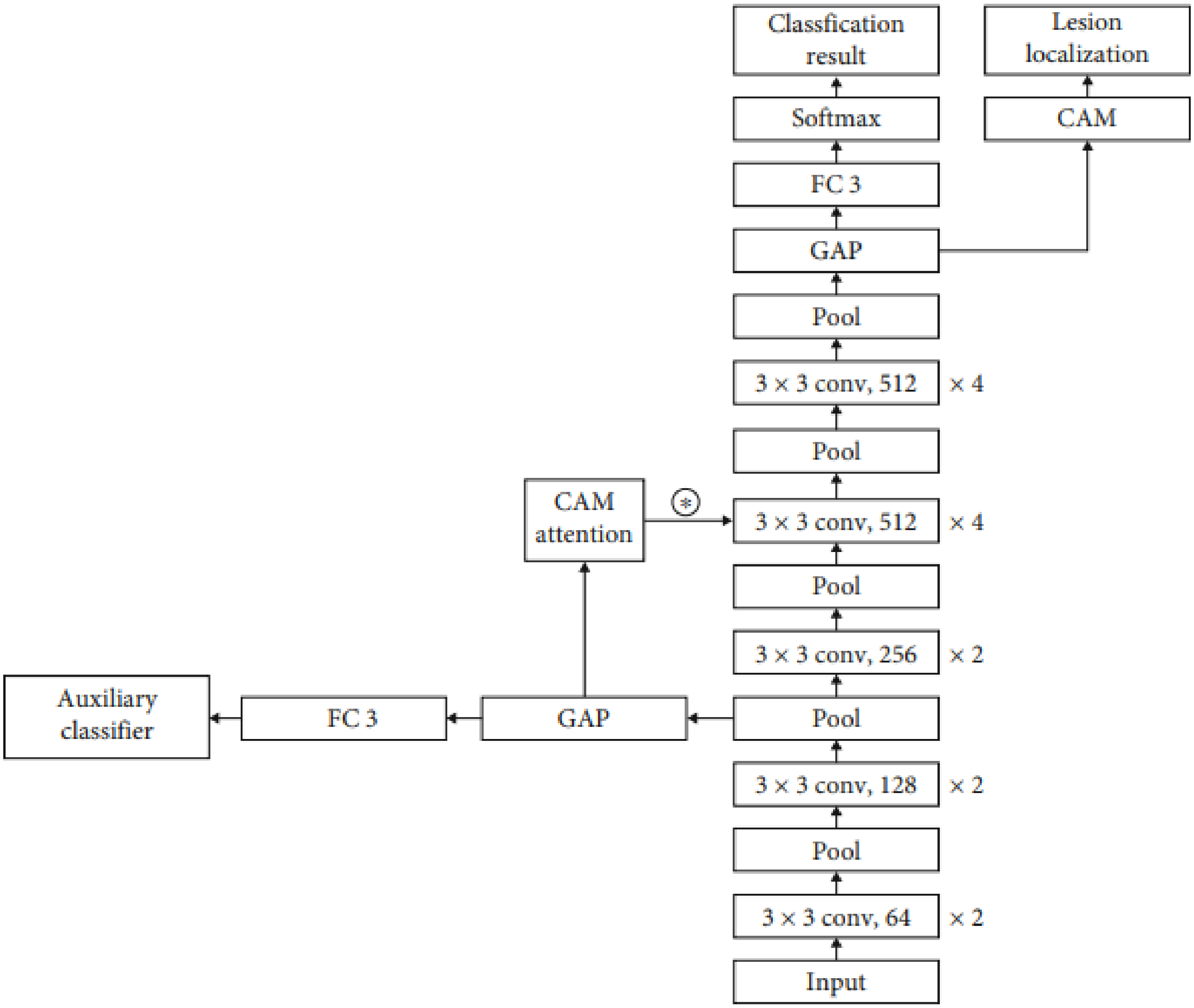

Fig. 2. VGG-19 Framework Architecture

images for computer vision tasks. VGG-19 is known for its simplicity and strong performance, and it has been widely used in various image recognition and classification tasks. The image processing in the network happens through a series of convolutional layers which extract features at various scales, followed by fully connected layers that learn the connections between the extracted features. The last layer of the network is a SoftMax layer that generates a probability distribution for the possible classes of the input image.

The VGG-CAM is an adjusted version of the VGG-19 network designed specifically for detecting lesions. To optimize it for this purpose, the number of fully connected layers is reduced and replaced with a global average pooling (GAP) layer, and a class activation mapping (CAM) attention layer is added to increase the model's sensitivity to the lesion region. The CAM layer works in conjunction with the GAP layer to detect lesions, and the network provides a prediction of the various classes to which the lesion can be assigned.

The VGG-19 and VGG-CAM networks are examples of convolutional neural networks that have been trained on the ImageNet dataset and optimized for image recognition and lesion detection tasks, respectively. The VGG-19 is known for its simplicity and strong performance, while the VGG-CAM is designed for lesion detection by incorporating a CAM attention layer.

D. Implementation Tools

The implementation can be done using various tools and technologies such as Python, OpenCV, Tensorflow, and Keras. Python is a widely used computer programming language that is ideal for building websites, software, and conducting data analysis. OpenCV is a free, open-source library for computer vision and machine learning that has image pre-processing capabilities. Meanwhile, Tensorflow facilitates the application of best practices in data automation, model tracking, performance monitoring, and retraining. Finally, Keras provides deep learning models with pre-trained weights that can be used for prediction, feature extraction, and fine-tuning. These tools and technologies come together to form a powerful toolkit for implementing complex image processing and machine learning projects.

IV. Result and Discussion

Preprocessing is a crucial stage in image analysis, with the aim of improving image quality and eliminating noise. One popular preprocessing approach is color space conversion, which transforms a colored image into a grayscale model, making it simpler to handle and presenting a consistent image representation.

Grayscale images can be further improved by utilizing contrast-limited adaptive histogram equalization (CLAHE), which improves contrast in various regions of the image by adjusting lightness values based on histograms computed for different parts. CLAHE is useful in enhancing edge sharpness and increasing local contrast, unlike traditional adaptive histogram equalization (AHE), which may amplify noise in uniform regions of the image by lacking contrast limits per neighborhood.

The VGG-CAM network is an adapted version of the VGG-19 network, optimized for recognizing lesions in images. This network has fewer completely linked layers and features a global average pooling (GAP) layer that increases the sensitivity of the model to the lesion area. The network also includes a class activation mapping (CAM) attention layer, which works in conjunction with the GAP layer to recognize lesions and predict the various categories to which the lesion may be assigned.

Several performance metrics, such as accuracy, confusion matrix, precision, and recall, are utilized to assess the system's performance. Accuracy measures the overall accuracy of the system's predictions, while the confusion matrix provides details about the particular kinds of errors made by the system. Precision calculates the ratio of true positives among all positive predictions, while recall calculates the ratio of true positives among all actual positive instances. These metrics provide useful insights into the system's ability to accurately detect and classify lesions.

V. Conclusion

Retinal occlusion refers to a situation where the retina, which is the light-sensitive portion at the rear of the eye, is deprived of blood flow. There are two primary categories of retinal occlusion: retinal vein occlusion (RVO) and retinal artery occlusion (RAO). These can be further divided into central and branch subtypes, with central referring to a blockage in the main blood vessel and branch referring to a blockage in a smaller blood vessel. Automated diagnosis of retinal occlusion can aid in early detection and improve clinical workflow. Treatment options include medications, laser surgery, or injections. A new VGG-CAM network model has been developed to classify retinal vascular occlusions and detect lesion areas. This model is based on the VGG19 CNN architecture and uses an unsupervised learning method to classify RVOs and detect lesion areas in retinal fundus images. The dataset was collected from Kaggle and the tools used in the project include Python, OpenCV, TensorFlow, and Keras. The accuracy of the model for classifying into these three types can also be obtained.

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