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Classification of Cataract Disease with a DenseNet201 Based Deep Learning Model

Halit ÇETİNER[1*], İbrahim ÇETİNER[2]

ABSTRACT: Cataracts are among the most serious eye diseases and can cause blindness if left untreated. Since it is a treatable disease, professional knowledge of specialist ophthalmologists is needed. Ophthalmologists need to analyze images of the eye to detect clinical cataracts in an early stage. Detection of cataracts at an early stage prevents the disease from progressing and causing serious costs such as blindness. At this point, it is a tiring and costly process for specialist ophthalmologists to constantly check their patients. It is not possible for ophthalmologists to constantly monitor their patients. Due to the stated problems, in this article, a study was carried out to develop a deep learning model that helps specialist ophthalmologists through cataract images. In the developed model, an automatic classification of images with normal and cataract lesions was performed by proposing a model based on pre-trained neural networks. During the development of the proposed model, the performance of the classification process was increased by making fine adjustments to the pre-trained neural network called DenseNet201. To compare the performance level of the proposed model, the results obtained from the model consisting of the basic DenseNet201 structure without using any additional layers were used. When both models are evaluated, it has been shown that the proposed deep learning model achieves 10% more success than the basic DenseNet201 deep learning model. The proposed model can be used as an auxiliary tool for doctors in different health problems such as cataracts, which are commonly encountered today.

Keywords: Cataract, DenseNet201, Transfer Learning, Classification

[1] Halit ÇETİNER (**Orcid ID:** 0000-0001-7794-2555), Isparta University of Applied Sciences, Vocational School of Technical Sciences, Isparta, Türkiye

[2] İbrahim ÇETİNER (**Orcid ID:** 0000-0002-1635-6461), Burdur Mehmet Akif Ersoy University, Vocational School of Technical Sciences, Burdur, Türkiye

***Corresponding Author:** Halit ÇETİNER, e-mail: halitcetiner@isparta.edu.tr

INTRODUCTION

Cataracts are one of the most serious eye diseases that can lead to blindness if not diagnosed and treated early (Kumar and Shimna, 2017). It is the most common cause of blindness, affecting 314 million people worldwide (Pizzarello et al., 2004). This disease occurs when a clouding or opacity occurs in the natural inner lens of the eye. In some cases, this opacity is a small dot, while in others it covers the entire lens. When this problem occurs, light entering the eye is scattered (Zhang et al., 2017). As a result of light scattering, the images begin to appear blurry and hazy. In this case, it can cause dyslexia and make it difficult to drive (Fraser et al., 2013). Studies on cataract risk factors suggest that it is caused by risk factors such as smoking and UV-B contact (Mobley and Brueggemeier, 2002; Foster et al., 2003; Allen and Vasavada, 2006; Wong et al., 2006). In addition, half of the blind people living in the world and about one-third of the visually impaired cases are caused by cataract disease (Guilbert, 1999). At this point, the advice of experts is to diagnose and treat cataract disease early. For the reasons stated, ophthalmologists should follow up the cataract patients closely and make an accurate diagnosis.

Ophthalmologists cannot continuously monitor patients. It is necessary to save ophthalmologists who are under a potentially high cost and strenuous workload. For many patients, the lack of immediate access to ophthalmologists makes early intervention difficult. Failure to make difficult early interventions causes patients to deteriorate. Surgical methods are recommended as the best treatment for people with cataracts. In surgical intervention, the natural cataract lens should be replaced with an artificial lens. Although it is generally seen in older people, cataract disease can also be seen in young and healthy people. This disease can be seen in approximately 4.2% of the world population (Li et al., 2019). In general, cataract diagnosis and detection are made using clinical information from ophthalmologists using fundus images.

Deep learning, which is one of the subfields of classical machine learning, can conduct research such as natural language processing, image processing, and voice recognition. With the decrease in computer hardware costs and the increase in data sets in different application areas, the interest in deep learning applications has increased (Pacal et al., 2020). Unlike machine learning algorithms, in deep learning methods, distinctive features can be obtained directly from raw images without the need for any preprocessing. With the power brought by this feature, it has been used intensively in different fields such as health (Pacal et al., 2020), and agriculture (Çetiner and Kara, 2022). The convolution layer provides feature extraction from raw data, which is the most important feature that distinguishes deep learning algorithms from machine algorithms. Deep learning algorithms that include convolution algorithms are generally called Convolutional Neural Network (CNN) algorithms. CNNs are effectively used with cloud-based systems created by large companies such as Amazon, NVIDIA, and Google in the processing of biomedical images (LeCun et al., 2015).

In ophthalmology, fundus images obtained in different ways have important potential for the diagnosis, prediction, classification, screening, or detection of eye diseases with artificial intelligence-supported software (Flaxman et al., 2017; Grewal et al., 2018). In general, cataract diagnosis and detection can be made using the clinical information of ophthalmologists on fundus images. Therefore, cataract detection must be simplified to avoid blindness, one of the potential costs of cataract disease. It is necessary to increase the workload of ophthalmologists on diseases and surgery of the visual pathways and to develop automatic methods for the prevention of visual disorders and the detection of cataracts. AI-assisted diagnosis and diagnosis based on fundus images have recently attracted the attention of researchers. Depending on the developments in remote health services, there is a significant spread of automatic diagnosis architectures that provide access with high success rates (Bakator and Radosav, 2018; Grewal et al., 2018; Ertuğrul et al., 2021). For the reasons mentioned, it is seen that different deep learning methods are being studied to automatically extract fundus image features (Xu et al., 2020; Imran et al., 2021). The incorporation of deep learning methods into decision-making in the field of ophthalmology is happening faster than many expect (Lee et al., 2017).

In general, conventional ultrasound diagnostic equipment is available in most hospitals, but it has deviations that can be misdiagnosed (Wang et al., 2021). To solve the scarcity of ophthalmologists and the inadequacy of traditional equipment, systems that can make computer-assisted diagnoses are being studied (Doi, 2007; Gao et al., 2015; Liu et al., 2017). Methods based on classical machine learning techniques have been seen to be used in traditional computer-assisted cataract diagnosis systems to date (Fraser et al., 2013; Fan et al., 2015; Manchalwar and Warhade, 2017; Qiao et al., 2017; Xiong et al., 2017). In these methods, classification is made by manually extracting the features of the lesion regions. The extracted features may have low classification accuracy because they are subjective and meaningless. Inadequate classification accuracy is not sufficient to provide confidence in systems that assist ophthalmologists.

Automatic cataract classification studies based on retinal fundus images can be divided into two categories: heuristic methods and deep learning methods. Heuristics use professionally skilled invention methods to extract predetermined features (Xu et al., 2021). To predict a cataract, it is tried determined by calculating the ratio between the dish-disc ratio and the center of the optic disc. Although many of the heuristics have shown effectiveness in automatic cataract diagnosis, predefined feature sets require significant engineering skills and domain expertise. This process is time-consuming and tedious. Furthermore, physicians and specialists can be influenced by personal factors in manual diagnostic processes and are likely to miss some important hidden patterns.

To improve the disadvantageous feature extraction steps of classical machine learning methods, which are heuristic, feature extraction layers based on deep neural networks have been developed. Deep learning models containing these layers can automatically distinguish between the cataract image and the normal image without performing any preprocessing. By using a large image data set such as ImageNet, it is possible to classify the lesion images quickly and with high success by fine-tuning the pre-trained neural networks. It is important to fine-tune the layer structures of the proposed deep learning models to reduce the similarity rates of medical images between classes by increasing in-class consistency. Since deep learning networks can learn features that can be transferred between more than one dataset, certain features can be transferred with the transfer learning method (Pacal and Karaboga 2021). Unlike the traditional machine learning procedure, the motivation for transfer learning is to improve model performance under limited target dataset samples by leveraging knowledge from the source dataset. In addition, when the weights in the first layer of the deep learning model trained with the transfer learning dataset are kept constant, only the last layer can be trained with the datasets. At the end of this training, classification and estimation can be performed easily and quickly.

The main contributions of this article to the literature are presented below.

- The proposed DenseNet201 model achieved 99% accuracy and success rates in normal and cataract images.
- The proposed DenseNet201 model performed an average of 6% better than the basic DenseNet201 model.
- The proposed DenseNet201 model was more successful in classifying cataract and normal images from studies in the literature, in the range of 0.75, 9.5, and 1.75 and 10.5 points, respectively.

The next part of the article consists of 3 sections. In Section 2, information is provided about the data set and the performance measurement techniques used in the article. In Section 3, the results obtained with the proposed deep learning models for the classification of cataract disease are presented. In the last section, the net results obtained as a result of the study analysis are shared.

MATERIALS AND METHODS

Materials

The data set used in the article is taken from the data set community, which includes data sets in different fields called Kaggle. In this study, the basic architectural model and the performance of the proposed architectural model to be used in experimental studies were tested on a data set that can be accessed by all researchers, including normal and cataract images (Matryx, 2019). This publicly available data set contains images of 5 000 patients from different aspects. These images may contain more than one different disease at the same time. These images are known as normal, diabetes, glaucoma, cataract, AMD, hypertension, myopia, and other diseases/abnormalities. A separate data set was created by selecting only normal and cataract images from the images with these diseases. The number of fundus images in the generated dataset is 1 088. In the data set files, the total of images with cataracts on the left eye and images with cataracts on the right is 588. Images that are normal in terms of fundus images taken from the left and right are 500. In the dataset, two different groups were created, which were divided into training and testing according to the k-fold 5 rule. In both groups, there are different images of the two classes: cataract and normally healthy. These images are color fundus images taken from the left and right eyes of 5 000 patients with their age information (Matryx, 2019).

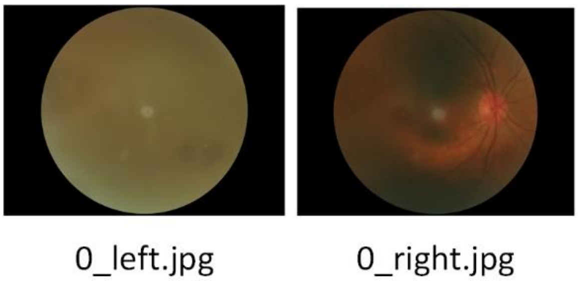

Figure 1. Cataract and normal fundus image, respectively

Fundus images are used to evaluate the training and test results of the proposed model together with different models. An example of the fundus images used for this purpose is shown in Figure 1. The image on the right of Figure 1 represents the normal fundus image, while the image on the left represents the image with cataracts. The images in the data set can be given as direct input to deep learning models, or they can be given by passing some preprocessing. Some pre-processing has been applied to the image due to its positive contribution to the performance of the model. The applied preprocesses are resizing and data duplication steps, respectively. In the resize step, all training and test images were resized to 224x224. CNN algorithms generally expect 224x224 pixel images at the input layer of the network (Xi et al., 2018). For the stated reason, the image size of 224x224 pixels is preferred. In the data augmentation step, data augmentation was performed using steps such as enlarging, rotating, and zooming on the image. With these processes, the aim is to classify the proposed model from all angles and distances.

Performance metrics

Specific indicators recorded on classification tasks are as follows: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). Here, TP refers to correctly predicted cataract images and FP refers to incorrectly predicted cataract images. TN represents correctly predicted normal fundus images, while FN represents incorrectly predicted normal fundus images. Based on these indicators, we calculate the accuracy, precision, recall, and F1 score to make performance comparisons of the models. The formulas used as measurement metrics in the literature are given below (Goutte and Gaussier, 2005):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 = 2x \frac{PrecisionxRecall}{Precision + Recall} \tag{4}$$

In this study, the metrics of Equations 1-4 are used to accurately evaluate the performance of the proposed methods. In addition to the performance measurements used, the loss and accuracy results are given graphically. In addition, the resulting confusion matrix is presented in each section title.

DenseNet201

DenseNet architectures are one of the deep learning architecture groups (Huang et al., 2017). DenseNet was developed on the ResNet architecture by optimizing the gradient flow. DenseNet can improve the information flow and gradient of the network with fewer parameters than traditional convolution networks. Each layer in the DenseNet structure connects to the original signal and loss function, making it easier to train the network. In addition, it has dense connections that affect the organization of datasets. DenseNet201 consists of a condensed network that provides highly parametrically efficient models that are easy to train due to the possibility of feature reuse by different layers increasing variation in layer inputs and improving performance (Pleiss et al., 2017).

DenseNet201 showed remarkable performance on datasets with various pretrained weights such as ImageNet and CIFAR-100. Connects directly from all previous layers to all subsequent layers to enhance connectivity in the DenseNet201 model. It is seen that disease prediction is performed with the DenseNet201 architecture model (Chouhan et al., 2020). DenseNet architectural models include three transition layers and four dense blocks. Dense blocks have convolution kernels with matrix sizes 1x1 and 3x3. Convolution kernels in dense blocks within DenseNet repeat six, twelve, twenty-four, and six times. There is a transition layer between the dense layers in this architectural model. Each convolution layer that extracts features in a dense block is feedforward connected to another feature extractor convolution layer. The transition layer in the DenseNet architecture consists of convolution, batch normalization, and pooling layers with a kernel size of 1x1. The pooling layer has a 2x2 stride.

To summarize the DenseNet architecture in terms of equations;

$$x_n = H_n(x_{n-1}) \tag{5}$$

In DenseNet architectures, the input and output layers are combined without aggregation between layers. From this point of view, Equation 6 is formed by reconstructing Equation 5.

$$x_n = H_n([x_0, \dots, x_{n-1}]) \tag{6}$$

The feature map in the n. layer is represented by x_n in Equation 6. The feature maps of the other layers are shown in the form of $x_0, \ldots, x_{n-1}$ according to the order of the layers. Batch normalization, ReLU activation layers, and convolution layers with a 3x3 filter represent the symbol H_n.

Proposed Method

In this article, a deep learning model is designed to distinguish between a normal eye image and an image with cataract disease. To assess the impact of the proposed model, another model was created, which we call the basic DenseNet201 model, without any additional layers. This basic DenseNet201 model was compared with the proposed DenseNet201-based deep learning model. Experimental studies have been effective in determining and evaluating the layer structure of the proposed model.

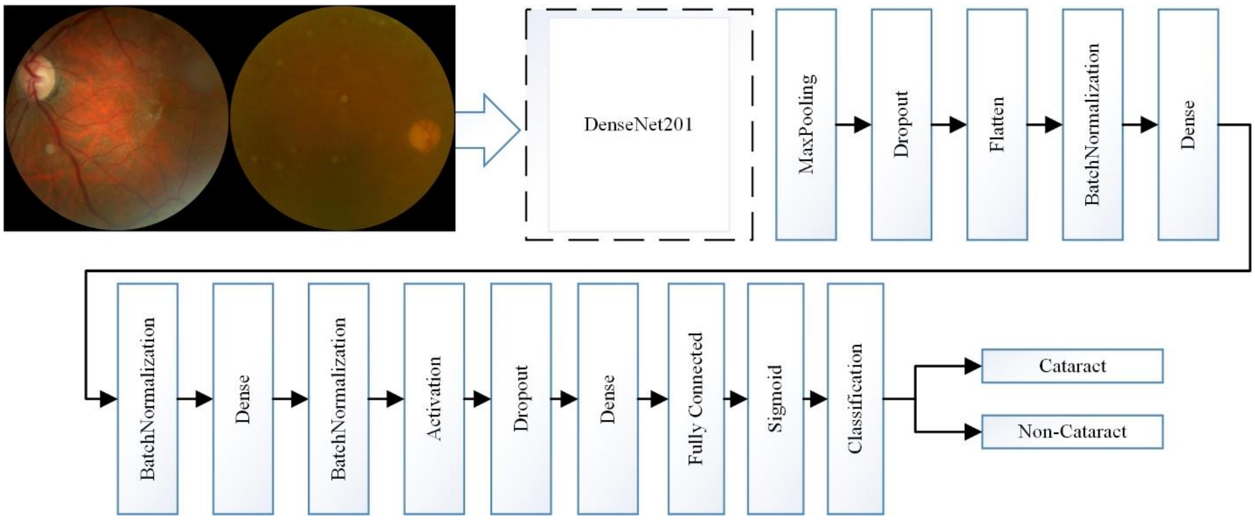

Figure 2. Proposed DenseNet201 based deep learning model

The proposed DenseNet201-based deep learning model is shown in Figure 2. The proposed model accepts 224x224x3 images as input. These dimensions represent the height, width, and color channel of the image. The RGB color channel is used as the color channel. It has not undergone any other color conversion. In the creation of the proposed structure, max pooling, dropout, flatten, batch normalization, dense, batch normalization, dense, batch normalization, activation, dropout, dense, fully connected, and classification layer with sigmoid activation function were used, respectively. 3x3 windows are used in the maximum pooling layer. The overfitting problem is avoided by performing 0.9 neuron dropout in forgetting layers. 512 neurons are used in dense connection layers. In the batch normalization layer, the axis value is set to -1 to normalize each feature. Before the dropout layer, the ReLU activation layer has been added, which can calculate much faster than the sigmoid and Tanh functions in CNN models. To prevent the network from memorizing before the classification layer, a 0.9 neuron dropout layer has been added. In binary classification, the sigmoid function recommended in the literature (Qin et al., 2017) is used in the classification layer where we estimate the output probability.

RESULTS AND DISCUSSION

The accuracy results obtained from the training and test images of the proposed model and the basic model are given in Figure 3. When Figure 3 is examined, it is seen that the proposed model yields more accurate results than the basic model by more than 10%. Below, respectively, the training accuracy and loss graphs and the test accuracy and loss graph are given separately.

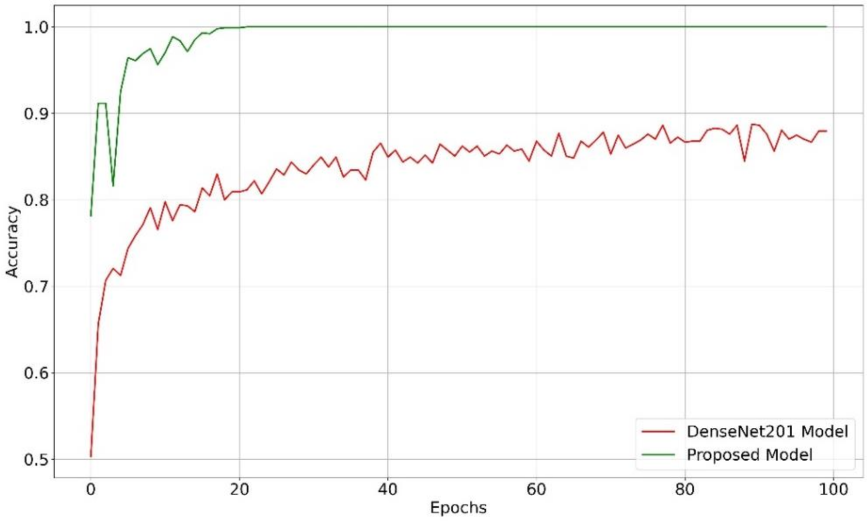

Figure 3. Training accuracy performance result graph of the proposed and basic models

In Figure 3, the training accuracy graphs of the proposed model and the basic DenseNet201 model are presented. The proposed model training accuracy value gave a more successful result of 11.27%. In Figure 4, training loss graphs of the proposed model and the basic DenseNet201 model are presented.

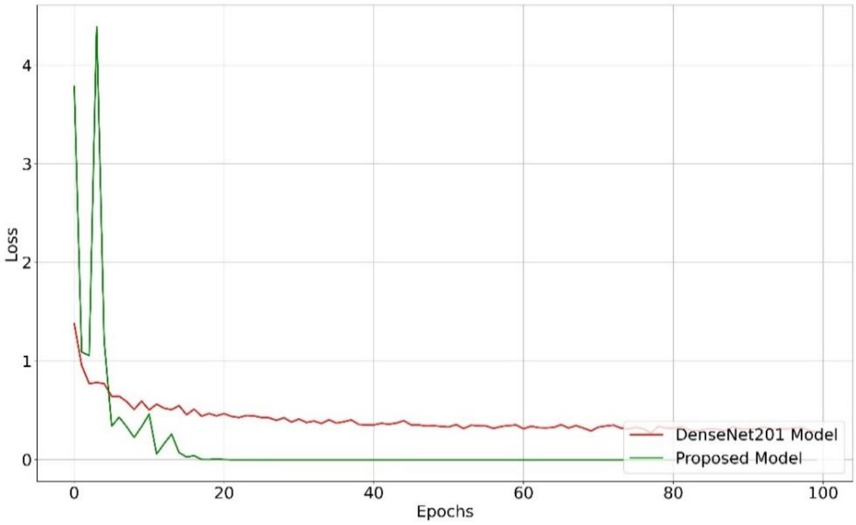

Figure 4. The training loss performance result graph of the proposed and basic models

Although the training loss value of the proposed model was high in the first iteration, it experienced a serious decrease after the 8th iteration. After the 18th iteration, the loss value remains constant. The loss graphs of the proposed model and the basic model move in the same direction and alignment after the 18th iteration. The loss value of the proposed model appears to have a lower loss than the base model. In Figure 5, the training accuracy graphs of the proposed model and the basic DenseNet201 model are presented. The proposed model training accuracy value gave a more successful result of 3.21%. Although the accuracy graphs move in the same alignment and direction after the 18th iteration, the accuracy value of the proposed model is much higher. The proposed model provided access to 0.9816 success points, while the basic model remained at 0.9495 success points. Although both models are successful, it is seen that one level more good results are obtained in the proposed model. It is seen that at the 38th iteration level, the iteration has reached the maximum test accuracy success rate. As the study can be terminated at the specified iteration point, it is run until equal iterations to make a correct comparison with the training iteration number.

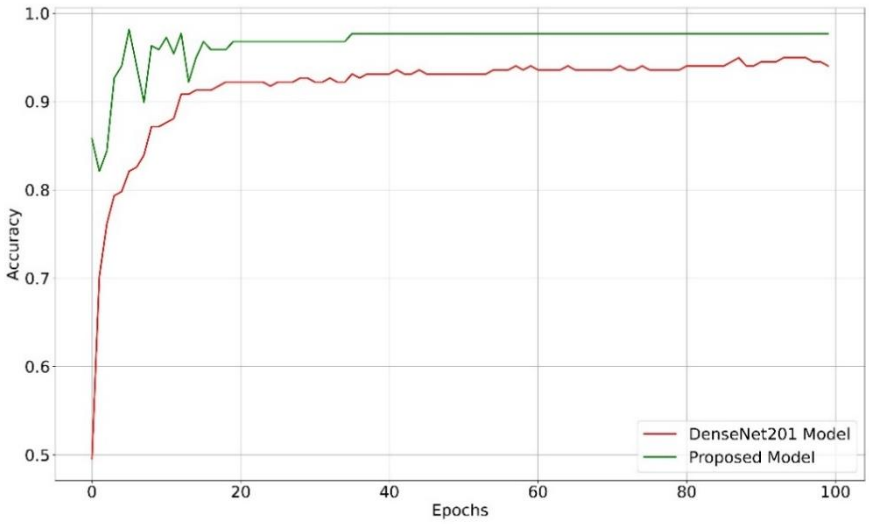

Figure 5. The test performance result graph of the proposed and basic models

In Figure 6, the test loss graphs of the proposed model and the basic DenseNet201 model are presented. Although the test loss value of the proposed model was high in the first iteration, it experienced serious decreases towards the 18th iteration. After the 20th iteration, the loss value remains constant. The loss graphs of the proposed model and the basic model move in the same direction and alignment after the 20th iteration. The proposed model minimum loss value is 0.2036, while the basic model loss is 0.1979. Although training and test accuracy and loss graphs are given in Figures 3-6, it is useful to examine the results according to general performance criteria to examine them in detail. For this purpose, numerical values obtained in terms of the precision, recall, and F1 score values of deep learning models are needed. To obtain these values, the confusion matrices of both models were obtained. Afterward, other results from the confusion matrix results were shared and the progress of the proposed model was analyzed from different aspects. The performance results of the proposed DenseNet201-based model for cataract classification are shown in Figure 7a. According to the confusion matrix shown in this figure, fundus images with cataracts can be classified with a success rate of 99%, while normal fundus images can be classified with a success rate of 99%. In the proposed model, no 1 cataract image could be found.

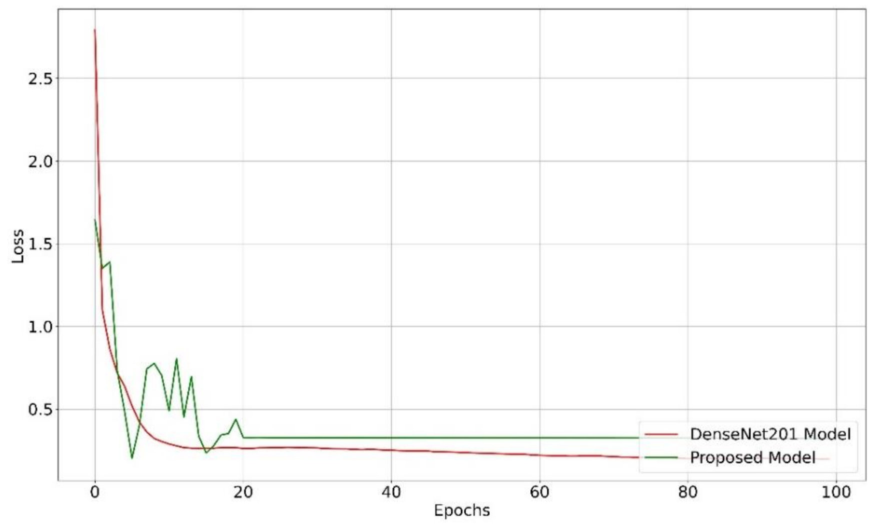

Figure 6. The test loss performance result graph of the proposed and basic models

The results of the performance of the DenseNet201-based model for cataract classification are shown in Figure 7b. According to the confusion matrix shown in this figure, fundus images with cataracts can be classified with a success rate of 93.94%, while normal fundus images can be classified with a success rate of 98.84%.

In the basic model, 1 normal image and 8 cataracts were detected incorrectly. To analyze the results obtained from the proposed and basic deep learning models in more detail, the precision, recall, F1 score, and accuracy values are presented in Table 1.

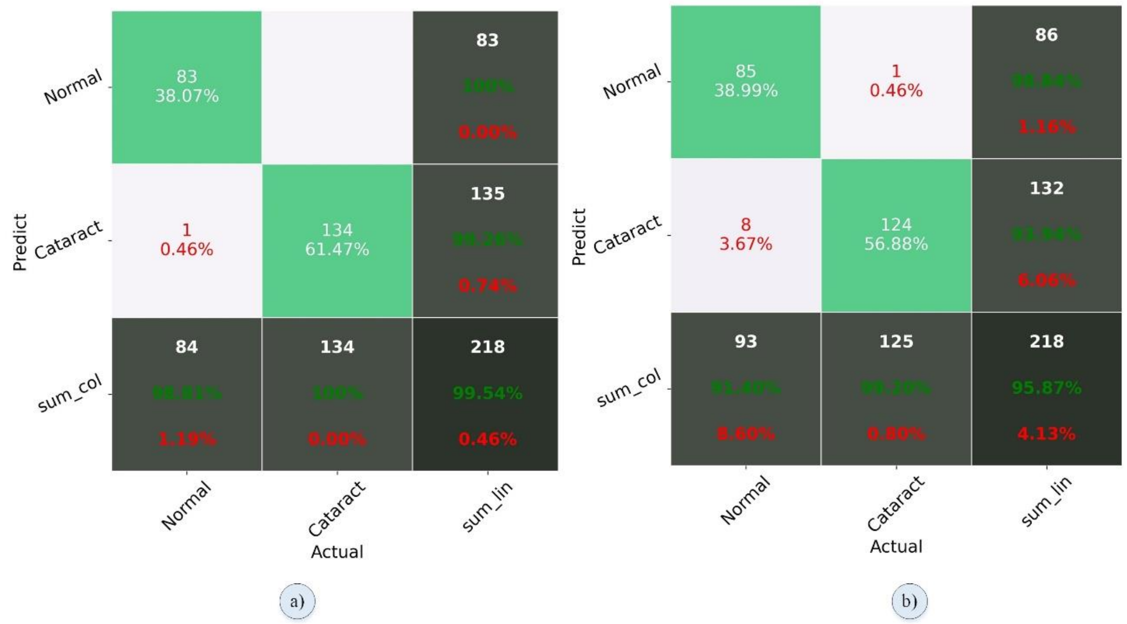

Figure 7. a) The proposed model confusion matrix, b) The basic model confusion matrix

Table 1. Performance results of deep learning model

Models	Type	Precision	Recall	F1 score	Accuracy
Proposed model	Non-Cataract	0.99	0.99	0.99	0.99
	Cataract	0.99	0.99	0.99	
Basic model	Non-Cataract	0.96	0.91	0.94	0.93
	Cataract	0.93	0.97	0.94	

The results obtained from the proposed deep learning model were evaluated according to the values of the precision, recall, F1 score, and accuracy criteria to better examine the difference from the existing studies in the literature. The results obtained suggest that the proposed model can be used to adapt it to different retinal diseases. In the proposed model, despite the addition of 14 different layers compared to the basic model, the progress in the performance result is shown in detail in both accuracy graphs and confusion matrixes. Except for the model structures used in the experimental studies, all parameters are the same. When the number of epochs was 100, the Adam optimization method was used as the optimization method. While the batch size is 32, the image size is entered as 224 in width and height. As a result of experimental studies, the success rate of the proposed model is one level higher than that of the basic model. Learning rate, epsilon value of 0.01, 1e-07 were preferred, respectively. Other parameters are used as default values. Adam (Kingma and Ba, 2014) offers an effective performance by training deep learning algorithms with minimal adjustments. In the literature, Adam optimization methods are seen to generally give better results than other optimization methods such as SGD (Pacal et al., 2022). For the stated reasons, the Adam optimization method was used.

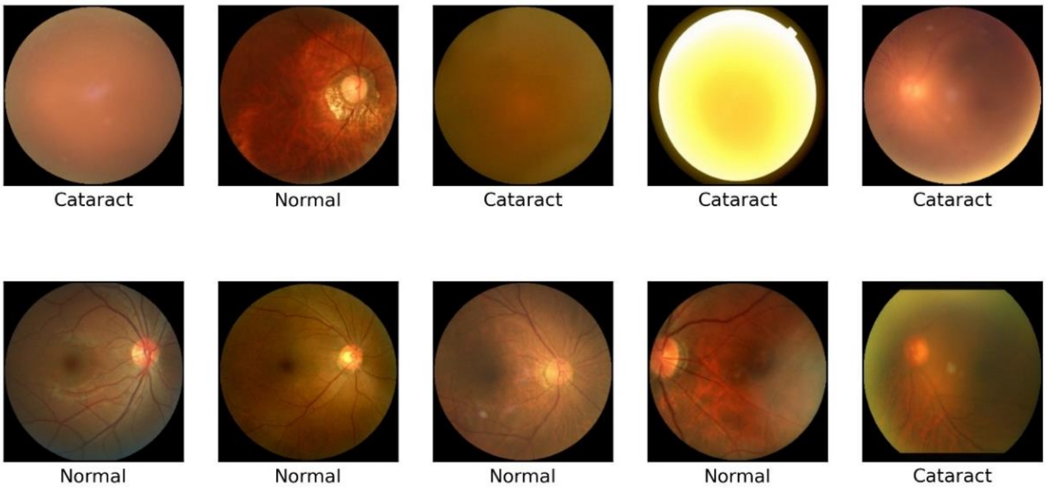

Figure 8. Test results of images with index 673, 991, 163, 400, 100, 12, 165, 225, 551, 624 in the test dataset

After the performance measurement results of the proposed deep learning model were obtained, it was made ready to be used on the test images. The test images with index numbers in the data set shown in Figure 9 are given as input to the proposed model. As a result of the input process, the sigmoid activation function was used to determine which class it belongs to. In the last stage, performance metrics are created by comparing the estimated class label obtained by the proposed model with the actual class label result. The results obtained were compared with different studies in the literature. The results of the comparison process are given in Table 2. When examined in these results, the proposed model for finding the cataract image in the performance metrics obtained was 0.75, 6.44, and 9.5 points better than the studies in the literature. In normal images, the proposed model gave better results by 0.75, 6.44, and 9.5 points.

Table 2. Comparison results with similar data sets

Class	Model	F1 score (%)	Precision (%)	Recall (%)	Accuracy (%)
Cataract	(Jayachitra et al., 2021)	--	82	--	89.5
	(K S et al., 2021)				92.56
	(Yadav et al., 2022)	98.21	99.99		98.25
	Proposed	99.00	99.00	99.00	99.0
Non-Cataract	(Jayachitra et al., 2021)	--	82	--	89.50
	(K S et al., 2021)				92.56
	(Yadav et al., 2022)	98.21	99.99	--	98.25
	Proposed	99.00	99.00	99.00	99.0

CONCLUSION

If not diagnosed early, it is important to automatically classify the images of cataract disease, which causes the most blindness in the world. For ophthalmologists, patients need to be able to constantly check. Realizing this involves potentially high costs, as well as tiring workload. The fact that many people with cataracts or those with the possibility of cataracts cannot reach the ophthalmologist immediately delays early intervention. Failure to provide delayed early interventions causes patients to worsen the situation they are in. Artificial intelligence-supported automatic classification systems are needed to facilitate patient follow-up by freeing ophthalmologists from their workload.

In this article, a deep learning model has been developed that automatically classifies data consisting of cataract and normal fundus images. With the help of the developed model, the transfer learning techniques were fine-tuned, creating a deep learning model that gives better results than similar studies in the literature. When the comparative results given in Table 2 are examined, the difference in the proposed model in terms of precision, recall, F1 score, and accuracy is presented. When this table is carefully examined, the proposed deep learning model can be used as an auxiliary tool for ophthalmologists to classify images with cataracts.

Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

The authors declare that they have contributed equally to the article.

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