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Optimized Screening of Glaucoma using Fundus Images and Deep Learning

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Abstract— Diabetic retinopathy, glaucoma, and age-related macular degeneration are among the leading causes of global visual loss. Early detection and diagnosis of these conditions are crucial to reduce vision loss and improve patient outcomes. In recent years, deep learning algorithms have shown great potential in automating the diagnosis and categorization of eye disorders using medical photos. For this purpose, the ResNet-50 architecture is employed in a deep learning-based strategy. The approach involves fine-tuning a pre-trained ResNet-50 model using over 5,000 retinal pictures from the ODIR dataset, covering ten different ocular diseases. To enhance the model's generalization performance and avoid overfitting, various data augmentation techniques are applied to the training data. The model successfully detects glaucoma-related ocular illnesses, including cataract, diabetic retinopathy, and healthy eyes. Performance evaluation using metrics like accuracy, precision, recall, and F1-score shows that the model achieved 92.60% accuracy, 93.54% precision, 91.60% recall, and an F1-score of 91.68%. These results indicate that the proposed strategy outperforms many state-of-the-art approaches in the detection and categorization of eye disorders. This success underscores the potential of deep learning-based methods in automated ocular illness identification, facilitating early diagnosis and timely treatment to ultimately improve patient outcomes.

Keywords- Ocular diseases, Glaucoma, ResNet, Deep Learning, Fundus Images.

I. INTRODUCTION

Ocular conditions are medical problems that can impact the eyes and the surrounding structures, leading to various visual impairments, and in severe cases, even blindness. These conditions can affect different components of the eye, including the cornea, lens, retina, optic nerve, and eyelids. Common eye ailments include cataracts, glaucoma, macular degeneration, and diabetic retinopathy. These disorders can affect individuals of all age groups, with cataracts and glaucoma being more prevalent in older people, and diabetic retinopathy being more common in patients with diabetes. Cataracts cause clouding of the natural lens of the eye and are a major global cause of blindness. Glaucoma comprises a group of disorders that affect the optic nerve and can lead to irreversible visual loss if left untreated. Macular degeneration affects the central region of the retina (macula) responsible for fine vision and can result in blindness. Diabetic retinopathy is a condition affecting the blood vessels in the retina and can lead to visual loss in diabetic patients. Detecting ocular illnesses is crucial for maintaining good eyesight and overall health. Untreated eye problems can lead to vision loss or blindness. Early detection and treatment can help prevent or slow disease progression and avoid permanent visual loss [1]. Various visual disorders, including diabetic retinopathy, age-related macular degeneration, and glaucoma, may not exhibit symptoms in the early stages, underscoring the importance of regular eye exams for early detection. Early identification and treatment of eye diseases can help avoid significant healthcare costs and emotional distress associated with vision loss. Moreover, maintaining good vision is crucial for preserving quality of life and independence, especially in older individuals. In conclusion, timely detection of ocular illnesses is vital for preserving vision, overall health, preventing vision loss, and enhancing quality of life.

Figures 1 and 2 display fundus images of a normal eye and the labeling of the fundus pictures, respectively. The proposed approach employs a ResNet-50 model to detect three ocular diseases: cataract, diabetic retinopathy, and healthy eyes. The process involves data collection, pre-processing, feature extraction, and classification. For this study, the ODIR dataset, comprising over 5000 retinal photographs from diverse individuals, was used. The ResNet-50 model, known for its success in detecting various objects and patterns in photos, is employed for feature extraction. The model is trained on the pre-processed dataset to learn unique features for each image class. The trained ResNet-50 [2] model is then used for classification, analyzing pre-processed fundus images and categorizing them as cataract, diabetic retinopathy, or healthy eyes. By leveraging the features learned during feature extraction, this method assists medical practitioners in early identification of eye disorders, potentially preventing vision loss or blindness.

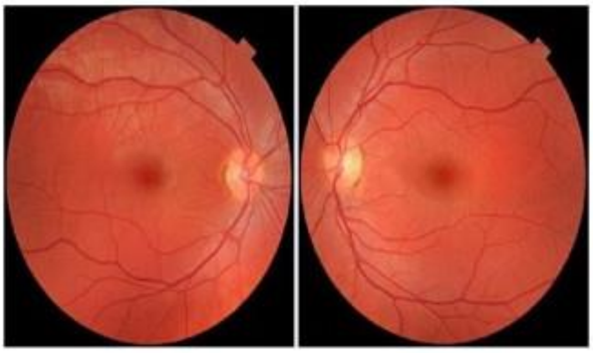

Figure 1: Fundus Image of Normal Eye

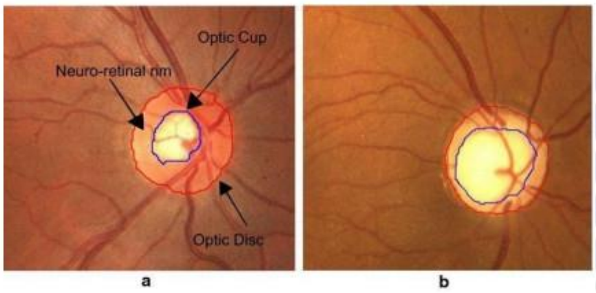

Figure 2: Labeling of Fundus Images.

II. METHODS AND MATERIALS

The research project revolves around the intersection of ophthalmology, medical imaging, and computer vision. Ophthalmology is a medical discipline concerned with diagnosing and treating eye-related illnesses. On the other hand, medical imaging involves utilizing various imaging techniques, such as optical coherence tomography (OCT) or fundus photography, to visualize the eye's anatomy and function. Computer vision is a field within artificial intelligence that focuses on developing algorithms and models for interpreting visual data. In this study, the primary focus is on the application of deep learning techniques, specifically convolutional neural networks (CNNs) [3-5], for automating the detection and categorization of ocular disorders from retinal images. This research topic is significant due to the growing need for accurate and efficient methods of identifying eye disorders, as well as the potential of machine learning to enhance diagnostic precision and reduce human error.

A. Real Life Objectives

The objective of this study is to develop a deep learning model based on convolutional neural networks (CNN) for the automated identification and categorization of ocular disorders using retinal images [6]. The performance of the constructed model will be evaluated using a large dataset of retinal pictures, and metrics such as accuracy, sensitivity, specificity, and other relevant measures will be assessed. Additionally, the proposed model's performance will be compared to existing approaches for detecting ocular diseases, including manual diagnosis by ophthalmologists or other computer-aided diagnostic (CAD) systems. The study will also explore the clinical utility of the developed model by assessing its feasibility, usability, and scalability in real-world scenarios.

B. Deep Learning Approach

The volume of data generated daily is incredibly vast, currently estimated at 2.6 quintillion bytes, and this abundant resource is the driving force behind deep learning. Deep learning algorithms [7] thrive on large datasets for effective learning, and the increase in data production has significantly contributed to the recent advancements in deep learning capabilities. Furthermore, the growth of Artificial Intelligence (AI) as a Service and increased processing power have also played a pivotal role. AI as a Service has democratized access to artificial intelligence technology, including the AI algorithms crucial for deep learning, making it more accessible to smaller enterprises without substantial upfront investments. Deep learning empowers machines to handle complex problems, even when dealing with diverse, unstructured, and interconnected datasets. As algorithms learn from more data, their performance improves accordingly.

C. Hybrid approach with CNN and ResNet-LSTM Model

CNN stands for Convolutional Neural Network, which is a type of artificial neural network commonly used for image processing, computer vision, and pattern recognition. CNNs are specifically designed to process and interpret visual input, making them well-suited for applications like image categorization, object detection, facial recognition, and image generation. CNNs [3-5] consist of interconnected layers of artificial neurons organized hierarchically. The core feature of CNNs is the convolutional layer, which applies convolution procedures to input data, extracting local patterns or features. These patterns or features are then passed through additional layers, such as pooling layers and fully connected layers, to learn higher-level representations and make predictions [8-9]. Most widely used fundus images datasets are listed in table below.

ResNet-50 is a deep convolutional neural network (CNN) model belonging to the Residual Network (ResNet) architecture. It is a variation with 50 layers, making it relatively deep. ResNet was proposed to address the issue of vanishing

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gradients in deep neural networks with numerous layers. ResNet-50 consists of convolutional layers, pooling layers, fully connected layers, and skip connections. It follows a "bottleneck" architecture, where the network is deeper in the middle layers and shallower at the beginning and end. ResNet-50 has been pretrained on extensive datasets like ImageNet, which contains millions of labeled images, and is widely used as a feature extraction or fine-tuning model for various computer vision applications, including image classification, object identification, and image recognition. Figure 3 illustrates the basic architectural flow of eye disease prediction [10]. The system is divided into three steps: data preprocessing, feature extraction, evaluation, and training.

TABLE 1: Summery of widely used Fundus Image Datasets.

	Glaucoma	Normal
Number of participants	601	487
Male	361	187
Female	240	300
Average age (years, SD)	60	49

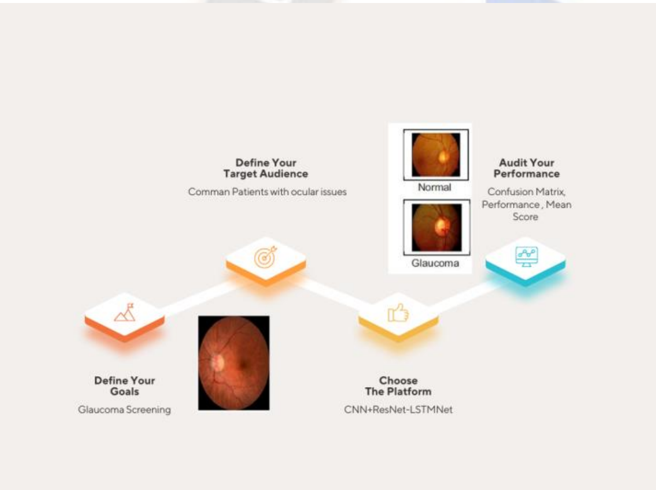

Figure 3: Architectural Overview

III. RESULTS AND DISCUSSION

In this stage, the ODIR dataset [11] is loaded and undergoes preprocessing. Preprocessing steps include resizing photos, standardizing pixel values, and dividing the data into training, validation, and test sets. Specifically, image resizing involves shrinking the images to a standard size, such as 224 x 224, to ensure uniform proportions for all photos, simplifying further processing.

A. Feature Extraction

.In ocular disease detection utilizing ResNet50, feature extraction entails capturing relevant features from the retinal fundus images using a pre-trained ResNet50 model. ResNet50 is a deep convolutional neural network architecture that has undergone training on an extensive dataset of images, including the ImageNet dataset, comprising millions of images.

CDR = Cup Diameter / Disc Diameter (1)

VCDR = Vertical Cup Diameter / Vertical Disc Diameter (2)

B. Training and Testing

Once the CNN architecture is defined, the model must be compiled, involving the definition of the loss function, optimizer, and evaluation measures. After compiling the model, it can be trained using the training data, wherein the CNN weights are iteratively adjusted to minimize the loss function.

During the ocular illness identification training phase with ResNet-50, the model is trained on the ODIR dataset for multiple epochs, where each epoch represents a complete iteration through the training dataset [12-13]. The number of epochs chosen for training significantly influences the accuracy and performance of the trained model.

Initially, the model learns to recognize simple features like edges and colors in the dataset over the first few epochs. As training progresses, it becomes proficient in identifying more complex patterns, such as shapes and textures of various eye disorders.

The model's performance allows it to predict class labels based on uploaded photographs. Upon execution, the model displays the home page with a picture selection button, as depicted in Figure 4. During training and validation, the accuracy curve represents the percentage of correctly identified occurrences and illustrates how effectively the model [14] learns to classify cases in both the training and validation sets during the training process. Over time, as the model improves its ability to generalize to new instances, the accuracy curve typically rises.

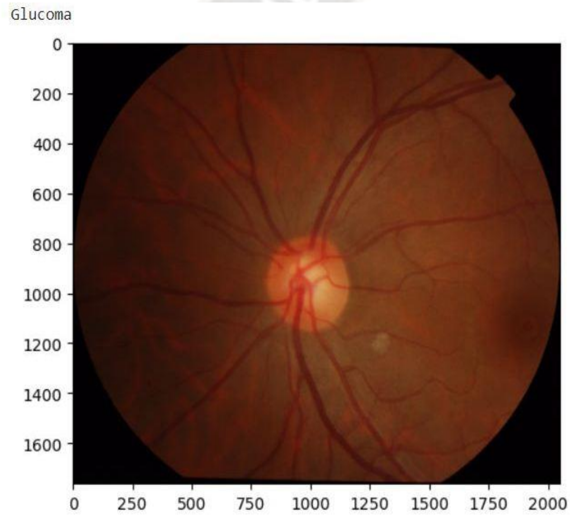

Figure 4: Fundus Model Prediction

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During training and validation, the loss curve represents the value of the loss function, which measures a model's ability to accurately predict the true output for each occurrence in the training and validation sets. As the model improves in making accurate predictions, the loss curve typically decreases over time.

In the case of a binary classifier system, the Receiver Operating Characteristic (ROC) curve is used to graphically depict its performance as the discrimination threshold is adjusted. However, when dealing with three class labels, the classifier may employ a one-vs-all strategy, treating one class as positive and the others as negative, resulting in three ROC curves. For example, if class normal has an area under the ROC curve (AUC) of 0.91, class cataract has an AUC of 0.96, and class diabetic retinopathy has an AUC of 0.92, it indicates that the classifier performs exceptionally well in distinguishing class cataract from the other classes with an AUC of 0.96. Similarly, the model performs well in differentiating diabetic retinopathy from the other classes, as shown by the AUC [15-16] of 0.92 for this class. However, the classifier's performance is somewhat lower when separating class normal from the other classes, with an AUC of 0.91. Overall, the classifier exhibits good discrimination in all three classes [17-19], particularly in the case of 0.96 AUC.

Using the ResNet50 architecture, a deep learning model has been developed for identifying eye illnesses from fundus images. The model's accuracy of 91.60% indicates its ability to correctly diagnose eye disorders from fundus images. Furthermore, high precision[20-22] and recall scores of 92.54% and 91.60% respectively demonstrate its capability to accurately identify true positives and avoid false positives. The model's high recall score[23-25] of 91.60% is particularly important for early detection of ocular disorders and preventing vision loss. The model also exhibits a low false-positive rate, which is significant in reducing unnecessary treatment and easing the workload for ophthalmologists [26-28], as evidenced by the high precision score of 92.54%. Overall, the model's strong accuracy, precision, and recall suggest its potential to assist medical professionals in early identification of ocular disorders [29], potentially preventing irreversible vision loss and improving patient outcomes. Figure 5 and Figure 6 provide graphical representations of the model's accuracy [30] and loss values.

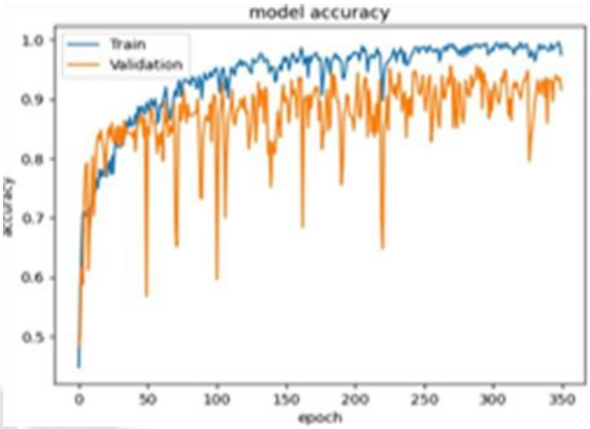

Figure 5: Model Accuracy.

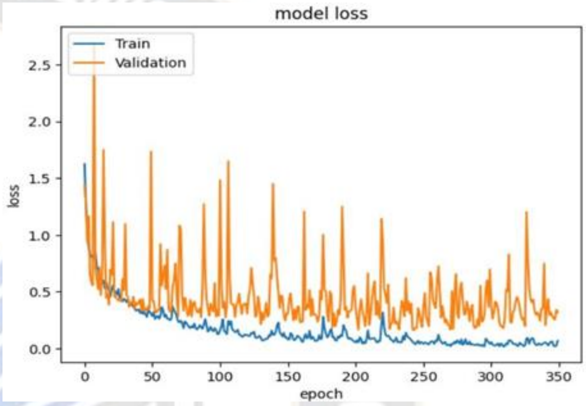

Figure 6: Model Loss.

IV. CONCLUSION

There is a critical need for an accurate and automated system to detect eye disorders. Early detection and diagnosis of ocular illnesses are crucial in preventing irreversible vision loss, which can be a potential consequence. However, ocular disorders may not exhibit signs until significant damage has already occurred. To facilitate early diagnosis, enable prompt treatment, and reduce the risk of vision loss, an automated and precise system for detecting ocular diseases from fundus images is essential. The proposed method groups pixels in the image space based on local maxima modes of each pixel, resulting in segmented images that are further categorized using the distance between two segmented areas. This categorization aids in disease diagnosis. The method's results show improved accuracy in sickness detection with reduced time and errors compared to DCNN's OD localization strategy. The findings of this study may have broader applications across various imaging modalities

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