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Dmitro PROCHUKHAN
Kharkiv National University of Radio Electronics

CONCATENATION OF EFFICIENTNETB7 AND RESNET50 MODELS IN THE TASK OF CLASSIFYING OPHTHALMOLOGICAL DISEASES OF DIABETIC ORIGIN

Diagnosing diabetic eye diseases by doctors using medical equipment requires significant resources. It is advisable to use automated tools. Using combinations of models improves classification accuracy.

The features of the architectures of convolutional neural networks EfficientNetB7 and ResNet50 are presented. The creation of a neural network model by concatenating the EfficientNetB7 and ResNet50 models is justified. Transfer learning is applied. The GlobalAveragePooling2D layer is added to each model. The models are combined using the Concatenate layer. The Flatten layer is added to the resulting model to convert the vector into a one-dimensional array.

Two Dropout layers are added to prevent overtraining. Two Dense layers with 512 and 256 neurons and the ReLU activation function are added for nonlinear data transformation and abstract feature extraction. A Dense layer with 4 neurons and the softmax activation function is added to determine the image class. l2-regularization is used in all Dense layers. The developed neural network model was applied to process a dataset of 4 classes: cataract images, diabetic retinopathy images, glaucoma images, and healthy retina images. The model is compiled using the Adam optimizer, the categorical cross-entropy loss function.

The callback functions ModelCheckpoint, LearningRateScheduler, EarlyStopping, and ReduceLROnPlateau are used to adjust the learning rate. The validation accuracy of the model is improved by augmentation (horizontal and vertical flipping), using l2-regularization, Dropout, and adjusting the callback functions. The training lasted 30 epochs.

The best validation accuracy of 97.39% was achieved at the 29th epoch. The best value of the validation function 0.4323 was achieved at the 30th epoch. The proposed neural network model outperforms the accuracy indicators of models proposed in similar studies. The model can be applied to disease detection and classification tasks.

Keywords: convolutional neural network, artificial intelligence, machine learning, ophthalmic diseases

Дмитро ПРОЧУХАН
Харківський національний університет радіоелектроніки

КОНКАТЕНАЦІЯ МОДЕЛЕЙ EFFICIENTNETB7 ТА RESNET50 В ЗАДАЧІ КЛАСИФІКАЦІЇ ОФТАЛЬМОЛОГІЧНИХ ЗАХВОРЮВАНЬ ДІАБЕТИЧНОГО ПОХОДЖЕННЯ

Діагностика офтальмологічних захворювань діабетичного походження лікарями за допомогою медичного обладнання вимагає значних ресурсів. Доцільно використовувати автоматизовані засоби. Використання комбінацій моделей покращує точність класифікації.

Наведено особливості архітектур згорткових нейронних мереж EfficientNetB7 та ResNet50. Обґрунтовано створення нейромережевої моделі шляхом конкатенації моделей EfficientNetB7 та ResNet50. Застосовано трансферне навчання. Шар GlobalAveragePooling2D додано до кожної моделі. Моделі об'єднуються за допомогою шару Concatenate. Шар Flatten додано до отриманої моделі для перетворення вектору в одновимірний масив.

Два шари Dropout додано для запобігання перенавчання. Два шари Dense з 512 та 256 нейронами та активаційною функцією ReLU додано для нелінійної трансформації даних та виділення абстрактних ознак. Шар Dense з 4 нейронами та функцією активації softmax додано для визначення класу зображення. l2-регуляризацію використано у всіх шарах Dense. Розроблена нейромережева модель застосована для обробки набору даних з 4 класів: зображення з катарактою, зображення з діабетичною ретинопатією, зображення з глаукомою, зображення здорової сітківки ока. Модель компілюється з використанням оптимізатора Adam, функції втрат категоріальна крос-ентропія.

Функції зворотного виклику ModelCheckpoint, LearningRateScheduler, EarlyStopping, ReduceLROnPlateau застосовано для коригування швидкості навчання. Валідаційна точність моделі покращена аугментацією (горизонтальне та вертикальне перевертання), використанням l2-регуляризації, Dropout та налаштуванням функцій зворотного виклику. Навчання тривало 30 епох. Найкраща валідаційна точність 97,39% досягнута на 29 епосі.

Найкраще значення валідаційної функції витрат 0.4323 досягнуто на 30 епосі. Запропонована нейромережева модель перевершує показники точності моделей, запропонованих в аналогічних дослідженнях. Модель може бути застосована для задач виявлення та класифікації захворювань.

Ключові слова: згорткова нейронна мережа, штучний інтелект, машинне навчання, офтальмологічні захворювання.

Introduction

Diabetes is a dangerous disease that affects millions of people around the world. The number of people with diabetes is constantly increasing. According to the forecasts of scientists from the International Diabetes Federation, the number of people aged 20 to 79 will increase to 643 million in 2030, and in 2045 - to 784 million [1]. The number of people with diabetes in Ukraine as of 2021 was 2 million 325 thousand patients. The development of the disease can cause vision problems. High sugar levels can destroy blood vessels in the eyes and lead to ophthalmological diseases of diabetic origin.

The development of the disease can cause vision problems. High sugar levels can destroy blood vessels in the eyes. The consequences of destruction of the eye vessels are ophthalmological diseases. Diabetic diseases can occur without symptoms in the early stages. Symptoms appear if not treated. Symptoms of ophthalmological diseases of diabetic origin are as follows: impaired vision, the appearance of flies before the eyes, blind spots, distortion of the contours of objects, photophobia, sudden loss of vision.

Diabetic retinopathy is one of the main causes of vision loss. Diabetic retinopathy occurs due to increased blood glucose levels. This disease can also damage the retina of the eye. Diabetic retinopathy can cause sudden blindness. The most severe stage of the disease is proliferative. Bleeding from the vessels of the eye can cause complete blindness. Diabetes can also cause the development of glaucoma. Damage to the vessels of the eye and increased intraocular pressure caused by diabetes contribute to the development of this disease.

Glaucoma causes a narrowing of the field of vision and degeneration of the fibers of the optic nerve. High sugar levels and diabetes also cause the development of cataracts.

Cataracts lead to clouding of the lens of the eye. Objects appear blurry in cataracts. Doctors use metric, iconic, and visual methods to diagnose ophthalmological diseases.

Metric methods are as follows: keratometry, keratopachymetry, refractometry, ultrasound biometry, optical biometry, tonometry.

Iconic methods are as follows: optical coherence tomography, confocal and scanning laser ophthalmoscopy, ultrasound scanning, ultrasound biometry, magnetic resonance tomography, fluorescence angiography, confocal microscopy.

Visual methods are as follows: ophthalmoscopy, biomyomicroscopy, biomicroscopy, transillumination of the eyeball, cycloscopy. The use of these methods allows ophthalmologists to diagnose diseases. A significant number of automated disease diagnostics systems developed in recent years. Improving the quality and accuracy of existing automated systems is a promising area of scientific research.

Related works

Many systems use clinical domain knowledge to make the final decision. Features based on clinical knowledge are called clinical features. The advantages of using clinical features are modeling, interpretation, and presentation of results. The use of clinical features also has disadvantages. The modeling process depends on segmentation: a small error causes global errors in disease detection. Models do not evolve with increasing data because they are created on prior knowledge. A system designed for one disease may not be suitable for another.

Detecting a single feature can lead to incorrect conclusions. To overcome these disadvantages, it is advisable to use artificial intelligence and machine learning tools. Computer vision has undergone significant changes due to the growing popularity of convolutional neural networks. Ophthalmological diagnostics has reached a new level thanks to the use of convolutional neural networks with visualization methods. A wide range of neural network models based on convolutional networks and other architectures are used to solve various problems of classification, prediction and segmentation of images obtained as a result of ophthalmic screening.

The increasing availability of large sets of medical images, such as Kaggle APTOS, MESSIDOR, has become a catalyst for the development of deep learning methods in ophthalmology. Scientists have created effective algorithms for automated diagnosis of eye diseases from retinal images.

The developed algorithms have significantly improved the accuracy and speed of diagnosis. [2], [3], [4]. Two modes of machine learning are used for disease diagnosis - ensemble learning and unensemble learning. Researchers use a certain artificial neural network to predict diseases when learning without an ensemble. Ensemble learning improves computing performance by combining and integrating models.

An ensemble of convolutional neural networks for the detection of 28 different pathologies was proposed in [5]. Fundus images were used in the specified study. The AUROC value was 0.9613. The SE-ResNeXt architecture achieved an accuracy of 0.9586. An ensemble of three models using the K-nearest neighbor algorithm and the soft voting method for glaucoma diagnosis was proposed in [6]. Results obtained on two different retinal image datasets demonstrated that the proposed ensemble model improves diagnostic capabilities. In [7] 26 networks were investigated to evaluate their performance in the diabetic retinopathy classification task using the Kaggle EyePACS retinal dataset. The EfficientNetB4 model demonstrated the best accuracy. EfficientNetB4 achieved a training accuracy of 99.37% and a validation accuracy of 79.11%. DenseNet201 achieved a training accuracy of 99.58% and a validation accuracy of 76.80%. The hybrid architecture of Inception-ResNet is proposed in [8]. The fundus image is preprocessed using the intensity normalized procedure. The trained model with Resnet50, Inception V3, VGG-19, DenseNet-121 and MobileNetV2 models achieved 93.79% accuracy using multiple activation functions. The concatenation of Xception and NasNetMobile models for diabetic retinopathy detection is proposed in [9]. The dataset contained images of a healthy retina and images with diabetic retinopathy. The study found that the image size of 214 by 214 provides the best accuracy of the network. The Adamax optimization method with a learning rate parameter value of 0.001 provided the best accuracy. High accuracy rates were obtained during binary classification on the training (99.23%) and validation sets (99.12%).

The synthesis of convolutional neural networks and long short-term memory for the detection of proliferative retinopathy was proposed in [10]. The work integrates the long short-term memory mechanism into the ResNeXt-101 convolutional neural network. A dataset of 3 classes was used - images with a healthy retina, images with non-proliferative retinopathy and images with proliferative retinopathy. Pre-processing of images by cropping black frames and increasing contrast improves the results of network training. Sufficiently high accuracy rates were achieved on the training set (98.3%) and validation set (97.3%).

The combination of the DenseNet121 and Inception-ResNetV2 model architectures was developed in [11]. The images were classified into three classes: healthy retina, non-proliferative diabetic retinopathy and proliferative diabetic retinopathy. The results of feature extraction from the two models are combined and classified using the multilayer perceptron method. The method provides an improvement in the accuracy of the improvement compared to the individual DenseNet121 and Inception-ResNetV2 models without combination. The following indicators were obtained: accuracy – 91%, macro average precision – 91%, macro average recall – 91%, macro average F1-Score.

The synthesis of Xception and InceptionV3 networks was proposed in [12] for the detection of diabetic retinopathy. Initially, the effectiveness of the InceptionV3, ResNet50, ResNet50V2, Xception and DenseNet121 models was investigated. The Xception and InceptionV3 models showed the best results.

The fusion and ensemble methods were used to combine the specified models. It was found that data augmentation improves the accuracy of the model. The performed augmentation did not distort the image. Scientists found that the fusion method provides better accuracy than the ensemble.

The ResNet50 model has been successfully used for disease detection [13],[14],[15]. The possibility of concatenating the EfficientNetB7 and ResNet50 models has not been considered in the studies. The specified combination of models has significant potential in solving classification problems. In the studies listed above, significant progress has been achieved in detecting diabetic retinopathy. Insufficient attention has been paid to the detection of glaucoma, cataracts and improving the accuracy of detecting these diseases.

The purpose of the study is to create an effective neural network model based on concatenation, set optimal hyperparameters, improve performance, ensure high accuracy of detecting glaucoma and cataracts, and conduct a comparative analysis with other models.

Modification Concatenation of EfficientNetB7 and ResNet50 models

The ResNet50 convolutional neural network is part of the Residual Network family of networks. This model has significant capabilities for training deep neural networks. A key feature of the architecture is the presence of residual connections [16].

They allow the neural network to learn residual functions. Residual block are presented in Fig. 1.

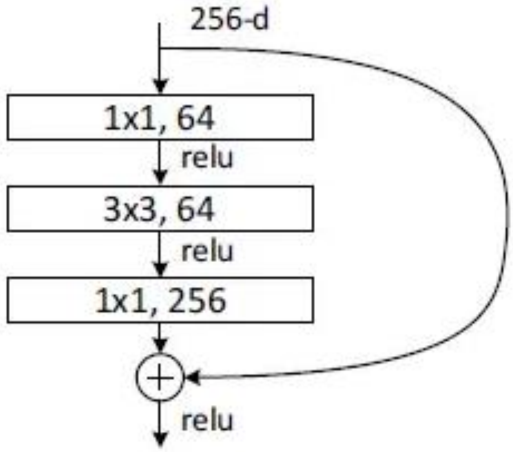


Fig. 1 Residual block

The ResNet50 model successfully overcomes the problem of vanishing gradient. The architecture allows for feature extraction. The model is adapted to work with images of 224 by 224 pixels. Pooling layers are used to reduce the spatial dimensions of feature maps. This feature helps to reduce computational costs and prevent overtraining. The final fully connected layer determines the class probabilities. The pre-trained ResNet50 model can be used for other tasks, which will significantly save system resources. EfficientNetB7 is a modern convolutional neural network, which is characterized by high efficiency and accuracy of image classification. This model uses a scaling method that allows for high accuracy. The model scales evenly in width, depth, and resolution. This feature leads to better performance compared to other models. Changing the number of parameters and their fine-tuning allow using EfficientNetB7 for classification tasks [17],[18]. The architecture of the model is presented in Fig. 2

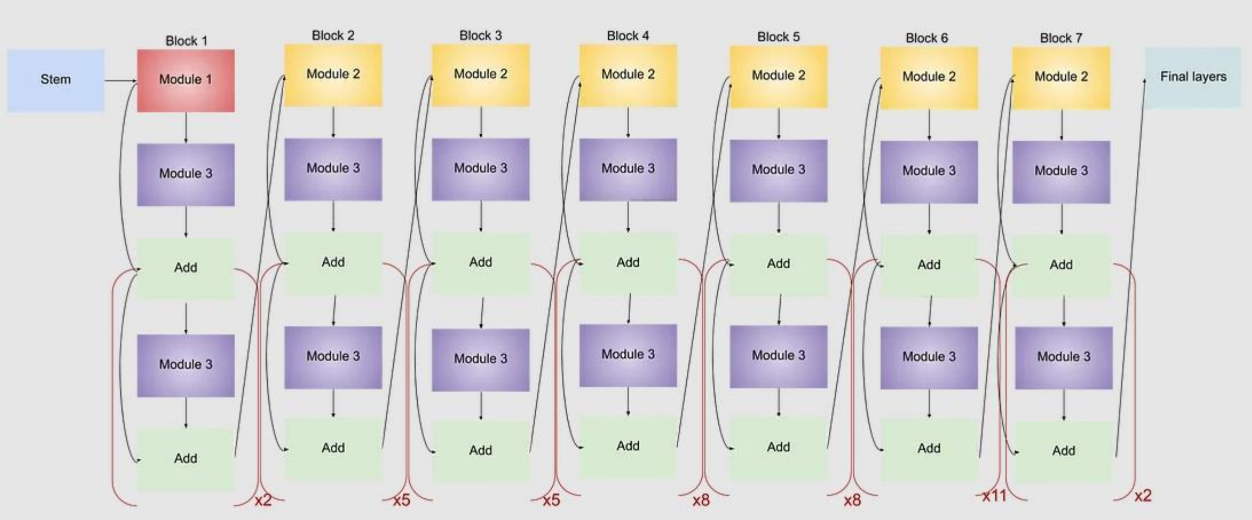


Fig. 2 EfficientNetB7 model architecture

The presented advantages of the EfficientNetB7 and ResNet50 models allow us to consider the possibility of their concatenation and application of the newly developed architecture for the task of classifying ophthalmological diseases of diabetic origin. We present the process of creating a neural network model by concatenating the EfficientNetB7 and ResNet50 models. Neural networks trained on the large ImageNet dataset were used as the basis for the study. Transfer learning was applied. The input layer was defined as a tensor containing an image of size 224 by 224. Pre-trained EfficientNetB7 and ResNet50 models were used without the last classification layer to adapt to our task. The GlobalAveragePooling2D layer was added to each model to reduce the output tensor and obtain a representation vector. The model weights are frozen. This feature allows them not to be changed, speeds up training, and helps avoid overtraining. The resulting representation vectors from both models are combined into one using the Concatenate layer. The Flatten layer converts the concatenated vector into a one-dimensional array. Dropout layers are used to prevent overtraining. Two Dense layers with 512 and 256 neurons and ReLU activation function are added for nonlinear data transformation and abstract feature extraction. A Dense layer with 4 neurons and softmax activation function is added for image class determination. l2-regularization is used in all Dense layers. The developed neural network model is presented in Figure 3.

Experiments

The developed neural network model was applied to process a dataset of 4 classes: cataract images, diabetic retinopathy images, glaucoma images, and healthy retina images. The number of images is given in Table 1.

Table 1

Number of images in each class

Class	Number of images
Cataract	1083
Diabetic retinopathy	1098
Glaucoma	1007
Normal	1074

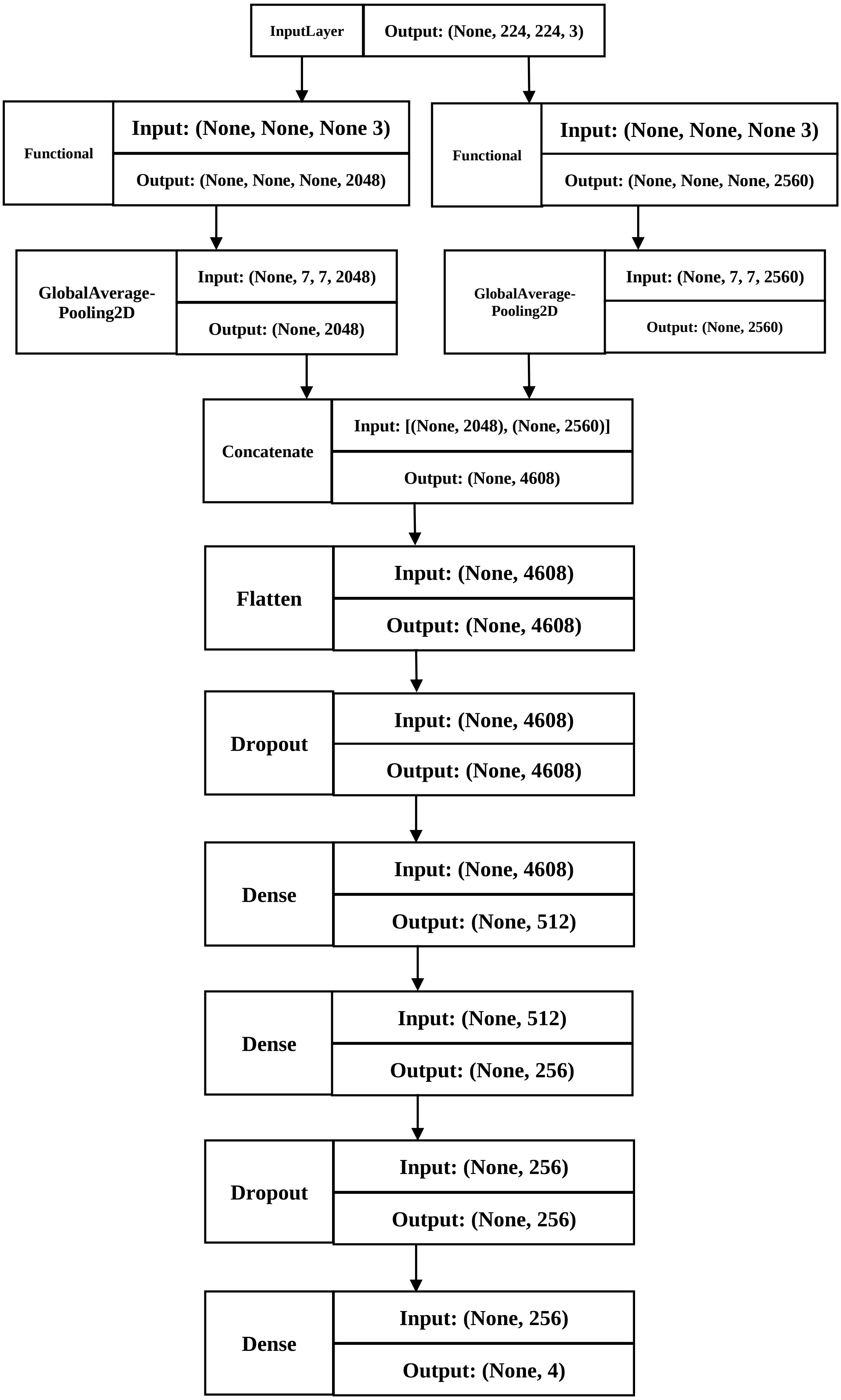


Fig. 3 Neural network model based on the concatenation of EfficientNet B7 and ResNet50 models

A training dataset was created, which contains 80% of the images. A validation dataset was created, which contains 10% of the images. A test dataset was created, which contains 10% of the images. Augmentation was performed to increase the amount of data.

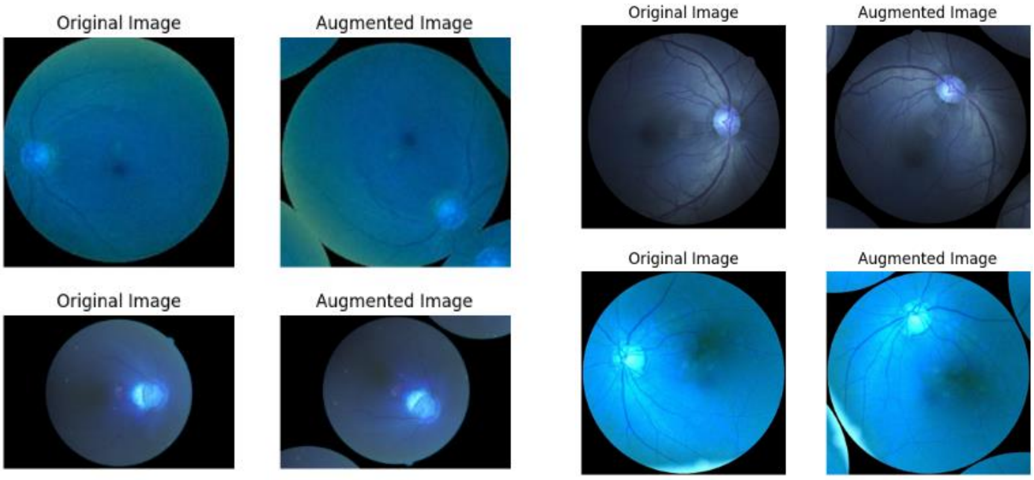


Fig. 4. Augmentation results

The developed neural network model creates filters that help classify the augmented data set in different positions. The model is compiled using the Adam optimizer, the categorical cross-entropy loss function. The callback functions ModelCheckpoint, LearningRateScheduler, EarlyStopping, ReduceLROnPlateau are used to adjust the learning rate. The goal of further experiments is to achieve the best validation accuracy. The influence of augmentation methods on the specified indicator is studied. Horizontal displacement of images by 20% of the width worsened the validation accuracy. Vertical displacement of images by 20% of degrees worsened the validation accuracy. Image shift by 20% worsened the validation accuracy. Zooming in and out by 20% worsened the validation accuracy. Changing the brightness by 20% worsened the validation accuracy. Horizontal and vertical flipping improved validation accuracy.

For hyperparameter optimization, the possibility of using such methods as Grid Search, Bayesian Optimization, and gradient-based optimization was considered. Bayesian optimization was applied due to the high speed of achieving optimal hyperparameter values compared to other methods. The function for hyperparameter optimization proposed in [19] was used. This mechanism provided effective adaptation of the model to changing parameters.

The effect of the rate parameter of the Dropout layers on validation accuracy was investigated. The rate values of 0.1, 0.2, 0.3, 0.4 worsened validation accuracy. The rate value of 0.5 improved validation accuracy. The effect of the l2-regularization parameter value on validation accuracy was investigated. The values of 0.01 and 0.0001 worsened validation accuracy. The value of 0.001 improved validation accuracy. The effect of callback function parameters on validation accuracy was investigated. The values of the factor parameter 0.2,0.3,0.4,0.5 of the ReduceLROnPlateau function worsen validation accuracy. A value of factor 0.1 of the ReduceLROnPlateau function improves validation accuracy. A value of patience 2 to 9 of the ReduceLROnPlateau function degrades validation accuracy. A value of patience 10 of the ReduceLROnPlateau function improves validation accuracy. The values of the ReduceLROnPlateau parameters to achieve the best validation accuracy are given in Table 2.

Table 2

ReduceLROnPlateau parameters

Parameter	Value
monitor	'val_accuracy'
factor	0.1
patience	10
min_lr	0.0001

EarlyStopping patience values in the range of 2 to 9 degrade validation accuracy. EarlyStopping patience value of 10 improves validation accuracy. The best EarlyStopping parameters for achieving validation accuracy are listed in Table 3.

Table 3

EarlyStopping parameters

Parameter	Value
monitor	'val_accuracy'
factor	0.1
patience	10
min_lr	0.0001

The best ModelCheckPoint parameters for achieving validation accuracy are listed in Table 4.

Table 4

ModelCheckPoint parameters

Parameter	Value
monitor	'val_accuracy'
verbose	1
save_best_only	True
mode	'max'

The neural network model was trained. The training lasted 30 epochs.

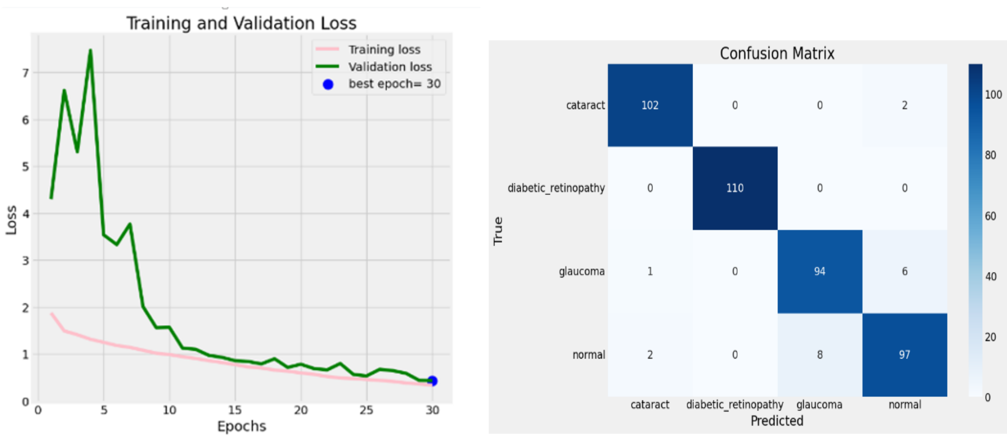
The best validation accuracy value was achieved at the 29th epoch and is 97.39%. Table 5 shows the values of training and validation accuracy during training.

Table 5

Training and validation accuracy

Epoch	Training accuracy	Training loss function	Validation accuracy	Validation loss function
1	0.6222	2.1691	0.2464	4.2971
2	0.8904	1.5299	0.2464	6.6164
3	0.9271	1.4162	0.2464	5.3080
4	0.9442	1.3239	0.2464	7.4664
5	0.9601	1.2427	0.2559	3.5372
6	0.9701	1.1844	0.3412	3.3290
7	0.9702	1.1541	0.3981	3.7669
8	0.9780	1.0788	0.7630	2.0074
9	0.9784	1.0262	0.8389	1.5599
10	0.9825	0.9912	0.8436	1.5678
11	0.9784	0.9689	0.9194	1.1247
12	0.9841	0.9044	0.9194	1.0985
13	0.9835	0.8676	0.9455	0.9707
14	0.9824	0.8410	0.9502	0.9274
15	0.9875	0.7732	0.9550	0.8562
16	0.9912	0.7394	0.9479	0.8385
17	0.9912	0.6960	0.9550	0.7878
18	0.9888	0.6661	0.9194	0.8973
19	0.9885	0.6323	0.9597	0.7122
20	0.9911	0.5974	0.9336	0.7799
21	0.9856	0.5814	0.9502	0.6876
22	0.9949	0.5328	0.9597	0.6599
23	0.9961	0.4898	0.9313	0.7958
24	0.9879	0.4879	0.9645	0.5625
25	0.9899	0.4560	0.9716	0.5320
26	0.9914	0.4295	0.9313	0.6714
27	0.9898	0.4178	0.9408	0.6439
28	0.9911	0.3894	0.9479	0.5872
29	0.9909	0.3770	**0.9739**	0.4382
30	0.9924	0.3421	0.9692	**0.4323**

The best value of the validation cost function 0.4323 was achieved at epoch 30. 102 out of 104 cataract images were correctly recognized. 110 out of 110 retinopathy images were correctly recognized. 94 out of 101 glaucoma images were correctly recognized. 97 out of 107 healthy retina images were correctly recognized. The graph of the loss function and the confusion matrix are presented in figure 5.



a) b)

Fig.5. Network training results: a – loss function graph; b – confusion matrix

High precision, recall, f1-score were obtained. The given indicators for images with diabetic retinopathy are 1.00, 1.00 and 1.00, respectively. Table 6 shows the values of the precision, recall, and f1-score metrics for each class.

Table 6

Metric values

Class	Precision	Recall	F1-Score
Cataract	0.97	0.98	0.98
Diabetic retinopathy	1.00	1.00	1.00
Glaucoma	0.92	0.93	0.93
Normal	0.92	0.91	0.92

The EfficientNetB7, EfficientNetB6, and ResNet50 models were trained to evaluate the effectiveness of the constructed model. Table 7 shows the validation accuracy of these models.

Table 7

Best validation accuracy of models without concatenation

Model	Best validation accuracy
EfficientNetB7	96.45
EfficientNetB6	96.31
ResNet50	95.87
EfficientNetB7	96.45

Analysis of the table shows that our model exceeds the performance of the EfficientNetB7, EfficientNetB6, and ResNet50 models. To assess the effectiveness of the constructed model, training was also carried out on models obtained as a concatenation of the InceptionV3 and EfficientNetB7 models, InceptionResnetV2 and EfficientNetB7, Resnet152 and EfficientNetB7, DenseNet169 and EfficientNetB5 models. Table 8 shows the values of the best accuracy of the specified models during training.

Table 8

Best validation accuracy of models with concatenation

Model	Best validation accuracy
InceptionV3+EfficientNetB7	96.45
InceptionResnetV2+EfficientNetB7	95.50
Resnet152+ EfficientNetB7	96.92
DenseNet169+EfficientNetB5	88.63

Analysis of the table shows that our model outperforms the models obtained as a concatenation of the InceptionV3 and EfficientNetB7, InceptionResnetV2 and EfficientNetB7, Resnet152 and EfficientNetB7, DenseNet169 and EfficientNetB5 models.

Conclusions.

The analysis of the features of convolutional neural networks EFF7 and ResNet50 is carried out. The creation of a neural network model based on the concatenation of the above architectures is justified. The created model contains three Dense layers with l2-regularization values of 0.001, two Dropout layers with a rate value of 0.5, a Flatten layer, callback functions ModelCheckpoint, LearningRateScheduler, EarlyStopping, ReduceLROnPlateau.

High accuracy rates for detecting diabetic retinopathy, cataracts, and glaucoma were obtained compared to analogues. The proposed neural network model outperforms the accuracy rates of models without concatenation. Four more models with concatenation were created and trained. The validation accuracy of these models during training was lower than that of the model based on concatenation EfficientNetB7 and ResNet50. The model can be used for disease detection and classification tasks. The prospect of further research is the use of the model for detecting such ophthalmological diseases as macular edema and in other classification tasks [20].

The proposed neural network model exceeds the accuracy indicators of models proposed in similar studies. The model can be applied to the tasks of detecting and classifying diseases. The prospect of further research is the use of the model for detecting such ophthalmological diseases as macular edema.

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Dmitro Prochukhan **Дмитро Прочухан**	Post-Graduate of Department of Computer Intelligent Technologies, Kharkiv National University of Radio Electronics, Ukraine. https://orcid.org/0000-0002-4622-1015 e-mail: viprochuhan@gmail.com	аспірант кафедри Комп'ютерних інтелектуальних технологій та систем, Харківський національний університет радіоелектроніки, Харків, Україна