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DETECTION OF OCULAR DISEASES USING FUNDUS IMAGES

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Abstract: Ocular pathology detection from fundus images presents an important challenge on health care. Identifying ocular pathology from fundus images is a significant difficulty for the medical field. The existence of lesions can be used to determine the severity stages of each pathology. Morphological characteristics define each lesion. Additionally, several lesions with various diseases share characteristics. We see that a patient may experience multiple diseases at once. As a result, the multi-class classification and intricate resolution approach for eye pathology detection are presented. There are several techniques for detecting ocular diseases in fundus imaging. Due to their ability to configure the network with respect to the detection objective, deep learning-based approaches are distinguished by higher performance detection.

This study suggests a deep learning-based survey of eye disease screening techniques. First, we research the pathology classification or lesion segmentation techniques that are currently in use. Following that, we extract the fundamental processing processes and evaluate the suggested neural network topologies. In the following section, we define the hardware and software environment needed to use the deep learning architecture. After that, we investigate the experimentation approaches used to assess the techniques and databases utilised throughout either the training or testing phases. Additionally presented and discussed are the execution timings and detection performance ratios.

Index Terms **- Ocular diseases, Fundus images, Age-related macular degeneration (AMD), Glaucoma, Diabetic retinopathy, Macula**

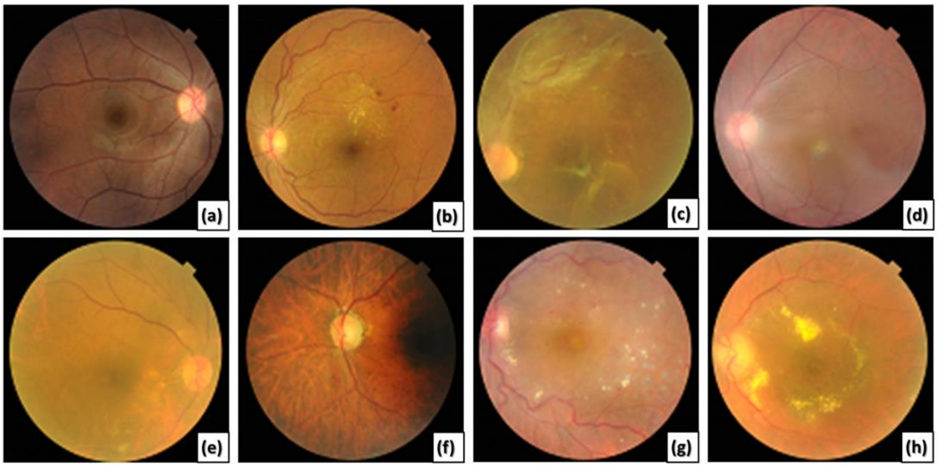
I. INTRODUCTION

Ocular diseases pose a significant threat to vision health and can lead to irreversible damage if not detected and treated early. Among the various imaging modalities available for ocular disease diagnosis, fundus photography stands out as a valuable tool for capturing detailed images of the retina, optic disc, and macula. These high-resolution images provide critical information about the structural and vascular changes associated with ocular diseases. In recent years, there has been a growing interest in leveraging fundus images and advanced image analysis techniques for the detection and diagnosis of ocular diseases. Traditional methods of ocular disease detection often rely on manual examination by experienced ophthalmologists, which can be time-consuming, subjective, and prone to human error. Moreover, the increasing prevalence of ocular diseases and the growing demand for efficient healthcare services necessitate the development of automated and objective diagnostic approaches.

The emergence of computer vision and machine learning techniques has opened new possibilities for ocular disease detection using fundus images. These techniques enable the automated analysis of large volumes of digital images and the extraction of relevant features that are indicative of specific ocular diseases. By combining advanced image processing algorithms with sophisticated classification models, researchers have made significant strides in developing computer-aided diagnosis systems for ocular diseases. The detection of ocular diseases using fundus images encompasses a wide range of conditions, including but not limited to glaucoma, age-related macular degeneration (AMD), diabetic retinopathy, and retinal detachment. Each of these diseases presents unique challenges in terms of image analysis and feature extraction. Consequently, researchers have focused on developing disease-specific algorithms that can accurately identify the presence and severity of ocular diseases based on distinctive patterns observed in fundus images.

The potential benefits of automated ocular disease detection using fundus images are manifold. Early detection can facilitate timely intervention and treatment, leading to improved patient outcomes and reduced healthcare costs. Moreover, computer-aided diagnosis systems have the potential to augment the capabilities of healthcare professionals by providing second opinions, reducing diagnostic errors, and enabling remote screening in underserved areas.

Fig. 1 Retinal color fundus images with different ODs



II. LITERATURE SURVEY

In this paper [1], they demonstrated a CAD system that classifies color fundus images using a dense correlation network (DC Net). They applied ML-C on a public dataset (ODIR 2019) made up of seven different OD kinds. The authors used two completely connected layers, one of which has a rectified linear unit (REL) activated. The number of the output categories for the ODs is 512 for one dense layer and 8 for the other. They used a soft margin loss function from ML. Their method's key benefit is that it may be applied to multi-modal picture analysis. Because their method is patient-based and the other research are image-based, they were unable to compare their model to other current works. They have a similar spine. To simplify computation, CNN will extract features from the right and left eyes. They were unable to manage the uneven distribution of patient cases as a result.

In this paper [2], used ML-C based on issue transformation to extract features from the color fundus images after using transfer learning to do so. An eight-label multi-label dataset was used by the authors. On both grayscale and colored photos, histogram equalization was used. Following that, they used two categorization models on the two sets of photos. The average of the sigmoid output probabilities from the two models was then calculated. As a result of the large number of unusual ODs labelled "other diseases" in the dataset used, the fundamental constraint of their research is the poor network performance. Additionally, their system has a data imbalance issue because of the scant information available for specific disease categories. As a result, some of the precise traits discovered remain unknown.

In this study [3], they employed a graphical convolution network (GCN) to identify eight DR lesions from color fundus pictures, including laser scars, drusen, hemorrhages, retinal arteriosclerosis, microaneurysms, and hard and soft exudates. For feature extraction, they used ResNet-101, followed by two convolutional (CONV) layers with a 3x3 kernel, stride 2, and adaptive max pooling. For laser scars, drusen, and hemorrhage lesions, their model's accuracy (ACC) and receiver operating characteristic (ROC) values demonstrated higher detection outcomes. Microaneurysms, soft exudates, and hard exudates, on the other hand, were difficult to detect using their system. This is mostly since retinal capillary microaneurysms manifested as tiny red dots. As a result, the model was unable to identify microaneurysms from the fundus's background. On the other hand, it was challenging for the model to extract the features of all fundus lesions because soft and hard exudate lesions frequently occurred alongside several other fundus lesions at the same time.

In this study [4], i ODIR2019 dataset was used to identify eight ODs using transfer learning. A few cutting-edge DL networks, including Resnet-34, EfficientNet, MobileNetV2, and VGG-16, were compared for performance. On the used dataset, the authors trained the state-of-the-art and then presented the findings. By calculating the ACC, they assessed the effectiveness of the models. They arranged the models into VGG-16, Resnet-34, MobileNetV2, and EfficientNet based on the ACC that resulted. To find the ODs, the authors did not create a new model. Furthermore, estimating the model performance required more than just calculating the ACC.

In this analytical study [5], DL was used to identify glaucoma in color fundus pictures. They first trimmed the pictures to include the optic disc. Then, further alteration techniques were used, including random rotations, zooming in and out by a factor of 0 to 0.2, and flipping images horizontally and vertically. They used ResNet50, Xception, InceptionV3, VGG16, and VGG19. Global average pooling followed each architecture. The SoftMax classifier was employed. For updating weights, the authors employed stochastic gradient descent (SGD). Epochs were set to 100 and 250. The learning rate (LR) was set to 104, the momentum rate was set to 0.9, and the batch size was set to 8. When the CNNs were tested using databases other than those used for training, the performance of fine-tuning was reduced.

III. Methodology

The methodology of detection of ocular diseases using fundus images is as follows:

- ***Data Collection***

  Fundus images are captured using specialized ophthalmic imaging devices, such as fundus cameras or retinal scanners. These devices employ non-invasive techniques to capture high-resolution images of the retina, optic disc, and macula. The images are typically saved in a digital format for further analysis.

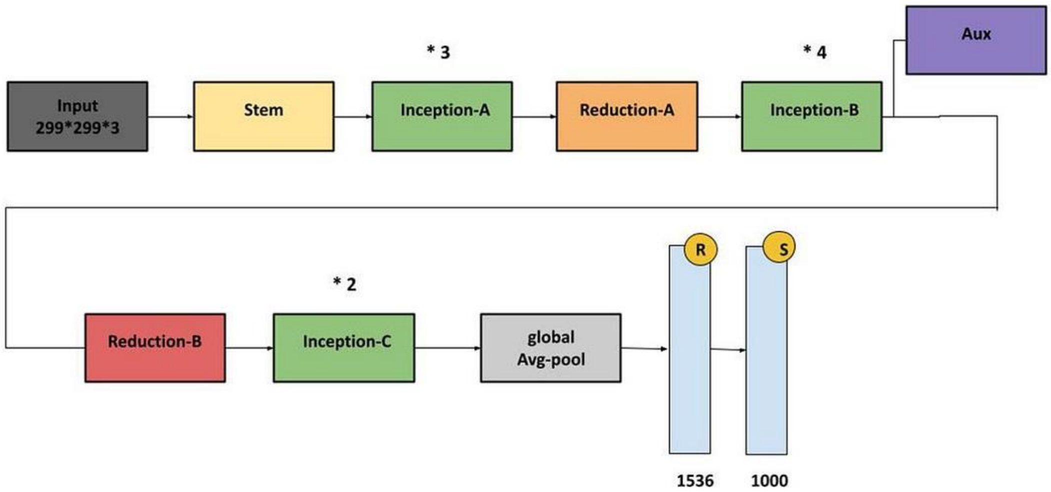
- ***Preprocessing***

  Preprocessing techniques are applied to enhance the quality of fundus images and remove artifacts or noise. Common preprocessing steps include image resizing, normalization, denoising, contrast enhancement, and removal of reflections or unwanted structures. Preprocessing helps to standardize the images and improve the robustness of subsequent analysis steps.

- ***Model Architecture***

  Convolutional Neural Networks (CNNs) are a type of deep neural network commonly used in image recognition and computer vision tasks. The key feature of CNNs is their ability to automatically extract relevant features from images, without the need for manual feature engineering. CNNs are made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers. In the convolutional layer, the network performs a mathematical operation called convolution, which applies a set of filters to the input image to extract features. Each filter is a small matrix of values that slides across the input image, performing element-wise multiplication and summation at each location. The pooling layer then down samples the output of the convolutional layer, reducing the spatial dimensions of the features while retaining their essential information. Common types of pooling layers include max pooling and average pooling.

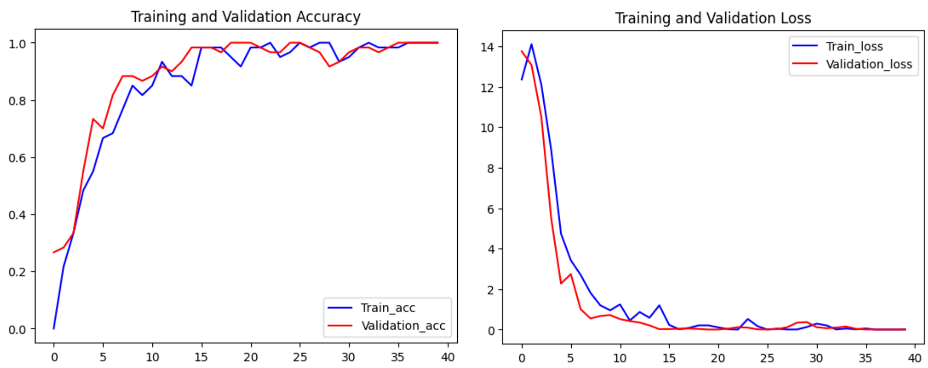
Fig. 2 Inception V3 Model



In fig 2, Inception V3 is a pre-trained model initially trained on a large-scale dataset (e.g., ImageNet), it is common to leverage transfer learning. Transfer learning involves using the pre-trained model's learned features as a starting point and fine-tuning the model on the specific task and dataset at hand. This step helps in leveraging the knowledge gained from a large dataset to improve the performance of the model on the footprint recognition task.

- Feed the preprocessed fundus images from the training set into the Inception V3 model and obtain the feature vectors from the last convolutional layer.
- Connect the feature vectors to the newly added fully connected layers and perform forward propagation.
- Compute the loss between the predicted disease labels and the ground truth labels using a suitable loss function, such as categorical cross-entropy.
- Update the weights of the fully connected layers using backpropagation and gradient descent optimization algorithms, such as Adam or RMSprop, to minimize the loss.
- Repeat steps (a) to (d) for multiple epochs, adjusting hyperparameters like learning rate and batch size to optimize the training process.
- Monitor the performance of the model on the validation set during training and perform early stopping if the performance plateaus or deteriorates.

Fig. 3 Accuracy and Loss Plot versus Epochs of Inception V3 Model



In fig 3, the accuracy and loss plot versus epochs is a common way to visualize the performance of a Inception V3 model during training. The plot shows how the accuracy and loss metrics change as the model is trained over a series of epochs, where each epoch represents one complete pass through the training data.

IV. Conclusion

The detection of ocular diseases using fundus images has witnessed significant advancements in recent years, driven by the integration of computer vision, image processing, and machine learning techniques. These approaches have shown great potential in automating and enhancing the accuracy of ocular disease diagnosis, thereby revolutionizing the field of ophthalmology. Fundus images provide a rich source of information about the structural and vascular changes associated with ocular diseases, enabling the identification of early signs and facilitating timely intervention. By leveraging advanced image analysis algorithms, researchers have developed computer-aided diagnosis systems capable of detecting various ocular conditions, including glaucoma, age-related macular degeneration (AMD), diabetic retinopathy, and retinal detachment.

The application of machine learning and deep learning models has been particularly impactful in ocular disease detection. These models can learn complex patterns and features from large datasets, enabling accurate classification and segmentation of fundus images. Furthermore, the integration of clinical data, longitudinal analysis, and the development of explainable models have the potential to enhance the diagnostic capabilities of automated systems and facilitate personalized treatment approaches. Despite the significant progress made, there are still several challenges and opportunities for future research. Multi-class classification, longitudinal analysis, integration of clinical data, explainability, transfer learning, and real-time applications represent important areas that require further investigation. Additionally, the validation and clinical translation of automated ocular disease detection systems through large-scale trials and collaboration with healthcare professionals are crucial for their successful implementation in routine clinical practice.

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