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MODELS AND ALGORITHMS UTILIZING DEEP LEARNING FOR THE DETECTIONAND ANALYSIS OF EYE DISEASES BASED ON MEDICAL IMAGING

Kuljanova Shukurjon Zaribovna[1], Khujayev Otabek Kadamboyevich[2]

[1]Urgench branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi master student Urgench, Uzbekistan
quljanova83@gmail.com
[2]Department of Computer Engineering Urganch Branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi Urgench Uzbekiston
otabek.hujaev@gmail.com

K E Y W O R D S	*A B S T R A C T*
image analysis, neural networks, diabetic retinopathy	This article describes one of the serious consequences of diabetes, the negative impact on the visual system.The purpose of the work is to review the resources devoted to the problem of diagnosing diabetic retinopathy from eye images using neural networks. Materials and methods.The use of modern methods, approaches and algorithms is considered at stages such as data set collection and preparation, data pre-processing, image recognition task, transfer learning, comparison of methods, model ensembles, system development. Possible promising steps in future research are outlined.Results.During the analysis of publications on methods of diagnosing diabetic retinopathy using neural network-based eye images, the following directions for improving the existing results were identified: increasing the image data set, image pre-processing methods, interpretation of the neural network model, computational power implementation algorithms on mobile devices, classification problems and eye lesion segmentation, false negative and false positive diagnoses, model ensembles, using recurrent and capsule neural networks.

Introduction. According to studies conducted over the past twenty years, the number of people with diabetes continues to increase. Diabetes mellitus affects many systems in the body, including the visual system. Visual impairment that occurs due to damage to the vessels of the retina is called diabetic retinopathy (DR) [1].

Due to the growing need for qualified medical care for patients in remote regions of the country and under conditions of restrictions caused by the pandemic, the pressure on the use of information technologies in medicine is increasing.

Telemedicine consultations on the Ophthalmology profile are gaining popularity:

- determination (confirmation) of treatment tactics;
- agreement on the conditions and duration of hospitalization in a federal medical organization;
- determination (confirmation) of the diagnosis; – the need to perform a new and/or rare type of surgical intervention, procedure, etc.;
- analysis of clinical cases;
- formation of an expert opinion based on the results of diagnostic studies; – other [2].

In ophthalmology, automated diagnosis of diseases using images of patients' eyes is carried out using deep machine learning methods [4]. Convolutional neural networks recognize eye pictures [5].

Thus, the positive dynamics in identifying diabetes mellitus in the population leads to an associated increase in the identified number of patients with impaired vision. During the pandemic, the workload on medical staff increases, which contributes to the increased use of telemedicine technologies.

The article presents the results of research into deep machine learning methods in solving computer vision problems in the field of ophthalmology for diagnosing eye diseases. Neural network methods of image analysis for diagnosing diabetic retinopathy have been studied.

Researchers in [7] note that it is difficult to compare different methods due to the fact that many methods are not tested on publicly available data. The authors of the work conclude that the results show problems in reproducing the results of deep learning methods. Therefore, the following improvements in reporting deep learning methods are recommended: use publicly available data or provide a detailed description of the data, publish the source code or all details regarding data preprocessing and all hyperparameters.

The authors of [6] note that the strength of this study is the use of well-known, large-scale, publicly available fundus photographs prepared for deep learning, as well as the ability to reproduce the results and compare with other studies.

The authors of the article [3] conclude that collecting data from one medical center and from one ethnic group makes the data set relatively small and less heterogeneous.

The study [8] focuses on the creation of two deep learning systems for predicting the development of diabetic retinopathy and is tested on two datasets: an internal validation set containing images of predominantly Hispanic patients from the United States, and an external validation set from Thailand.

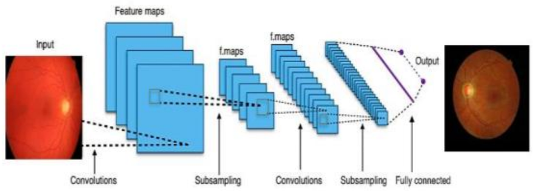

Figure 1. *An architectural diagram of deep convolutionalneural network from input leading to output different fullyconnected layers for processing glaucoma.*

The parameters set before the learning process begins are known as hyperparameters, which pertain to the Deep Convolutional Neural Network (DCNN) architecture. The performance of the model on the validation set is used as feedback to adjust these DCNN hyperparameters. These hyperparameters are tuned during the training and validation cycle to achieve optimal performance of the deep learning model. This study utilized the best neural network design and hyperparameters to enhance the model's effectiveness.

The study [4] proves that currently the need to use large datasets for training is one of the biggest drawbacks in image processing and classification using neural network architectures.

The authors of [5] conclude that it is difficult to distinguish images between stage 0 and stage 1 lesions. Therefore, when new data is collected, it is desirable to collect more images belonging to stage 0 and 1 lesions. Having more data will increase classification accuracy.

Researchers concluded.

In [9], the researchers conclude that a limitation of the developed approach, which is commonly found in deep learning models, is the completeness of the datasets used and the training time associated with using a very large number of images.

The authors of [10] conclude that the images in the dataset were obtained using cameras from different manufacturers and models. In addition, there may be noise in the images, such as blurred focus, underexposure or overexposure. Therefore, it is necessary to use image processing techniques

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to extract useful features from these images for further analysis.

The study [1] addresses several dataset issues, including: excessively noisy images, duplicate mislabeled images, uneven image resolution, and varying class sample sizes.

Based on the results of the study [2], a brightness normalization method was proposed as one of the preprocessing stages for accurate operation of the model with fundus images obtained from different cameras under different lighting conditions.

The authors of [6] conclude that the algorithm's accuracy hinges on the quality of the acquired retinal images, which is the primary limiting factor for its widespread use in non-mydriatic community diabetic retinopathy (DR) screening with portable cameras.

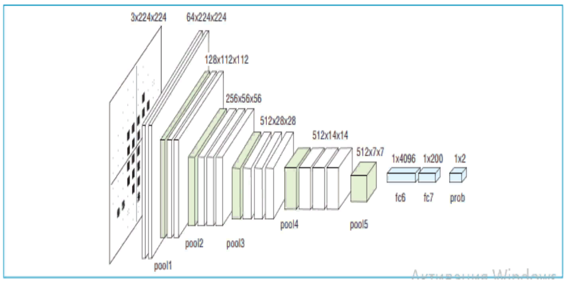

Fig 2. *Layer-by-layer dynamics of neural network training based on perimetric indicators of glaucoma patients.*

J.M. Ahn et al. (2018) created a deep learning model for diagnosing glaucoma using fundus photographs [3]. The study included 154 photographs (786 from healthy individuals, 467 cases of proven progressive glaucoma, and 289 photographs from patients with early stage glaucoma). These datasets were used to build a simple logistic classification and convolutional neural network. The simple regional classification training model achieved an accuracy of 82.9%, a validation accuracy of 79.9%, and a test accuracy of 77.2%. The convolutional neural network achieved an accuracy and area under the ROC curve of 92.2% and 0.98 for training data, 88.6% and 0.95 for validation data, and 87.9% and 0.94 for control data. The trained AI model achieved an accuracy and area under the ROC curve of 99.7% and 0.99 for training data, 87.7% and 0.95 for validation data, and 84.5% and 0.93 for control data. It was found that both advanced photographic and progressive glaucoma, as well as the initial stage of the disease, can be reliably diagnosed using machine learning using only the fundus. This model, which is trained using a vertical neural network, turned out to be more effective for diagnosing the early stages of glaucoma than previously presented models.

F Lee. and others. (2018) to develop a neural network, a method for differential correction of normal and glaucoma, selected visual field tests (SITA Standard 30–2 and 24–2 protocols, Humphrey 750i, Carl Zeiss-Meditec Inc., Germany) with reliability standards for losses Images. fixation of less than 2 out of 13 moments and false positive and negative factors of less than 15% from 3 different ophthalmology centers in mainland China [4]. A total of 4012 visual field protocols from 1352 patients were observed, which were divided into 2 sets of testing sets: 3712 for training and 300 for validation. Statistically significant differences were obtained in such indicators as age ($p=0.0022$), VFI ($p=0.0001$), MD ($p=0.0039$) and PSD ($p=0.0001$). In the control group, the accuracy of the AI network reached 87.6% with specificity and sensitivity of 82.6% and 93.2%, respectively. In the experiments, 3 traditional machine learning methods were also developed and evaluated, the accuracy of which is 0.670, 0.644 and 0.591, respectively. In addition, the responses of physicians: residents, general clinicians and professors-experts in the field of glaucoma research were analyzed, the average accuracy was 0.607, 0.585 and 0.626, respectively. The figure shows an example of network II used in the work. The digital symbols at the top of the figure are the shape of the image cut from the original printed perimeter report and the specified neural network for training (in pixels); pool 1–5 - the order of the series of frames presented for training the neural network (convolutional layers); fc6/7/prob - final series of fragments (result) [5].

The authors of [6] conclude that the accuracy of the algorithm is dependent on the quality of the retinal images obtained, making this the main limiting factor for its broad application in non-mydriatic community diabetic retinopathy (DR) screening using portable cameras.

R. Asaoka et al. (2019) built and evaluated the effectiveness of a deep learning AI model for diagnosing early glaucoma using spectral coherence tomography (SD OCT) data [37]. The study included pre-training data from 4316 OCT images (RS3000, Nidek, Japan) obtained from 1371 eyes of patients with different stages of POAG and 193 eyes of healthy volunteers. The AI network was trained using OCT scans of 94 eyes of patients with early stage POAG (MD score >-5.0 dB) and 84 eyes of controls. Testing included OCT scans of 114 eyes of patients with stage 1 glaucoma (MD > -5.0 dB) and 82 eyes of controls. If the AI network was pre-trained, the accuracy rate (AROC) was 93.7%, and without the training process it ranged from 76.6% and 78.8%. The authors also noted that when using classical machine learning algorithms, such as the random forest method or the Support vector machine (SVM), significantly lower AROC values were obtained (82.0% and 67 .4% respectively). As a result, it was concluded that the AI network model using OCT diagnostic results provides a significant increase in diagnosticefficiency.

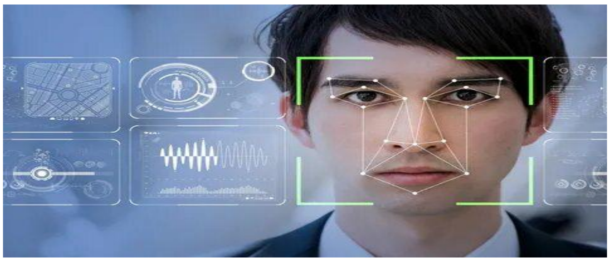

***Figure 3**. Facial recognition and biometric analysis technology.*

A similar study was demonstrated by G. An et al. (2019) [8]. Their goal was to develop a machine learning algorithm for diagnosing glaucoma based on OCT data (3D OCT-2000, Topcon, Japan) and color fundus images (fundus photographs). In this study, 208 glaucomatous and 149 normal eyes were enrolled. To train the AI network, the following types of input images were used: an image of the fundus of the optic disc in shades of gray, a map of the thickness of the RNFL of the optic disc and their changes, a map of the thickness of the complex of ganglion cells of the macular zone and their changes. The accuracy of the study under the ROC curve was 0.940 for color fundus photographs; 0.942 for RNFL thickness maps; 0.944 for the thickness of the ganglion cell complex of the macular zone; 0.949 for the RNFL and ONH deviation maps and 0.952 for the thickness deviations of the macular zone ganglion cell complex. The accuracy rate for all five measures was 0.963. The machine learning system proposed by the authors can accurately distinguish between glaucomatous and healthy eyes based on OCT images and color fundus images, which will improve the accuracy of glaucoma diagnosis.

So, M.S. Miri et al. (2017) were able to train an AI network to automatically detect the precise identification of the location of the minimum distance between two opposite edges of Bruch's membrane openinig (BMO) [9]. The proposed teaching method was tested on 44 patients with glaucoma and evaluated using manual delineations performed by experts. The results show that the proposed AI network method successfully identifies BMO locations with significantly fewer errors than existing routine identification approaches.

A.S. Thompson et al. (2019) proposed a deep learning algorithm for evaluating neuroretinal rim injury (NRR) from SD OCT fundus photographs, utilizing the anatomical features of the Bruch's membrane (MB), specifically the surface area from the edge of the MB to the internal limiting membrane (BMO-MRW) [4]. A total of 9282 pairs of optic disc images were selected, of which 80% of the scans were subjected to training and 20% to testing. An AI convolutional neural network was trained to predict the overall and sectoral values of the BMO-MRW metric. The results presented by the AI were compared with the actual measurements taken using OCT. The AI network results for the overall BMO-MRW in the test set of images were 228.8 ± 63.1 μm, which strongly correlated with the actual values obtained from the OCT study: 226.0 ± 73.8 μm; r=0.88; r2=77%.

For the most part, previous approaches using deep learning algorithms to classify glaucomatous lesions using fundus photographs have been limited by the requirement of expert human labeling of a reference set. F.A. Medeiros et al. (2019) proposed a new approach using SD OCT data to implement a deep learning algorithm for quantifying glaucomatous structural damage [4]. The dataset included 32,820 pairs of ONH and RNFL photographs (SD OCT) from 1,198 subjects (2,312 eyes). A deep learning convolutional neural network was trained to evaluate photographs of the optic disc and predict mean RNFL thickness (SD OCT). The performance of the algorithm was evaluated in an independent control set. The predicted average RNFL thickness for all ONH images in the control group was 83.3±14.5 μm, while the average RNFL thickness for all OCT images included in the study was 82.5±16.8 μm (p=0.164) . There was a very strong correlation between predicted and observed RNFL thickness values, with a mean absolute prediction error of only 7.39 μm.In [8], based on the results of the study, a DL algorithm is presented that is capable of performing an initial analysis of an image to determine whether it can be assessed or not, i.e. whether the image is of sufficiently high quality or needs to be repeated.

The authors of the article [10] conclude that assessing image quality using artificial intelligence can reduce the proportion of low-quality images. In addition, with improved image quality, diagnostic accuracy significantly increased, especially in mild cases of DR.

The study [4] shows that there are plans to make changes to some preprocessing methods in the future, and also discuss how these changes affect the model's performance in classifying the stages of DR.

The study [3] focuses on a hybrid approach for diabetic retinopathy classification using pre-trained deep convolutional neural networks such as InceptionV3 and VGG19. The hybrid approach consists of steps such as data selection, image scaling, feature extraction, feature fusion, and feature selection.

The study [5] proves that the proposed method using a hybrid approach outperforms other existing approaches. The authors of [7], based on the results of the study, conclude that the hybrid model, compared to a single basic model, can improve classification performance in all aspects: accuracy, sensitivity, specificity, precision and F1-score. The authors of the article [6], based on the results of the study, conclude that in the future it is possible to improve the performance of the model by adding additional layers. Research [9] proves that the diversity of base classifiers used for the ensemble structure is a key factor for high classification accuracy of the ensemble model.

In [8], based on the research results, both modified ResNet and Inception-v4 architectures were used for VeriSee for different network characteristics. The authors of the paper conclude that the proposed algorithms in this study were not trained to differentiate diabetic retinopathy from other retinal diseases such as age-related macular degeneration, retinal vein occlusion, etc. Based on the results of the study, the article [10] presents a combined model for the treatment of three eye diseases, i.e. diabetic retinopathy, diabetic macular edema and glaucoma. The authors of the article conclude that in the future, research work will be expanded to include the study of other retinal diseases, such as cataracts, age-related macular edema degeneration, etc. The study [7] proves that future work will pay more attention to neural networks designed based on feature aggregation (ensemble learning). Thus, based on the literature review, machine learning methods are widely used in solving computer vision problems for ophthalmology. At the same time, deep learning is characterized by high accuracy, sensitivity and specificity based on the results of recognizing diseases in eye images. In addition, in recent years there has been an increase in the incidence of diabetes mellitus and visual impairment from diabetic retinopathy. This necessitates an increase in the number of anonymized eye image datasets labeled by a specialized specialist at a medical institution for timely treatment and prevention of diabetic retinopathy. In this regard, it is necessary to consider the possibilities of improving image preprocessing methods.

However, the currently existing neural network methods for determining diabetic retinopathy are insufficiently interpretable, cause false-positive and false-negative diagnostic results, have insufficient ability to segment eye lesions in images and to classify to establish a diagnosis between the absence of the disease and the presence of an initial stage of mild severity of eye damage, and are not available for widespread adoption on mobile devices due to high computing power. Therefore, it is recommended to explore the combination of different models into ensembles, which, due to the advantages of each individual neural network, will improve the overall result.

Conclusion

Currently, methods such as capsule and recurrent neural networks have been developed and are successfully employed for similar image recognition problems. There are isolated studies in the literature describing the use of capsule and recurrent neural networks for determining diabetic retinopathy from eye images. Therefore, these proposed algorithms can potentially be used in diagnosing eye diseases.

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