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Using Transfer Learning Technique as a Feature Extraction Phase for Diagnosis of Cataract Disease in the Eye

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Abstract

According to the data of the World Health Organization (WHO), currently at least 2.2 billion people worldwide have visual impairment, and at least 1 billion of them have preventable visual impairment. Eye diseases have become a serious problem, especially in the developing and underdeveloped countries around the world. The eye is one of the most important organs in the maintenance of daily life. So, early detection of ocular disease is an effective and economical method of eliminating blindness caused by eye diseases. In this work, a deep learning model has been proposed for detecting the cataract disease from retinal fundus images. The proposed model consists of two phases. In the first phase, it is proposed to use some famous convolutional neural network architectures such as VGG-16, ResNet, Inception v3 and MobileNet as a feature extraction phase. In the second phase, some classical neural network layers have been adopted and trained using the features extracted in the first phase for conducting the classification process. The proposed model has been trained and tested using a dataset contains two classes selected from a retinal image dataset containing 6392 images related to 8 classes. The proposed model gave high detection accuracy, where the best results reached 95.51%, which has been obtained when the ResNet well-known deep learning model has been used as feature extraction phase in the proposed model. The proposed method has shown that it is largely effective and successful in the diagnosis of cataract disease, and it can be generalized to be used for diagnosing all eye diseases.

Keywords: Cataract, ophthalmology, fundus images, transfer learning, convolutional neural network

INTRODUCTION

According to data from the World Health Organization (WHO), at least 2.2 billion people worldwide currently have a visual impairment, and at least 1 billion of them have preventable visual impairment (WHO, 2019). Cataract is a type of disease caused by the formation of blurry areas on the lens part of the eye, the loss of transparency of the lens, the formation of yellow or brown areas, resulting in a decrease or complete loss of vision.

The occurrence of cataract disease is highly dependent on age, as high as 90%. Very rarely, some eye diseases may emerge due to wrong drug use, trauma and new-born babies. It is known that cataracts that occur due to aging are genetic at a rate of 50%. However, such a gene has not been identified yet. For this reason, it is important for adults over the age of 35 to have regular eye examinations at intervals of 2 to 3 years. After the age of 65, it is recommended to be examined by a specialist physician every 1 to 2 years. The diagnosis and treatment of cataract disease at an early stage plays an important role in preventing the visual disturbances of these patients or stopping the progression of the disease. It takes a lot of time for cataract patients to see a doctor every few years and the process requires specialist experience. It has become inevitable to benefit from deep learning-based automatic scanning systems in order to make these transactions more rapid and to reduce financial and moral losses.

With the developments in technology, new hardware has removed the barriers to deep learning and machine learning. Especially in 2012, many convolutional neural network architectures have been designed under the leadership of AlexNet (Shin et al., 2019), which made its name with the ImageNet competition and succeeded in classifying the images with the ability to be trained with millions of images.

Related Works

In the medical field, the processing of data and the detection of hierarchical connections with the use of graphical neural networks have begun to attract the attention of ophthalmology. For example, Shin, et al. (Shin et al., 2019) provided segmentation of vascular structures in the retina layer by using graphical neural networks and positive results were obtained. Gulshan, et al. (Gulshan et al., 2016) made the first study using deep learning algorithms on fundus photographs in 2016. They carried out their work on detecting moderate, very severe and predictable conditions on 9963 and 1748 fundus images. Tufail et al. 2017 introduced an experimental study to invistigate if RIAS can be safely introduced into DR screening pathways to replace human graders. It is stated that the early diagnosis of Diabetic Retinopathy can get ahead of the human practice**.** Poplin et al. (2018) trained a deep learning model using millions of images from a large number of patients in order to predict the risk of cardiovascular, age and gender based on retinal fundus images. The model showed accurate and highly reliable age estimates, especially in normal participants under 60 years of age. Retinal fundus images from participants with the other condition (hypertension, diabetes, or smoking) showed relatively low coefficients of determination (R2) between predicted age and chronological age. This led to the conclusion that the aging process and pathological vascular changes show different characteristics. Fundus-estimated gender demonstrated accuracy of 0.96 AUC score in all groups. The CNN-based age and gender prediction model has shown the most advanced performance until now. As a result of the research, it was revealed that aging and systemic vascular diseases have different effects on the retina. Abramoff, et al. (Abràmoff et al., 2016) proposed using deep learning models to improve the accuracy of Diabetic Retinopathy (DR) detection. It has been stated that deep learning based moethod can give more accurate results in automated detection of DR. Porumb et al. (2020) managed to determine whether the patient had hypoglycemia by classifying the ECG image signals using convolutional neural networks. Li et al. (2019) used more than 200,000 images to classify age-related macular degeneration (AMD) and diabetic macular edema (DME) using the VGG-16 well-knwon pre-trained CNN model and achieved a successful result with a sensitivity rate of 98.6%. This result clearly demonstrates that the system gives high sensitivity and reliable results. Poly et al. (2019) systematic review and meta-analysis study has been conducted to investigate the efficiency of artificial intelligence in diabetic retinopathy domain. Ting et al. (2017) proposed a deep learning model for diagnosing diabetic retinopathy and other eye related diseases. The proposed deep learning model has been tested using multiple datasets contain a big number of images. As a result, they achieved a sensitivity of 90.5% and a specificity of 91.6% in the detection of DR. Burlina et al. (2016) studied the ability to use CNN pretrained models to detect age-related macular degeneration (AMD) based on eye fundus photographs. It has been stated that the tested models gave good accuracy between 92% and 95%. Grassmann et al. (2018) proposed a deep learning model that successfully detects Age-related macular degeneration (AMD). Peng et al. (2019) proposed DeepSeeNet, which a deep learning model that aims at classifying patients automatically by ranking them between 0 and 5 based on Severity. The results of the proposed model have been compared with the manual evaluations of health professionals and encountered better results in detecting pigment anomalies, but lower results in detecting AMD. Yang et al. (2016) and Yang et al. (2013) proposed a backpropagation neural network model to diagnose cataracts using eye fundus photographs and reached an accuracy rate over 90%. They also made comparisons between the obtained results and the results of both modern and traditional methods.

MATERIAL AND METHOD

Diagnosis and Classification of Cataract Disease

In this section, the structure of the eye and retinal layer, the importance of diagnosing Cataract disease at an early stage, and the architecture and algorithms used in the proposed model for the diagnosis of Cataract disease have been discussed.

Retinal Structure and Cataract Disease in the Eye

The human eye is a spherical organ with a diameter of approximately 2.5 cm and a weight of 10-15 grams, which perceives distant or near objects, interprets their shape and color, and provides our relationship with the environment. The anatomy of the human eye basically has three layers as illustrated in Figure 1. The hard layer surrounding the outer part of the eye is the region where the light rays from the outside world are refracted for the first time in the eye. This layer's task is to protect our eyes from external impacts. The vascular layer under this layer consists of vessels that feed the eye. The region where the visual process is carried out is the retina (retina layer). The nerve cells in this region are composed of sensors that are sensitive to light and enable the perception of colors. Thanks to these sensors, the light coming into the eye is converted into electrical signals and transferred to the optic nerves to reach the central nervous system.

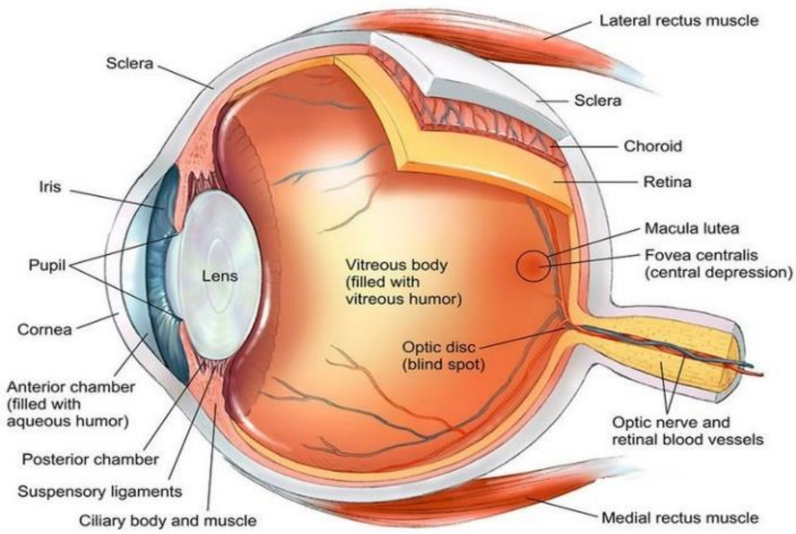

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Figure 1. Anatomy of the human eye

After these signals reach the central nervous system, the image is perceived.

Interruption of vision at any point is called an eye defect. Cataract disease is one of these defects. Cataract is the blur of the lens of the eye. When this blurring occurs, it prevents light rays from passing through the lens and focusing on the retina. The retina is a light-sensitive tissue lining located at the back of the eye. This blur occurs when part of the protein that makes up the lens of the eye begins to change its structure. In their early stages, cataracts may not cause a problem. The blur may affect only a small part of the lens. However, cataracts can grow over time and affect more of the lens. Cataracts can be seen in both eyes, or they can be seen in only one of the eyes. Under ideal conditions, the lens of the eye, which has a transparent structure, passes the light to the back of the eye, which is the visual region, and vision occurs. However, the blurring that occurs in the lens partially or completely blocks the penetration of light coming into the eye, and this causes vision loss. If no precautions are taken, this blur will increase and make the person completely invisible.

The reason for cataract disease has been determined as the chemical change in the structure of the protein called crystalline and proteolytic decompositions that form the lens of the eye. This change creates protein clusters with high molecular weight in the structure and causes foggy and blurred vision problems in the eye. These clusters grow day by day, making it difficult for the light coming into the lens to pass through the lens and preventing the image from falling on the retina. Cataract can be detected by a specialist physician by performing an eye examination with a device called an ophthalmoscope. The ophthalmoscope is a device that allows a detailed examination of the inner structure of the eye with an intense beam of light. This disease cannot be treated with diet or medication. Its treatment is provided only by surgical intervention. However, early diagnosis of cataract disease and taking some precautions can reduce the risk of getting the disease.

Deep Learning and Convolutional Neural Networks

Deep learning is a type of machine learning that mimics the way the human brain works. The process consists of processing data in layers and algorithms that produce increasingly useful results. The term 'deep' in deep learning expresses the depth of the structure formed by the combination of many layers. The number of layers created for the model determines the depth of the model. The shallow and deep neural network structure is modelled as shown in Figure 2. While classical neural networks consist of several layers, deep neural networks may consist of tens or even hundreds of layers. While the data passes through the neural network's layers, these layers provide the calculation of the features used for classifying the data. An optimization algorithm is used to minimize the loss function value such that increasing the classification accuracy of the neural network model. On the other hand, CNN (Convolutional Neural Network) is a type of artificial neural network used especially for solving image recognition and processing problems. Neural network structure basically consists of input layer, hidden layers and output layer.

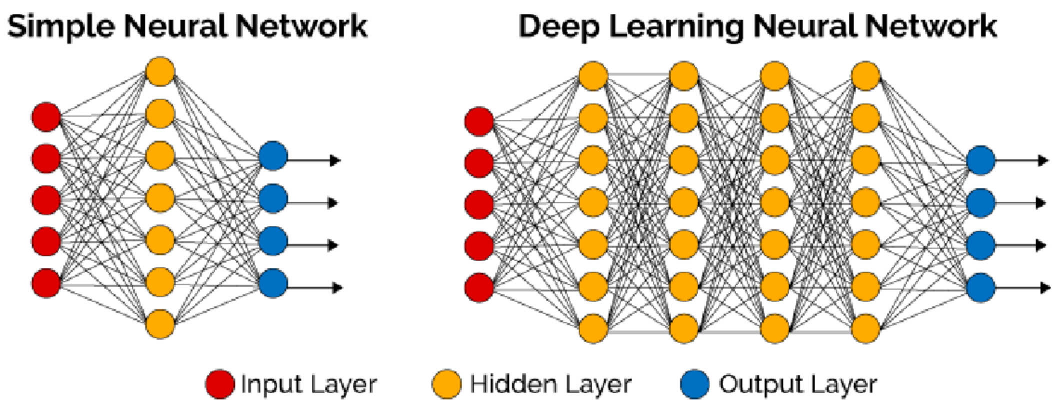

Figure 2. Structure of shallow and deep neural networks

In the first layer, the data is transferred to the system. The number of nodes formed in this layer is equal to the number of features that represent the data samples. The hidden layer applies the transformation process obtained by multiplying the data from the input layer with certain coefficients and transferring them to the output layer. The output layer, on the other hand, makes an estimation based on the feature maps obtained from the previous layers. The CNN structure is generally expressed by the equation (1).

$$\mathbf{F(X,W) = Y} \qquad \mathbf{(1)}$$

X represents the input data, Y represents the output vector, and W represents the weight vector of the connection between the neurons of the two adjacent layers. The classification process is achieved using this weight vector. In this study, a deep learning model composed of two-phase has been proposed. In the first phase, some well-known CNN architectures such as VGG-16, ResNet, MobileNet, and Inception V3 have been used for feature extraction. In the second phase, some artificial neural layers have been used to classify images. CNN consists of some layers to perform the feature extraction and data classification process. These layers are convolution, pooling, activation, and fully connected layers. The convolution process provides an attribute map with the values obtained from the results obtained by passing an input photo through a filter. A two-dimensional convolution calculation process is shown in Figure 3.

The feature maps obtained from the convolutional layer are inserted into an activation function. This function is called the ReLu function (rectified linear unit). The size of the feature maps coming from this convolutional layer is reduced using the pooling layer so that the number of operations and computational costs can be reduced.

Transfer Learning

In transfer learning, which is one of the most frequently used techniques in the deep learning domain, the model is not built from scratch. The method here is to classify images on a specific dataset and transfer the training information to another dataset. It is aimed to generalize the models trained for a specific problem to be used for similar problems. In this study, pre-trained VGG-16, ResNet, Mobile Net, and InceptionV3 models have been used for detecting cataract disease and the results have been compared with each other.

VGG-16: this model has been introduced by Simonyan et al. (2014). VGG16 is a type of CNN (Convolutional Neural Network) structure that is considered one of the best computer vision models to date. VGG Net structure has 16 or 19 layers. VGG Net is an object detection and classification algorithm that can classify a large number of images belonging to 1000 different categories with 92.7% accuracy. It is one of the popular algorithms for image classification and is easy to use as a pre-trained model.

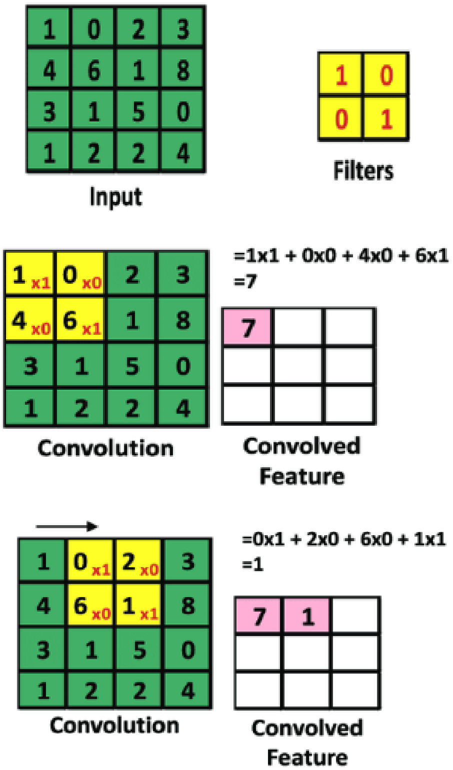

Figure 3. Two-dimensional convolution calculation process

Inception V3 Szegedy et al. (2015)**:** Sometimes referred to as Google Net, it is version 3 of a set of Deep Learning Convolution Architectures created by Google. Inception V3 was trained using a dataset containing 1000 classes from the original ImageNet dataset. The basic idea of Inception Net is to use multiple sizes of filters that work at the same level. This multidimensional filter is called the filter bank. This way the network will be a little wider rather than more depth.

ResNet He et al. (2016)**:** It is one of the very famous CNN architectures proposed by Microsoft researchers in 2015. This model consists of deep neural networks inspired by VGG CNN architecture, called plain network. However, the plain network used in the original ResNet architecture contains 34 convolutional layers. To solve the Vanishing/Exploding gradient problem, this architecture introduced the concept called Residual Network. Particularly, a technique called skip connection is used in this network. The skip connection bypasses the training through several layers and connects directly to the output. The advantage of adding this kind of jump connection is that if any layer is detrimental to the architecture's performance, it will be skipped by the network. Thus, a very deep neural network can be trained using this logic without the Vanishing/Exploding problems.

MobileNet Howard et al. (2017)**:** MobileNet is a kind of convolutional neural network introduced by Google researchers. This model is low-latency and powerful parameterized to meet the resource constraints of various use cases. MobileNet can be used for classification, detection, placement, and segmentation, similar to the use of other popular large-scale models. In the MobileNet model, the flat convolution layer has been replaced with a convolution block called Depthwise Separable Convolutions. The Depthwise Separable Convolution block consists of two subconvolution operations. The first sublayer is known as Depthwise convolution, and the second is known as Pointwise convolution. The separable convolution operation significantly reduces the number of parameters in networks compared to the network with regular convolutions of the same depth.

Data Set

The dataset used in this study was provided by Shanggong Medical Technology Co. Ltd. It represents the information of patients obtained from different hospitals and medical centers in China. The data set consists of 6392 color fundus images of the right and left eyes obtained from approximately 5000 individuals. Thye data were classified into eight labels: Normal (N), Diabetes (D), Glaucoma (G), Cataract (C), AMD (A), Hypertension (H), Myopia (M), and Other diseases/abnormalities (O). In the work, only the Normal (N) and Cataract (C) classes have been selected and the classification process has been applied. Some example images for cataract and normal fundus are given in figure 4.

When the data set is examined, it is seen that there is an imbalance in the number of images belonging to the classes. In order to improve the success of the model, the names of the cataract and healthy eye pictures were separated as right and left and put into 4 different lists in total. Among these four lists, 304 left cataract, 290 right cataract, 2898 left normal and 2777 right normal photo were identified. The number of images must be close to each other for the model to work correctly. Therefore, the number of photos of healthy eyes was equated with the number of photos with cataracts, and the samples were randomly selected to have a random distribution. In the newly created list, 304 left cataract, 290 right cataract, 250 left normal and 250 right normal photos were obtained and these photos were combined in two lists as cataract and healthy. There are 500 normal and 594 cataract fundus photographs in this list.

Used Methodology

In this section, the material and method used for the early diagnosis and classification of cataract disease are discussed. A dataset from normal eye fundus images and eye fundus images with cataract disease has been used to diagnose cataract disease. A framework has been proposed for detecting cataract disease using the aforementioned dataset. First, when we looked at the number of data samples under each class of the dataset, a huge imbalance has been noticed. Therefore, to reduce this imbalance, the data reduction technique was applied to the normal fundus image class, and a certain level of balancing has been achieved between the two classes. Then, the images in the dataset were pre-processed. In this phase, the size of the images was first reduced to reduce model computational complexity. After that, the values of the pixels in each image are normalized to be between 0 and 1.

The pre-processed fundus images have been used for training and testing the proposed deep learning model. In the proposed model, pre-trained VGG-16, ResNet, MobileNet, and InceptionV3 models have been adopted as a feature extraction phase. In this study, 80% of the dataset has been used for training the model, 10% of the remaining 20% of the data set has been used for the validity of the model, and the remaining 10% has been used to test the performance of the created model. The performance of the model has been evaluated using classification performance metrics such as F1-score, accuracy (acc), sensitivity (rec), and precision (prec).

The flow chart of the process applied in order to construct the proposed deep learning model is illustrated in figure 5.

The Proposed Model:

In this study, a deep learning-based model has been proposed to detect cataract eye disease. The proposed model consists of two sub-phases i.e. the feature extraction phase, and the classification phase. In the first phase, the Transfer learning technique has been adopted and four different deep learning architectures namely VGG-16, ResNet, InceptionV3, and MobileNet have been used for feature extraction. The feature map obtained using the first phase has been used as an input for the second phase. The second phase consists of two classical artificial neural layers (Dense layer) with 128 neurons in the first and one neuron in the second. In the first Dense layer, ReLu has been used as an activation function. Since the problem in this work is binary classification, Sigmoid has been used as an activation function in the output layer. In addition, Adam is used as an optimization algorithm and binary_crossentropy is used as a loss function. The batch size has been configured at 32 for all classification models. Figure 8 shows the proposed deep learning model.

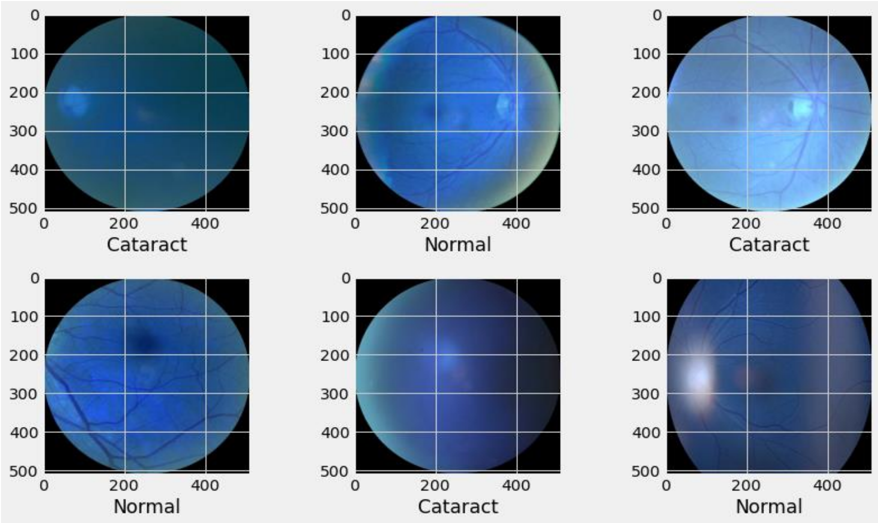

Figure 4. Example of fundus images

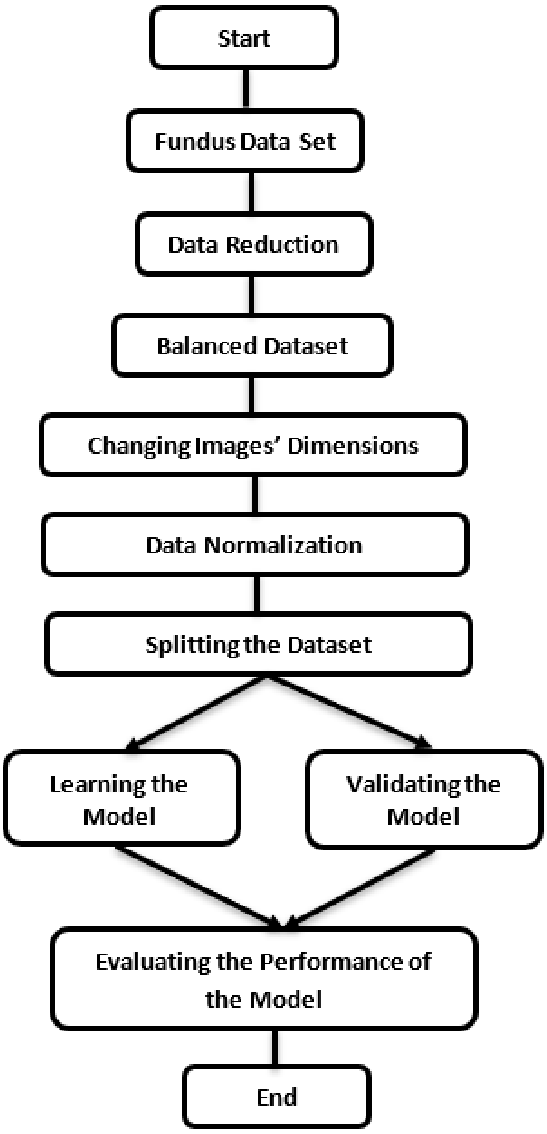

Figure 5. Conducted detection process flow chart

Performance Metrics

Confusion matrix: a classification performance evaluation method by visualizing the performance of the model using the following evaluation metrics:

True Positives (TP): The number of data samples that have a true label of 1 and can be predicted as 1 by the model.

True Negatives (TN): The number of data samples that have a true label of 0 and can be predicted as 0 by the model.

False Positives (FP): The number of data samples that have a true label of 0 and predicted as 1 by the model.

False Negatives (FN): The number of data samples that have a true label of 1 and predicted as 0 by the model.

Moreover, the performance of the model will be measured by classification performance metrics such as F1-score, accuracy, sensitivity, and precision.

Accuracy: Accuracy is a metric that is widely used to measure the success of machine learning and deep learning models but does not appear to be sufficient alone. It is a measure of how often the classifier predicts correctly and is calculated using the equation (1).

Precision: as illustrated in equation (2), it shows the proportion of the samples that estimated as positive and they actually positive.

Recall: as illustrated in equation (3), it shows the proportion of the samples that were correctly estimated as positive out of the total positive estimated data samples.

F1 Score: It shows the harmonic mean of Precision and Recall values using equation (4).

$$ACCURACY = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$PRECİSİON(Pre) = \frac{TP}{TP+FP} \quad (2)$$

$$RECALL(Rec) = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - SCORE = \frac{2\ x\ Rec\ x\ Prec}{Rec + Prec} \quad (4)$$

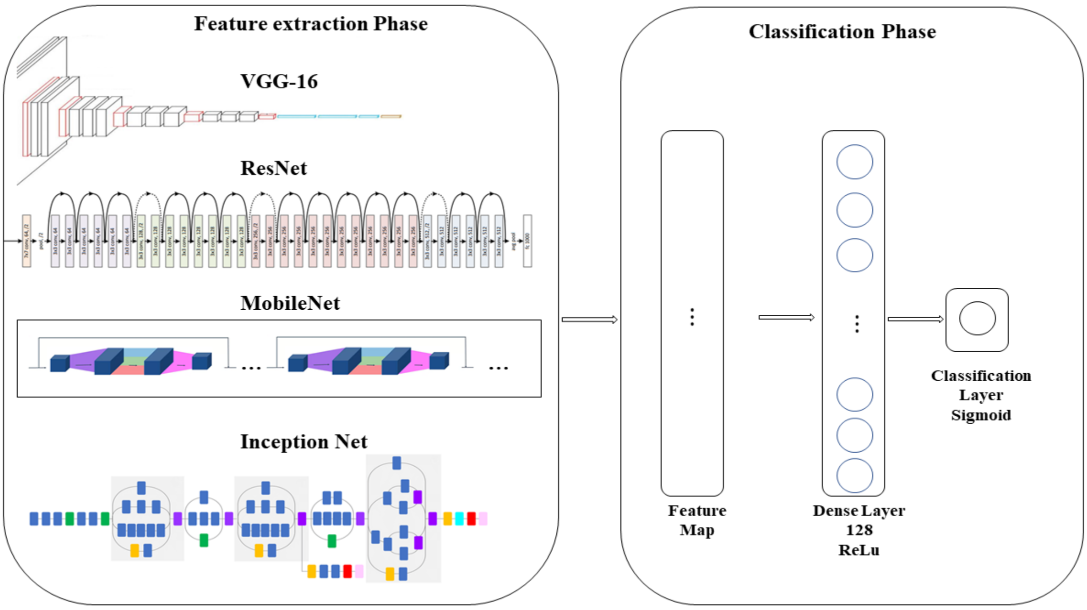

Figure 6. Proposed Deep Learning Model

Experimental Results and Discussion

In the proposed model, four different pre-trained CNN models, namely VGG-16, ResNet, InceptionV3, and MobileNet, have been used as the feature extraction phase. The size of the fundus images used was adjusted to be 512 x 512 x 3 for faster model training. 80% of the dataset has been used for training the models, creating feature maps, and selecting features that will be used in the classification of eye fundus images. 10% of the remaining 20% of the data set has been used for the validition of the model and the remaining 10% for testing the performance of the trained model. It can be seen that the loss in the training and validation stages of the model for each epoch is close to each other. This shows that the model does not fall into an overfitting situation. Among the models, the highest test accuracy rate of 94% has been obtained when InceptionV3 has been used as the feature extraction phase. Four different pre-trained models have been

used as a feature extraction phase in the proposed model namely VGG-16, MobileNet, ResNet, and InceptionV3.
Furthermore, the accuracy, precision, recall, and F1-score performances of the models used in the study are presented in Table 1. The obtained results showed that when the VGG-16 model has been used as a feature extraction phase, the accuracy, precision, recall, and F1- score performances in the proposed model were 92.20%, 92%, 92%, and 92%, respectively. When the MobileNet model has been used as the feature extraction phase, the accuracy, precision, recall, and F1-score performances in the proposed model were 90.97%, 91%, 91%, and 91%, respectively. When the ResNet model has been used as the feature extraction phase, the accuracy, precision, recall, and F1-score performances in the proposed model were measured as 95.51%, 96%, 95%, and 95%, respectively. Finally, when the InceptionV3 model was used as the feature extraction phase in the proposed model, the accuracy, precision, recall and F1-score performances of the proposed model were 92.86%, 93%, 92%, and 93%, respectively. Moreover, the confusion matrixes of each of the VGG-16, MobileNet, ResNet, and InceptionV3 models are illustrated in Figures 7, 8, 9, and 10 respectively. By investigating the confusion matrix of the VGG-16 pre-trained model we can see that this model was able to correctly detect 56 cataract diseases out of 63 ones, and it was able to correctly detect 83 normal eyes out of 88 ones. Also, the MobileNet model was able to correctly detect 68 cataract diseases out of 72 ones, and it was able to correctly detect 73 normal eyes out of 83 ones. Also, the InceptionV3 model was able to correctly detect 86 cataract diseases out of 89 ones, and it was able to correctly detect 57 normal eyes out of 65 ones. The ResNet model, on the other hand, was able to correctly detect 55 cataract diseases out of 60 ones, and it was able to correctly detect 94 normal eyes out of 96 ones. Finally, the results of these models (VGG-16, ResNet, MobileNet and InceptionV3) have been compared with each other.
In this study, it is clearly seen that it is possible to detect various eye diseases using convolutional neural networks. The ResNet-based model gave the most accurate results in cataract detection with an accuracy rate of 95.51%. We think that using a larger dataset will increase the accuracy of the predictions and eventually automate the process of detecting ocular diseases.

Tablo 1. Performance metrics table

Performans Metrikleri	**VGG-NET Tabanlı**	**ResNet Tabanlı**	**MobileNet Tabanlı**	**InceptionV3 Tabanlı**
Doğruluk	%92.20	**%95.51**	%90.97	%92.86
Kesinlik	%92	**%96**	%91	%93
Duyarlılık	%92	**%95**	%91	%92
F1-Skoru	**%92**	**%95**	**%91**	**%93**

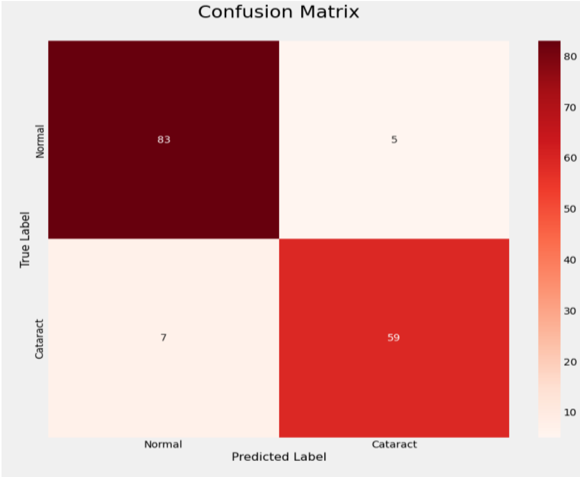

Figure 7. Confusion matrix obtained for Cataract classification with the VGG-16 based model

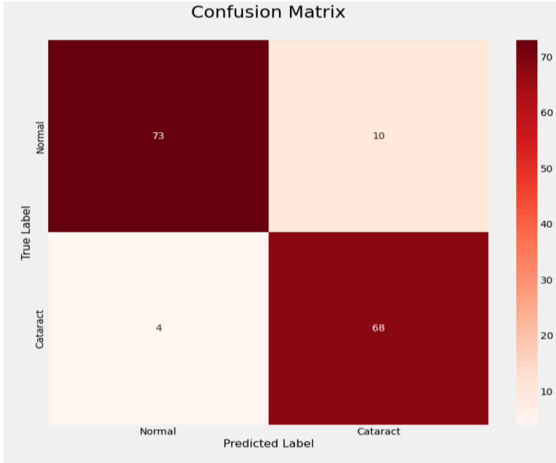

Figure 8. Confusion matrix obtained for Cataract classification with the MobileNet based model

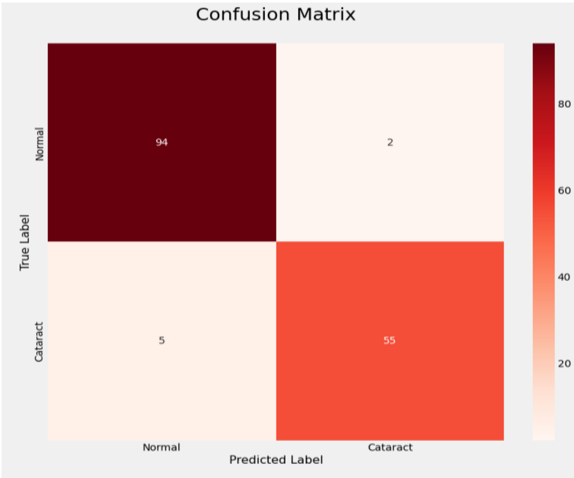

Figure 9. Confusion matrix obtained for Cataract classification with the ResNet based model

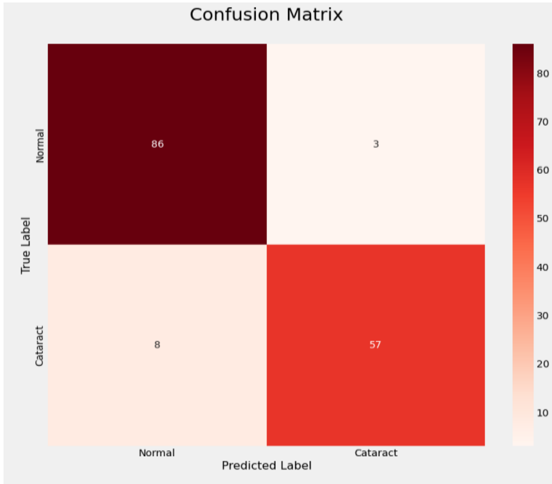

Figure 10. Confusion matrix obtained for Cataract classification with InceptionV3 based model

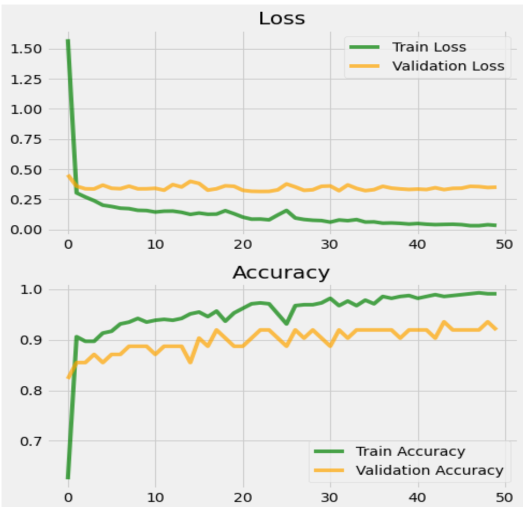

Figure 11. Success and loss graph of VGG-16 based model

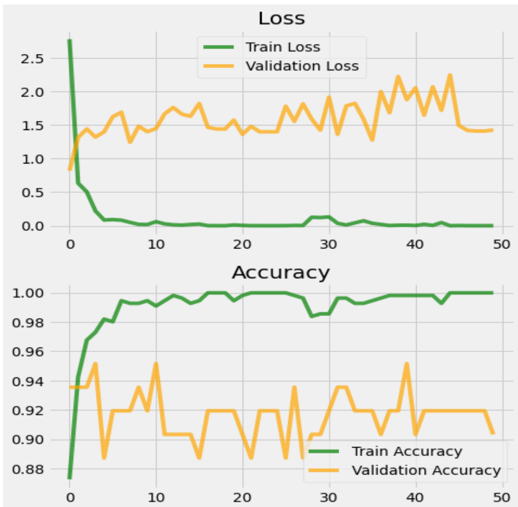

Figure 12. Success and loss graph of the MobileNet model

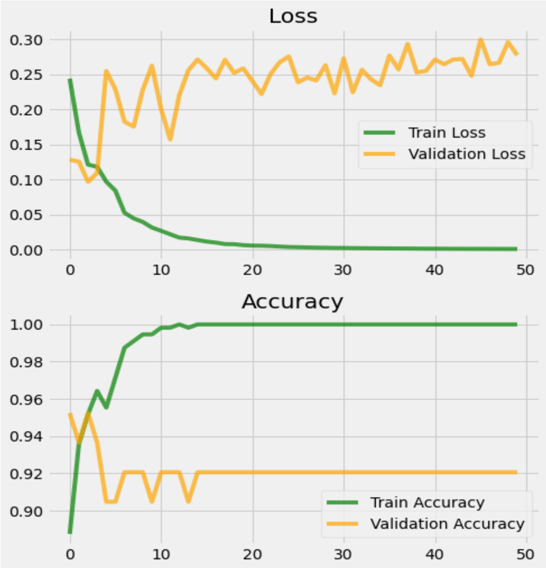

Figure 13. Success and loss graph of ResNet based model

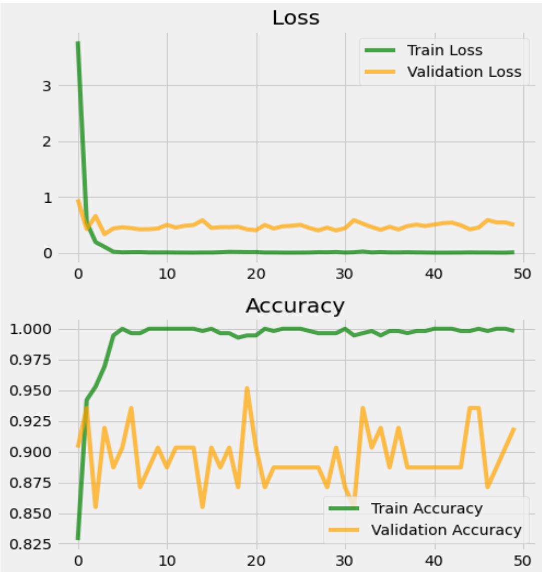

Figure 14. Success and loss graph of InceptionV3 based model

Future Studies

In this work, multiple pre-trained CNN models have been adopted as a feature extraction phase in order to detect eye diseases, especially cataract disease. The obtained results were promising and the used models can be fine-tuned to achieve more accurate results. So, in future works, we are planning to test the proposed model in terms of detecting other types of eye diseases. Also, we will test the proposed model using other datasets. Finally, we will apply the hyperparameters fine-tuning process to select the best values for the model's parameters so that the results of the proposed model will be improved.

DECLARATION OF ETHICS STANDARDS

The authors of this article declare that the materials and methods used in their studies do not require ethical committee approval and/or special legal permission.

CONFLICT OF INTEREST:

There is no conflict of interest in this study.

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