Detecting Eye Ailments Using Transfer Learning

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***Abstract*— In the last ten years, dangerous eye diseases that lead to low vision and blindness have increased significantly. Due to the importance of this issue, in this project, the diagnosis of eye diseases has been investigated to minimize the error of disease diagnosis. In this project, several deep learning models were used to investigate the dimensions of the problem. Considering that every artificial intelligence model has errors, it has been tried in this project using image processing and techniques that use image processing and the doctor to diagnose the disease. Among the methods used in this project is the segmentation of eye vessels, which is particularly important in diagnosing eye diseases.**

***Index Terms*— eye disease, transfer learning, convolutional neural network**

I. Introduction

AMONG the factors that increase eye diseases, we can mention the aging of the population and the effects of digital life. Quick diagnosis and proper treatment will have a significant impact on preventing blindness and increasing the quality of life. Conventional diagnostic methods are highly dependent on the professional experience and knowledge of doctors, which can increase misdiagnosis and irreparable losses. The combination of ophthalmology and artificial intelligence has the potential to create a revolution in the usual methods of diagnosing eye diseases. It can have a significant impact on the treatment process. Considering that the early diagnosis of the disease can have the most excellent effect on its control, artificial intelligence has flourished in the field of disease diagnosis using images and medical data, which increased research in the field of diagnosis of diseases such as cancer, diseases cardiovascular diseases and Alzheimer's disease show this problem. According to our research in the eye and health field, the possible projects in this field are divided into three main parts: disease diagnosis, disease severity diagnosis, and image processing to extract areas of high importance for the doctor. In the following, eye diseases are first introduced, and then the available data are reviewed. Then, a summary of the previous methods in this field is presented, and finally, the path taken in this project is presented, and the results are reviewed.

II. EYE AILMENTS

Considering that the signs and symptoms of eye diseases play a significant role in the diagnosis of these diseases, in this section, some diseases that can be diagnosed using medical images have been examined.

Diabetic retinopathy: High blood sugar (diabetes) causes blockage of blood vessels, blockage of blood vessels in eyes causes the eye to try to create new vessels. However, because this is not done correctly, it causes blood leakage in the retina.

Cataract: Cataract is cloudiness and darkening of the lens of the eyes. It is common to get this disease with age. If not treated in time, the gradual progress of this disease leads to blindness.

Glaucoma: Due to the increase in pressure in the eyes, the optic nerves, which have the task of transmitting visual messages to the brain, are gradually destroyed, and this gradually leads to blindness in the person.

Macular Degeneration: This disease, which is also called macular disease, is the creation of a dark spot in the center of the human visual field. This disease is caused by the formation of substances called Drusen in the pupil of the eye and is usually directly related to aging.

Hypertension: High blood pressure and fat affect the retinal vessels and cause damage to these vessels, which leads to leakage of blood and blood substances from the vessels into the tissues, especially inside the retina, or causes blockage of the vessel in the retina.

Myopia pathologic: Myopia occurs due to the long diameter of the eyeball compared to the focusing power of the cornea and lens, which can be due to excessive curvature of the cornea or lens. This causes the light rays to focus in front of the retina instead of falling on the retina.

According to reports, 400 million people in the world have diabetes, and one-third of these people have diabetic retinopathy. In Iran, 10% of people have diabetes, and diabetes is one of the most important causes of blindness and vision loss in Iran. Since retinal disorders occur in old age and Iranian society is aging, the cases of retinal disorders are increasing.[1]

III. Datasets

Fortunately, in the field of eye diseases, good data sets have been collected with free access. In these parts, we summarize the characteristics of these data. A more complete report of the dataset is available in the file Review-Detection-Datasets. According to our research in this field, three types of imaging with different characteristics are performed, which leads to three types of image modalities.

Fundus: This type of imaging, which accounts for the enormous amount of available data, is used to diagnose various diseases, including glaucoma, cataracts, and diabetic retinopathy. In this method, by using a drop and a window that opens the front of the eye more, the doctor can see clear images of the inner parts of the eye using an imaging device. In the literature of this field, fundus imaging is a process in which the light reflected from the device is used to obtain a two-dimensional view of the three-dimensional and semi-transparent tissue of the retina.

Retinal Optical Coherence Tomography (OCT):

It is a non-invasive imaging method that uses light waves to take pictures of the retina. With oct, the doctor can observe each of the distinct layers of the retina and measure the thickness of the retinal layers. In Ibn Rosh, a special laser light is shone into the eye. After passing through different layers of the eye, this light is finally reflected, and the device's sensor analyzes the light reflection of different layers of the eye. Finally, the device detects regular layers as abnormal with light analysis and shows the type of lesion with micron clarity and precision.

Diagnosis of eye diseases: An ophthalmic database of 3,500 patients with age and color fundus photographs of left and right eyes and disease type. In addition to the type of disease, this data does not contain other information about the patient, such as the age and gender of the patient.

Retinal OCT images: In this dataset, 84,450 x-ray images were divided into train, test, and validation. Image labels are one of three diseases: CNV, DRUSEN, DME, or no disease.

Diagnosis of glaucoma: This dataset has 520 train images and 130 images for validation. This collection is collected only for the diagnosis of glaucoma and does not have any other label about other diseases.

Eye OCT datasets: This dataset, a collection of existing datasets, has OCT and Fundus images. For this reason, it can help convert these two modalities to each other.

IV. Review Resources

The existing methods in this field are divided into two categories: traditional methods and methods based on deep learning. Among the traditional methods, SVM and Random Forest are the most used classical machine learning methods in ophthalmology. Considering that there is good data collection in this field and according to the conducted studies, methods based on deep learning have better performance in the intended application. In this section, a summary of the investigated methods is presented. More details of each article are available in the review papers report.

Diagnosing diabetic retinopathy using a deep network has been investigated in the article [2]. The available images are of the fundus type, and the network output of zero means no disease, and one means disease. As with other methods in this field, pre-processing is first performed on the image, which includes normalizing the pixels and limiting the image of the inner region of the retina. Also, in this research, data addition has been done by changing the color and brightness of the image, as well as by rotating the image. Then, a deep network was used to obtain the essential features of the image, and finally, using these features, a tree-based classifier was trained and used. This article is essential because it has gathered the fundus images available in different sources for the diagnosis of diabetic retinopathy and identifies the important points of the image.

Considering the importance of biomarkers for the diagnosis of diabetic retinopathy, in [3], first, these markers are identified manually, and then they are trained by a deep network to detect the presence or absence of these markers.

In [4], diabetic retinopathy is diagnosed using a computer-aided diagnosis system. In this method, twelve different retinal layers are first extracted from the oct image, and then features such as roughness, reflection, and curvature of each layer are calculated. These features proposed by the Deep Fusion Classification Network are combined, feature dimensions are reduced, and classification is done. Although perfect accuracy has been reported for this method in practice, this method requires an expert in the segmentation stage and cannot be implemented automatically.

A method based on deep convolutional network has been proposed to diagnose glaucoma [5]. This grid captures the optic disc area of the fundus image and determines the likelihood of disease. In this research, SCES and ORIGA data sets were used, which are specific for glaucoma diagnosis.

In another article, research has been done on the diagnosis of glaucoma to investigate the effect of using the area of interest on the accuracy of the diagnosis. [6] This research showed that the use of an optical disc for detection has better accuracy than the use of the entire image.

In [7], a method for diagnosing glaucoma is presented. The interesting point of this research is the use of five existing datasets in the field of glaucoma diagnosis. So, training is done on four data sets, and testing is done on one data set.

As we know, the U-Net network is used for image segmentation, and it has been very accurate in practice. In [8], two U-Net networks are used in series to segment the blood vessels of the image. This network is named W-Net. Among the applications of this type of segmentation are blood flow analysis, retinal image analysis, and calculation of the ratio of artery to vein.

V. Suggested Methods

After reviewing various articles and data, the definition of the project was selected based on the diagnosis of several different eye diseases from Fundas images.

Several methods have been provided to diagnose eye diseases, which were discussed in the previous section. By examining these methods, the better performance of methods based on deep learning can be seen in the diagnosis of eye diseases. Therefore, disease diagnosis using deep networks was chosen. In general, this project was divided into two primary phases. In the first phase, we made a better and more accurate diagnosis of diseases, and in the second phase, we presented images containing useful information to the doctor. This helpful information includes images with similar diseases as well as images in which essential parts are highlighted more prominently.

TABLE I

SUMMARY OF THE CHARACTERISTIC OF DATASETS

Name	Ailment labels	Modality	Number of photos	Number of patients
Diagnosis of eye diseases	All ailments	Fundus	6,392	3,500
Retinal OCT images	Drusen, DME, CNV	OCT	84,495	84,495
Diagnosis of glaucoma	Glaucoma	Fundus	650	650
Retinal OCT and OCTA	-	OCT	+1,000	2
Yangaki with model	-	Fundus	18,394	5,825
Cataract dataset	Glaucoma, Cataract, Retail disease	Fundus	601	601
OCT classification Challenge	Diabetic retinopathy	OCT	650	165

VI. DETECTION

A. *Fundas Images*

For diagnosing several different types of eye diseases, fundus-type imaging was used because more diseases can be diagnosed using this type of image, and a good data set is freely available to the public. In addition, many studies that have already been done on the diagnosis of eye diseases from these images show the high capability of these images in diagnosing diseases with high accuracy. Fundus imaging is a standard method in medical centers all over the world, which makes deep learning models that work based on fundus images useful.

ODIR (Ocular Disease Recognition) Dataset

Among the reviewed data sets, this data set was chosen as the primary data set for diagnosing eye diseases. This collection of fundus images consists of left and right eyes separately. Each image has different labels, such as gender, age, etc., as well as seven types of diseases. Six specific diseases are labeled under the heading "other diseases." Each image may have one or more concurrent diseases or may be healthy in general.

This collection has 7000 images, of which 1000 images have been separated for testing. However, for validation and training, we did the separation ourselves to better observe how the model is trained.

Cataract Dataset

Considering that the ODIR dataset has a very different number of diseases, it was decided to add more data for cataract disease, which has very little data compared to other classes, to increase the impact of this increase. Check the data on the accuracy of the model. For this, we went to the cataract dataset, which contained Fundus images for four different categories of cataracts, glaucoma, other diseases, and healthy eyes.

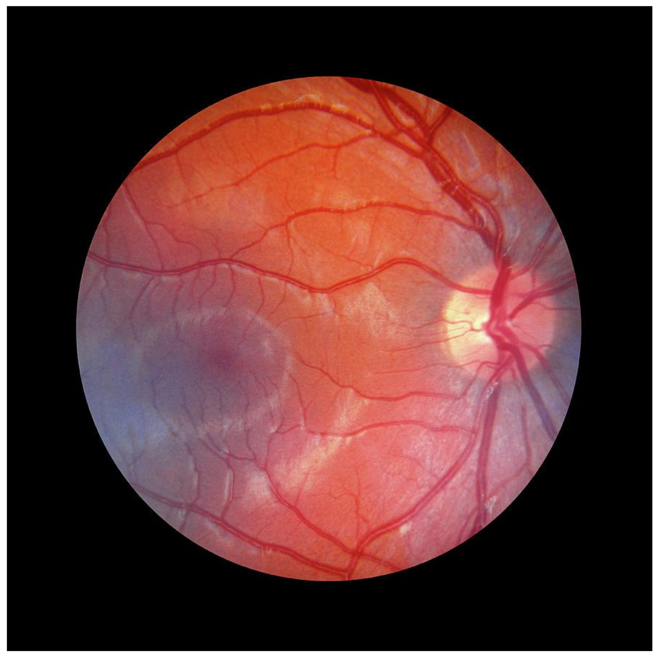

Figure VI-1 An example of Fundus image

B. *Using Renown Image Recognition Models*

For diagnosing diseases, five well-known image recognition models were used as the basis of disease diagnosis models, and the last layer of these models was connected to a layer with eight outputs. This output independently shows eight possibilities for eight different classes. For example, the figure shows the two VGG-16 models used to diagnose diseases.

In the first phase of the project, five models were built based on famous models, and we compared their results. The basic models were as follows: VGG16, VGG19, Inception V3, Resnet V2, and Xception.

The results related to the comparison of models are placed in the results section.

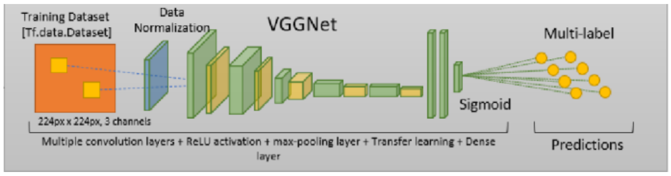

Figure VI-2 A model based on VGG16.

C. Mixing Models

For better and more practical use of these five models, we designed a basic class for models and put these models in its framework so that we can get the necessary functionality from them apart from the structural difference of the models. This allowed us to replace the models with the lowest cost.

In addition, the creation of the base class allows us to switch from the Keras framework to the Pytorch framework with minimal cost and concern for maintaining the overall performance of the project.

D. Using MLflow

MLflow was used to better evaluate and monitor the learning factors of the models and compare the results of different models, which provided us with a lot of information about the learning process of models and relevant parameters.

Various factors for learning each of the test models and relevant information were stored using MLflow to finally lead us to the best model for more accurate disease diagnosis. More complete information is provided in the results section.

E. Pre-processing Images

One of the things that is effective in learning models better is the pre-processing of images, which can provide better information to the model for better disease diagnosis. For this, we used the following pre-processing for images:

Remove padding: Usually, there are black margins in Fundus images that do not have any useful information about the disease, so removing this margin will make the model learn better.

Resize: The available images were of different sizes, and for the input of the network, it was necessary to make these images the same size.

Ben Graham: An innovative pre-processing from someone with the same name who won Kaggle competitions. This method processes the input images and highlights the important points.

Random Flip: Matches images randomly. This pre-processing can be useful because we use left and right eye images simultaneously in network training.

Random Shift: Randomly shifts the images.

F. Using SVM

Along with the previous models that connected the last layer of the famous models to a layer with eight outputs, we decided to classify the output of the deep network with an SVM model to improve the classification accuracy.

VII. Visualization

In the second phase, we investigated information display methods to provide useful information about the input image, which are listed below. Authors should consider the following points:

1) **Render similar images using KNN**: To further help the doctor to diagnose the disease from the images, presenting images with the same disease can be very useful and help the doctor to diagnose the disease more accurately and easily. For this, we trained a KNN model that finds images like the input image in terms of possible disease.
2) **Showing sharper features in fundus images**: Fundus imaging produces a flat image of the entire depth of the retina, which makes it more difficult to understand and interpret this image. One idea is the segmentation of eye vessels, which are clearly identified in the image format using the W-Net network. An example of eye vessel segmentation is shown in Figure VII-1. The second idea was to present the output image of the Ben Graham method, which provides a clearer image to the doctor. This clear image can help the doctor make a better diagnosis. Figure VII-2 shows an example of this pre-processing.

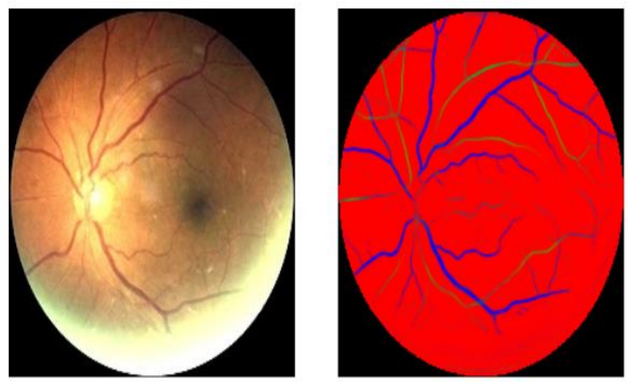

Figure VII-1 Sharpening the vessels of eye.

Figure VII-2 Sample of input and output of Ben Graham R: Raw image, L: Ben Graham Output

VIII. Results

At first, the basic models with the entire dataset and batch size of 4 were given in 20 epochs because if the error did not change in 3 epochs, the training would stop. All models were trained for less than 10 epochs. The results of these models on the training set and validation are given in the tables.

According to the analytical charts and tables above, the best model is the Xception model, which performs better on the validation data. The analytical diagrams of these base models are presented in the report Diagram-base-models along with this paper. Please refer to the results of this report for further review.

Next, experiments were conducted to analyze and check the performance of pre-processing and the use of transfer learning. The results showed that the use of transfer learning for Resnet did not lead to improvement, but for other models, better results were obtained with transfer learning. Also, experiments on pre-processing showed that Ben Graham's pre-processing can greatly affect the speed of learning and as a result, the model will be faster and more suitable. For the Resnet model that had the problem of overflowing, using pre-processing because of slowing down the training process causes better accuracy on the validation set. As for the Xception model, matching the images increased accuracy in both sets. The diagrams related to these tests can be seen in the Diagram-preprocess-effect and Diagram-Pretrain-effect reports.

Table 2 - The accuracies obtained on the training sets.

Model	*Accuracy*	*AUC*	*Loss*	*Precision*	*Recall*
VGG16	0.8939	0.9061	0.2444	0.6380	0.4716
VGG19	0.8910	0.9046	0.2492	0.6201	0.4692
ResnetV2	0.9511	0.9771	0.1249	0.7449	0.8721
InceptionV3	0.8660	0.7993	0.3166	0.0337	0.4628
Xception	0.9320	0.9566	0.1691	0.6289	0.8190

Table 3 - The accuracies obtained on the validation sets.

Model	*Accuracy*	*AUC*	*Loss*	*Precision*	*Recall*
VGG16	0.8326	0.7990	0.3813	0.3757	0.2374
VGG19	0.8498	0.7942	0.4214	0.4527	0.1833
ResnetV2	0.8403	0.7779	0.5965	0.3778	0.3559
InceptionV3	0.8553	0.5603	16.1981	0	0
Xception	0.8660	0.8435	0.3380	0.5469	0.3535

IX. Conclusion

This project will finally be able to diagnose six types of specific diseases using FUNDAS images accurately. This is very helpful in correct and timely treatment of patients. In addition, more information, including similar images and segmentation of eye vessels, is provided to the doctor.

The application of this project is not only at the time of disease diagnosis, but it will also be instrumental in educational departments. Estimating the probability of disease and presenting images with the same disease, presenting the image of eye vessels, and providing more explicit images will be more practical than only fundus images during training.

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