Al-Nahrain Journal for Engineering Sciences **NJES** 26(4)314-319, 2023
http://doi.org/10.29194/NJES.26040314

Simplified Convolutional Neural Network Model for Automatic Classification of Retinal Diseases from Optical Coherence Tomography Images

Noor B. Khalaf[1], Hadeel K. Aljobouri[2], Mohammed S. Najim[3], Ilyas Çankaya[4]

Authors affiliations:
1) Department of Biomedical Eng., College of Engineering, Al-Nahrain University, Baghdad, Iraq
noorbk98@gmail.com.

2) Department of Biomedical Eng., College of Engineering, Al-Nahrain University, Baghdad, Iraq
hadeel.k.aljobouri@nahrainuniv.edu.iq
3) College of Medicine, Al-Mustansiriya University, Baghdad, Iraq.
drmohammedsuhaild@yahoo.com

4)Electrical and Electronics Engineering Department, Ankara Yıldırım Beyazıt University, Ankara, Turkey.
icankaya@ybu.edu.tr

Paper History:
Received: 4th Aug. 2023
Revised: 21st Aug. 2023
Accepted: 8th Dec. 2023

Abstract

Optical coherence tomography (OCT) allows for direct and immediate imaging of the morphology of retinal tissue. It has become a crucial imaging modality for diagnosing eye problems in ophthalmology. One of the most significant morphological characteristics of the retina is the structure of the retinal layers, which provides important evidence for diagnostic purposes and is related to a variety of retinal diseases.

In this paper, a convolutional neural network (CNN) model is proposed that can identify the difference between a normal retina and three common macular diseases: Diabetic macular edema (DME), Drusen, and Choroidal neovascularization (CNV). This proposed model was trained and tested on an open source dataset of OCT images also with professional disease classifications such as DME, CNV, Drusen, and Normal. The suggested model has achieved 98.3% overall classification accuracy, with only 7 wrong classifications out of 368 test samples. The suggested model significantly outperforms other models that made use of the identical dataset. The final results show that the suggested model is particularly adapted to the detection of retinal disorders in ophthalmology centers.

Keywords: Retinal diseases, OCT, Convolutional Neural Network (CNN), Retinal diseases classification, Deep learning

تصميم موديل مبسط للشبكة العصبية التلافيفية لتصنيف امراض الشبكية تلقائيا بالاعتماد على التصوير المقطعي التوافقي البصري

نور باسم خلف ، هديل قاسم الجبوري ، محمد س نجم، إلياس جنكاي

الخلاصة:

التصوير المقطعي البصري (OCT) هو وسيلة تصوير أساسية لتشخيص مشاكل العين في طب العيون. يوفر OCT ميزة للتصوير اللحظي والمباشر لنسيج شبكية العين، بما في ذلك بنية طبقات الشبكية. ترتبط بنية طبقات الشبكية بمعلومات تشخيصية مهمة لمجموعة متنوعة من أمراض الشبكية.

في هذا البحث، نقترح نموذجًا للشبكة العصبية التلافيفية (CNN) يمكنه تحديد الفرق بين شبكية العين الطبيعية وثلاثة أمراض شائعة متعلقة بالمركز البقعي للشبكية: الوذمة البقعية السكرية (DME)، وdrusen، وظهور الأوعية الدموية المشيمية (CNV). تم تدريب النموذج المقترح واختباره على مجموعة بيانات عامة ومفتوحة المصدر لصور OCT، والتي تم تصنيفها من قبل أخصائيي العيون إلى ٤ فئات: drusen، CNV، DME Normal.يتميز النموذج المقترح بدقة تصنيف شاملة أفضل بنسبة ٩٨,٣٪، مع وجود ٧ تصنيفات خاطئة فقط من بين ٣٦٨ عينة اختبار. حقق النموذج المقترح أداءً أفضل من النماذج الحالية التي استخدمت نفس مجموعة البيانات. تشير النتائج إلى أن النموذج المقترح ملائم بشكل جيد للكشف عن اضطرابات الشبكية في عيادات طب العيون.

1. Introduction

Visual loss is a major health issue around the world. It not just affects normal vision, but it also has a big impact on the quality of life and costs a lot for patients as well as healthcare systems. DME and Age-related macular degeneration (AMD) are the leading causes of permanent visual loss around the world [1].

Because of its high resolution and practicality in clinical practice, OCT, which is a non-invasive, non-contact imaging technology, so it becomes an essential diagnostic instrument for retinal illnesses [2]. In comparison to further imaging techniques such as ultrasound, fundus-photography, and fluorescein-angiography, OCT is considered to be the most accurate method for diagnosing macular disorders. OCT pictures are important for easing medical intervention decisions. Clinical practice should profit from the creation of an automatic and reproducible OCT classification. By increasing the efficiency of diagnosis and facilitating access to medical care and professional knowledge, especially when there are few qualified readers [3].

Deep learning algorithms are commonly employed in the diagnosis of various diseases and have yielded encouraging results. The best ways to classify OCT images are through convolutional neural networks and transfer learning [4].

Naz et al. [5] addressed the problem of identifying DME from OCT images through automatic classification. They suggested a practical and straightforward method for robustly classifying DME by using OCT image data and coherent tensors. The thickness profile and cyst features were assessed by using (55) unhealthy and (53) healthy OCT scans from the Duke Dataset. According to the evaluations, the support vector machine (SVM) had the highest accuracy of (79.65%). While a straightforward criterion based on the difference in thickness of the OCT layer produced acceptable accuracy (78.7%) for diagnosing DME.

Najeeb et al. [6] utilized a single layer CNN structure for classifying retinal abnormalities in retinal OCT scans at a low computational rate. The model obtained adequate classification accuracy after training with images from patients from free retinal OCT data. The model achieved 95.66% accuracy in a multiple class comparison DME, CNV, Drusen, and Normal).

Nugroho [7] used a variety of methods for features extraction from OCT scans, including the histogram of oriented gradient (HOG), local binary pattern (LBP), DenseNet-169, and ResNet-50 and compare the effectiveness of the characteristics of deep and custom neural networks. 32,339 cases were present in the evaluated dataset, distributed across the classes (DME, CNV, Drusen, and Normal). The deep neural network based techniques like DenseNet-169 and ResNet-50, respectively, had accuracy values of 88% and 89%, which were greater than HOG and LBP's values of 50% and 42% respectively, than those for the models without automated functions. In the underrepresented class, the deep neural network-based techniques likewise produced higher outcomes.

Kermany et al. [8], propose a diagnostic model depending on the deep learning architecture that is employed to assess individuals with public curable blinding retinal disorders. With a fraction of the data needed in comparison to traditional methods, A neural network might be trained using the deep learning structure. While training a neural network with an OCT dataset, the precision in identifying DME and AMD was similar to that of human specialists. In a comparison of four different classes DME, CNV, Drusen, and Normal, the model's accuracy was 96.1%.

Tayal et al. [9] The suggested framework analyzes retinal OCT images using three different models of convolution neural networks (5th, 7th, and 9th layers) to distinguish between the several retinal layers by collecting important information and observing any abnormalities and predicted the four ocular pathologies DME, CNV, Drusen, and Normal. Results achieved from the experimental testing show that the optimum statistical model with a 96.5% accuracy is the seven-layer CNN model. While for five and nine-layer were 96.5% and 96.05% respectively.

In this paper, propose a four-layer CNN model with improved implementation for the analysis of OCT images, free datasets are fed to the presented model. Dealing with multi-classifications among 4 classes of images: DME, CNV, Drusen, and Normal (with no significant pathology). According to experiment results, the proposed approach is superior to existing algorithms in terms of accuracy.

The current state-of-the-art in retinal disease classification using CNNs involves the use of advanced architectures such as ResNet, DenseNet, and EfficientNet. Many recent studies have also focused on developing multi-task learning models that can perform both image quality assessment and disease classification simultaneously. Additionally, there is increasing interest in developing models that can detect specific pathological features in OCT images, such as drusen, CNV, and geographic atrophy. Overall, The field of retinal disease classification using CNNs is advancing rapidly, with new developments and advancements being made regularly.

2. Dataset and Preprocessing

In this study, retinal OCT scans from the public Mendeley database are used to train a deep learning model. The selection of these Optical Coherence Tomography (OCT) images was conducted from retrospective cohorts comprising adult patients who were treated at the University of California San Diego's Shiley Eye Institute and the California Retinal Research Foundation.

These data were obtained from the dataset and divided into two folders training and testing, each folder has sub-folders for 4 different classes CNV, DME, Drusen, and Normal, as well as b-scan views of OCT images in the Joint Photographic Experts Group (jpeg) format [10]

From the presented database, 1336 images have been utilized in this work for the classification procedure, with 334 images from each class.

Figure (1) presents images of OCT from the dataset used in the study.

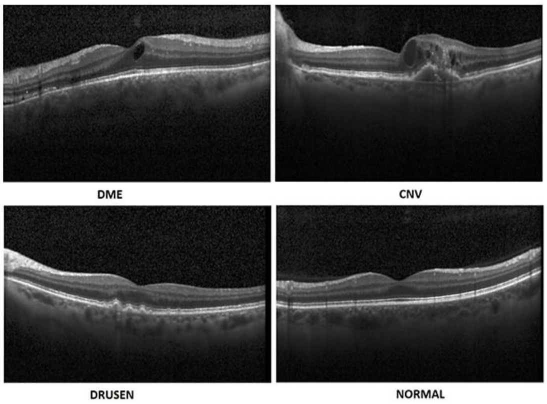

Figure (1): Examples of OCT B-scans with diseases and normal images.

Data preprocessing is the initial and most critical stage in cleaning and preparing data for use in models [4]. Since the real OCT images of the data set are of varying dimensions so each image is rescaled to (256, 256, 3) without changing the amount of data in the image. The range of pixel [0, 255] for every image is normalized to [0, 1], so this will fit well into the model structure as well as minimize the problem of computational complexity during training. With a 70-30 Train-Test Split mean 70% of OCT images (968) were utilized to train the design model, while 30% of OCT images (368) were utilized for testing.

3. Deep Learning with CNN model

A subset of artificial intelligence that identifies representations with multiple levels is called deep learning. The most commonly used image classification technique is CNNs, which use deep learning to extract essential features from unstructured data.

A typical CNN model consists of these basic layers which are an input layer, a convolution layer, an activation function, pooling layers, dense layers, and an output layer [5].

The transformation of each image into a vector is a critical process initiated by the initial convolutional layer, acting as the input layer. This transformation involves the application of various filter kernels across the entire image, enabling the extraction of spatial and temporal features. As these filters traverse the image, they engage in element-wise multiplicative operations with the image's pixel values, factoring in the filter's respective weights. The results of these multiplicative operations are then summed at each stride of the filter, thereby generating a novel feature or activation map. This activation map is subsequently propagated through the hidden layers of the CNN, further refining the feature extraction process.

Within the hidden layers, the Rectified Linear Unit (ReLU) activation function is employed to process the output. This choice of activation function is favored for its computational efficiency and its capacity to mitigate the vanishing gradient problem commonly encountered in deep neural networks. The output from this stage undergoes additional refinement through a max pooling layer, aimed at reducing the dimensionality of the feature map.

Finally, the last layer of the model comprises fully connected dense neural networks responsible for classifying the extracted features, enabling the model to make informed predictions based on the underlying data patterns. This intricate series of operations collectively empowers the CNN to interpret and categorize the input images effectively. [11],[12], [13].

In the proposed CNN Model, a convolutional neural network was used to extract heightened features from OCT images, and the fully connected layers were used for image classification into four classes as shown in the structure of the CNN architecture in Figure (2)

The parameters of the model are enumerated:

1. Conv2D. filter size of the layer the convolutional is (3x3), the number of filters is (32), padding = 'same', activation function is (Relu).
2. Conv2D. filter size of the layer the convolutional is (3x3), the number of filters is (32), and the activation function is (Relu).
3. MaxPooling2D.
4. Conv2d. filter size of the layer the convolutional is (3x3), the number of filters is (64), and the activation function is (Relu).
5. Conv2d. filter size of the layer the convolutional is (3x3), the number of filters is (64), the and activation function is (Relu).
6. MaxPooling2D.
7. Flatten feature vector length of 9216.
8. Dense unite (128), and Activation function is (Relu).
9. Dense activation function for multi-classification is 'Softmax'.

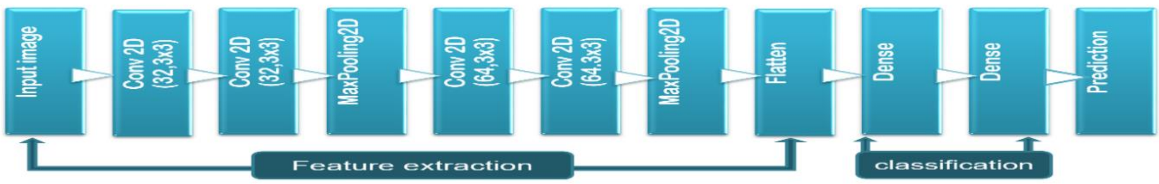

Figure (2): The structure of the CNN architecture.

4. Experimental Results

In this study, a four-layer CNN model was suggested to classify 4 types of retinal disorders which are CNV, DME, DRUSEN, and NORMAL. The viability of the suggested model where determined by computing performance assessment metrics (accuracy, precision, recall, F1-score, and confusion matrix) to determine the model's efficiency [14]. The confusion matrix aids in the exploration of the summary of prediction outcomes utilizing these matrices, true-positive class classification is denoted by TP, the wrong-negative class classification is denoted by FN, the wrong-positive class classification is denoted by FP, and the true-negative class classification is denoted by TN [15], [16].

The suggested model was assessed using performance assessment measures in this study, which include [17]:

1- Precision is defined as the percentage of true positives to total positives.

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

2- Sensitivity (recall) is used to calculate the percentage of true positives properly identified by a model.

$$\text{Sensitivity} = \frac{TP}{(TP + FN)}$$

3- F1 Score is a metric used to assess the balance of precision and recall (sensitivity).

$$F1\ \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

For this study Table (1) summarize the performance of the CNN model:

Table(1): The performance of the CNN model (70% - 30% train_test split)

	Precision	Sensitivity	F1-score
CNV	1.00	0.98	0.99
DME	0.99	0.98	0.98
DRUSEN	0.97	0.99	0.98
NORMAL	0.97	0.98	0.97
ACCURACY	0.98		

We trained the proposed model for twenty epochs by using the Adam optimizer. The accuracy and cross-entropy loss are shown in Figure (3), and Figure (4) respectively. The trained model was then evaluated using the test dataset, and an overall accuracy of 98% was obtained.

The graph below demonstrates the variation in accuracy value throughout training epochs, as well as the loss value for training and testing. The blue line is presenting how correctly the model is learning by each epoch, on the other side the orange line is the learning curve calculated from a testing dataset that gives an idea of how appropriately the model is generalizing. Since there isn't a significant difference between the accuracy of training and the testing accuracy in this instance, the model is performing satisfactorily.

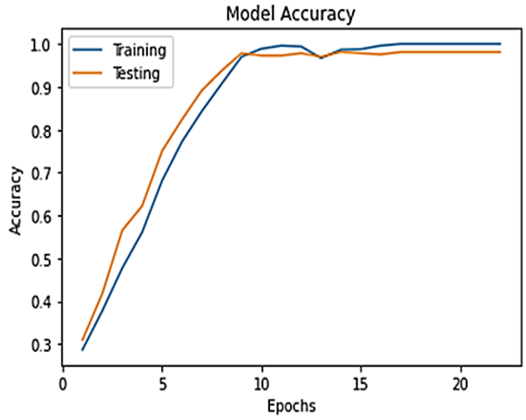

Figure (3): CNN model accuracy curves on (70-30) % data split

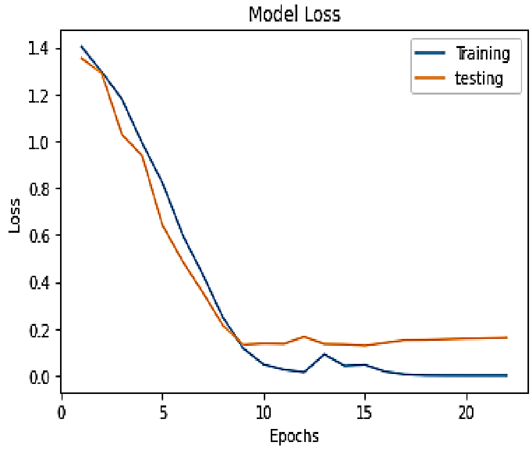

Figure (4): CNN model loss curves on (70-30) % data split.

In order to enhance our comprehension of the performance exhibited by our model, we formulated a confusion matrix to facilitate a comprehensive juxtaposition between the actual and predicted values. This matrix serves as a fundamental tool in the refinement of machine learning models. The configuration of the confusion matrix is of a 4 x 4 dimensionality, corresponding to the total number of classes encompassed within the study, as illustrated in Figure (5).

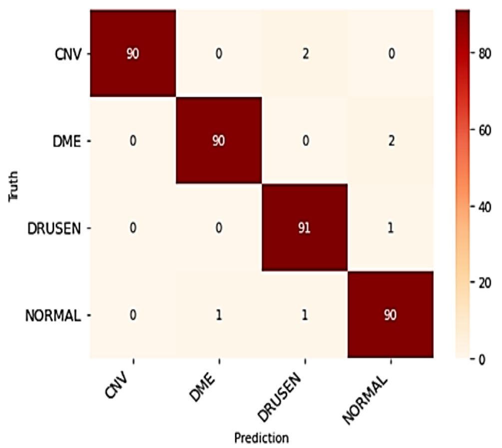

Figure (5): confusion matrix of CNN (70% - 30% train_test split**)**

5. Discussion:

A challenging aspect of accurately diagnosing diseases is medical image classification. Deep learning models often require big annotated datasets. In this paper, we use deep learning's learning capabilities to create a CNN model for retinal disease detection.

Comparisons were made between the proposed convolution neural network and existing models presented by Kermany and Tayal whose proposed CNN model with nine and seven layers respectively [8], [9]. As a result, these models were trained and evaluated utilizing the same dataset and the same number of four classes. Models with similar performance are compared and found to outperform each other as in Table (2) below.

Table (2): Performance of different models at OCT B-scan level for detection of four classes.

Reference	Class	Number of CNN Layers	Accuracy
Kermany et al.	NORMAL/CNV/ DMD/DME	9	96.1
Tayal et al.	NORMAL/CNV/ DMD/DME	7	96.5
Proposed model	NORMAL/CNV/ DMD/DME	4	98.3

The outcomes of our study provide empirical evidence supporting the capacity of the Convolutional Neural Network (CNN) model we introduced to acquire intricate features. This model demonstrates a remarkable level of accuracy, reaching 98.3%, surpassing the performance of other intricate models. This achievement is particularly noteworthy due to its successful application on a limited clinical dataset.

6. Conclusion

This study introduces an advanced Convolutional Neural Network coupled with an Adam optimizer, designed for precise identification and categorization of retinal anomalies within OCT images. The model under consideration has undergone training utilizing fundamental CNN architectures, yielding remarkable classification precision, as evidenced by a blind test accuracy of 98%.

Future work will involve adding more retinal diseases to improve the effectiveness of the proposed model. The study provides a novel contribution to the diagnosis of retinal diseases using OCT images, enhancing the efficiency and accuracy of diagnosis, and facilitating access to care and professional knowledge. The proposed approach can be a valuable tool in clinical practice, aiding medical professionals in diagnostic prediction and classification, thereby improving the accuracy of diagnosis and enhancing access to care and professional knowledge, particularly in situations where qualified readers are limited.

7. References

[1] F. Li, H. Chen, Z. Liu, X. Zhang, and Z. Wu, "Fully automated detection of retinal disorders by image-based deep learning," *Graefe's Archive for Clinical and Experimental Ophthalmology*, vol. 257, no. 3, pp. 495–505, Mar. 2019, doi: 10.1007/s00417-018-04224-8.

[2] W. Geitzenauer, C. K. Hitzenberger, and U. M. Schmidt-Erfurth, "Retinal optical coherence tomography: Past, present and future perspectives," *British Journal of Ophthalmology*, vol. 95, no. 2. pp. 171–177, Feb. 2011. doi: 10.1136/bjo.2010.182170.

[3] W. Lu, Y. Tong, Y. Yu, Y. Xing, C. Chen, and Y. Shen, "Deep learning-based automated classification of multi-categorical abnormalities from optical coherence tomography images," *Transl Vis Sci Technol*, vol. 7, no. 6, Nov. 2018, doi: 10.1167/tvst.7.6.41.

[4] S. Asif, K. Amjad, and Qurrat-ul-Ain, "Deep Residual Network for Diagnosis of Retinal Diseases Using Optical Coherence Tomography Images," *Interdiscip Sci*, Dec. 2022, doi: 10.1007/s12539-022-00533-z.

[5] S. Naz, T. Hassan, M. U. Akram, and S. A. Khan, "A practical approach to OCT based classification of Diabetic Macular Edema," *Proceedings - International Conference on Signals and Systems, ICSigSys 2017*, pp. 217–220, Jun. 2017, doi: 10.1109/ICSIGSYS.2017.7967044.

[6] S. Najeeb, N. Sharmile, M. Sajid Khan, I. Sahin, M. Tariqul Islam, and M. Imamul Hassan Bhuiyan, "Classification of Retinal Diseases from OCT scans using Convolutional Neural Networks," 2018.

[7] K. A. Nugroho, "A Comparison of Handcrafted and Deep Neural Network Feature Extraction for Classifying Optical Coherence Tomography (OCT) Images," Sep. 2018, [Online]. Available: http://arxiv.org/abs/1809.03306

[8] D. S. Kermany *et al.*, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," *Cell*, vol. 172, no. 5, pp. 1122-1131.e9, Feb. 2018, doi: 10.1016/j.cell.2018.02.010.

[9] A. Tayal, J. Gupta, A. Solanki, K. Bisht, A. Nayyar, and M. Masud, "DL-CNN-based approach with image processing techniques for diagnosis of retinal diseases," in *Multimedia Systems*, Aug. 2022, vol. 28, no. 4, pp. 1417–1438. doi: 10.1007/s00530-021-00769-7.

[10] D. Kermany, K. Zhang, and M. Goldbaum, "Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification," vol. 2, 2018, doi: 10.17632/RSCBJBR9SJ.2.

[11] A. A. Almindelawy and M. H. Ali, "Improvement of Eye Tracking Based on Deep Learning Model for General Purpose Applications," *Al-Nahrain Journal for Engineering Sciences*, vol. 25, no. 1, pp. 13–19, Apr. 2022, doi: 10.29194/njes.25010012.

[12] A. Abed, E. Fawzi, and S. S. A. Naser, "Retina Diseases Diagnosis Using Deep Learning," 2022. [Online]. Available: www.ijeais.org/ijaer

[13] M. Jahid Hasan Hajee Mohammad and M. Shahin Alom Hajee Mohammad, "Classification Performance Analysis of Retinal OCT Image using Handcrafted and Deep Learning Feature with Support Vector Machine," 2021. [Online]. Available: https://www.researchgate.net/publication/351925377

[14] R. K. Ara, A. Matiolański, A. Dziech, R. Baran, P. Domin, and A. Wieczorkiewicz, "Fast and Efficient Method for Optical Coherence Tomography Images Classification Using Deep Learning Approach," *Sensors*, vol. 22, no. 13, Jul. 2022, doi: 10.3390/s22134675.

[15] Z. Ma, Q. Xie, P. Xie, F. Fan, X. Gao, and J. Zhu, "HCTNet: A Hybrid ConvNet-Transformer Network for Retinal Optical Coherence Tomography Image Classification," *Biosensors (Basel)*, vol. 12, no. 7, Jul. 2022, doi: 10.3390/bios12070542.

[16] Chan, G.C., Muhammad, A., Shah, S.A., Tang, T.B., Lu, C.K. and Meriaudeau, F., 2017, September. Transfer learning for diabetic macular edema (DME) detection on optical coherence tomography (OCT) images. In 2017 IEEE international conference on signal and image processing applications (ICSIPA) (pp. 493-496). IEEE.

[17] S. A. Kamran, S. Saha, A. S. Sabbir, and A. Tavakkoli, "Optic-Net: A Novel Convolutional Neural Network for Diagnosis of Retinal Diseases from Optical Tomography Images," Oct. 2019, doi: 10.1109/ICMLA.2019.00165.