International Journal for Modern Trends in Science and Technology, 9(01): 82-88, 2023

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0901015
Available online at: http://www.ijmtst.com/vol9issue01.html

A Rapid and Automated Learning Model for the Detection of Age-related macular degeneration (AMD) using OCT Images

Nutalapati Ashok[1] | Dr. K. Gangadhara Rao[2]

[1]Research Scholar, Department of CSE, Acharya Nagarjuna University, nutalapati.ashok@gmail.com
[2]Principal, University College of Science, Acharya Nagarjuna University, HOD, Department of CSE, Acharya Nagarjuna University

To Cite this Article
Nutalapati Ashok and Dr. K. Gangadhara Rao. A Rapid and Automated Learning Model for the Detection of Age-related macular degeneration (AMD) using OCT Images. International Journal for Modern Trends in Science and Technology 2022, 9(01), pp. 82-88. https://doi.org/10.46501/IJMTST0901015

Article Info
Received: 22 December 2022; Accepted: 18 January 2023; Published: 28 January 2023.

ABSTRACT

Age-related macular degeneration (AMD) is a leading cause of vision loss in older adults. There are two types of AMD: dry and wet. Dry AMD is characterized by the accumulation of drusen, and yellow deposits under the retina, while wet AMD is characterized by the growth of abnormal blood vessels under the retina. Early detection and accurate classification of AMD are crucial for effectively treating and managing the disease. This paper introduces the rapid and automated system (RAS) developed to find the types of AMD from the OCT image datasets. AMD divided into two types such as type-1 is dry AMD and type-2 wet AMD. The proposed Multilayer Perceptrons (MLPs) model classifies the dry and wet AMD. A pre-trained model, Deep Residual Neural Network with 50 layers (ResNet50), was used to train the model using the KERMANY dataset consisting of 32,931 OCT images of dry and wet AMD. Multilayer Perceptrons (MLPs) are a popular deep learning algorithm used in various classification problems. The MLP model uses features extracted from the input dataset images. The features included statistical measures such as mean, variance, skewness of the pixel intensities, and morphological features such as the area and perimeter of the drusen and blood vessels. The trained RAS model achieved an accuracy of 97.8% in classifying dry and wet AMD. Our results demonstrate the potential of RAS for the classification of AMD and suggest that it can be a helpful tool for the early detection and diagnosis of the disease.

KEYWORDS: rapid and automated system (RAS), Age-related macular degeneration (AMD), Dry AMD, Wet AMD, convolutional neural network (CNN).

1. INTRODUCTION

Age-related macular degeneration (AMD) is a chronic, progressive, and degenerative disease of the retina that is the leading cause of blindness among older adults in developed countries [1]. It affects the macula, the part of the retina responsible for central vision, which is critical for reading, driving, and other daily activities. There are two types of AMD: dry and wet. The dry form is more common, accounting for about 90% of cases, and is characterized by the gradual breakdown of the light-sensitive cells in the macula [2]. The wet form is less common but more severe, and is caused by the

growth of abnormal blood vessels beneath the retina, leading to rapid and severe vision loss. The exact cause of AMD is not known, but several risk factors have been identified, including age, genetics, smoking, high blood pressure, and a diet lacking in fruits and vegetables [3]. There is no cure for AMD, but treatment options are available to slow its progression and prevent vision loss. These include medications, laser therapy, and surgery. Early detection is crucial in managing AMD, as early treatment can help preserve vision and prevent the disease from progressing. Regular eye exams, especially for those over the age of 50 or with a family history of the disease, are important for detecting and monitoring AMD [4].

Age-related macular degeneration (AMD) is a common eye disease that affects the macula, the central part of the retina, causing central vision loss [5]. There are two main types of AMD, dry and wet, and their classification is important for determining appropriate treatment options and predicting disease progression. Machine learning (ML) algorithms have shown great potential in medical image analysis and classification tasks, including the diagnosis of AMD [6]. ML algorithms can analyze large amounts of data and identify patterns that may not be apparent to the human eye, providing an objective and accurate diagnosis. To classify AMD types using machine learning, a dataset of retinal images can be used to train the algorithm. The dataset should include both dry and wet AMD images, as well as healthy retinal images for comparison [7]. The images can be pre-processed to remove noise and enhance image quality, such as adjusting contrast and brightness [8]. The ML algorithm can then be trained using various supervised learning methods such as decision trees, support vector machines (SVMs), neural networks, or random forests. The algorithm will learn to differentiate between the different types of AMD based on features extracted from the images, such as lesion size, location, and morphology. Once the algorithm is trained, it can be tested on a separate set of retinal images to evaluate its accuracy and performance. The algorithm's performance can be measured using metrics such as sensitivity, specificity, and accuracy [9]. The algorithm can also be further optimized by adjusting hyperparameters or using different feature extraction techniques. In summary, using machine learning algorithms to classify AMD types can provide an accurate and objective diagnosis, which can help in the development of appropriate treatment plans and disease management.

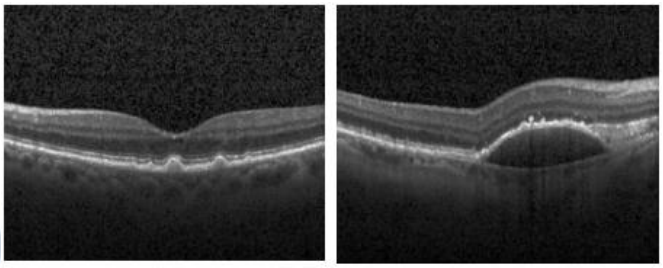

Figure 1 (a) (b): Retinal OCT images of an AMD infected retina [11]. (a) Retinal OCT image of a dry AMD (b) Retinal OCT image of a wet AMD

One potential approach to improving diagnosis and treatment of AMD is to use deep learning, a subset of artificial intelligence that can learn to recognize patterns in large amounts of data. By training a deep learning algorithm on a large dataset of images of the retina, it may be possible to develop a system that can accurately classify different types of AMD and predict disease progression. Deep learning algorithms can be trained to classify these different types of AMD by analyzing features in retinal images, such as the size, shape, and density of drusen, or the presence of fluid or bleeding in the retina. By accurately classifying different types of AMD, deep learning could help clinicians make more informed treatment decisions and improve patient outcomes.

2. LITERATURE SURVEY

U. S-Erfurth et al. [10] discussed several artificial intelligence (AI) methods for detecting Retina abnormalities. The retina is an essential component of the human eye for accurate vision management. The AI was primarily focused on classifying OCT images based on retinal diseases. S. G. Zadeh et al. [11] use the U-Net-CNN architecture to develop and compare three automated methods for Drusen segmentation. Cross-validating on over 50,000 annotated images shows that all three approaches outperform the current state-of-the-art method. The highest accuracy is obtained when the CNN is trained to segment the BM and RPE, and the drusen are detected in a post-process by combining shortest path finding with polynomial fitting. G. An et al. [12] used OCT images to develop the DL model to classify normal and AMD, AMD with

fluid, and AMD without fluid. In this study, 185 standard OCT images from 49 normal subjects were used as training data, 535 OCT images of AMD with fluid and 514 OCT images of AMD without fluid from 120 AMD eyes were used as test data, and 49 typical images from 25 normal eyes, 188 AMD OCT images with fluid, and 154 AMD images without any fluid from 77 AMD eyes were used as training data. Data augmentation was used to build deep-learning models to increase the number of images. In total, two classification models were constructed in two steps. The fine-tuned model from the first step was then transferred and learned again in the second step to distinguish images of AMD with fluid from those without. The first model classified typical and AMD OCT images with 0.999 area under the receiver AUC and 99.2% accuracy. The second model classified AMD in the presence of any fluid and AMD without fluid with 0.992 AUC and 95.1% accuracy. To classify the three categories directly, we achieved higher classification performance with our unique approach than with a transfer-learned VGG16 model pre-trained on the ImageNet dataset.

C. S. Lee et al. [13] proposed that an OCT imaging database was automated, extracted, and linked to clinical endpoints from the EMR. Heidelberg Spectralis was used to obtain OCT macula scans, but each OCT scan was linked to EMR clinical endpoints extracted from EPIC. The central 11 images were chosen from each OCT scan of two patient cohorts: regular and AMD. A random subset of patients was used for cross-validation. ROC were created at three levels: independent image, macular OCT, and patient. F. Li et al. [14] proposed a deep transfer learning method based on the VGG-16 network that shows significant effectiveness in classifying retinal OCT images with a relatively small dataset, which can provide medical decision-making assistance. Furthermore, the proposed approach's performance is comparable to human experts with extensive clinical experience. As a result, it has the potential to be helpful in the automatic diagnosis and classification of common retinal diseases. This paper presents the automatic detection of DME and AMD on OCT images developed by S. Kaymak et al. [15]. The method employed is based on training a deep learning algorithm to categorize them as healthy, dry AMD, wet AMD, and DME. This method outperforms a transfer learning-based method recently proposed for categorizing OCT images into AMD and DME. A. Serener et al. [16] proposed deep convolutional neural networks for automated and fast dry and wet AMD classification. Both dry and wet types must be accurately detected to provide timely treatment. The performance results of deep neural networks show that dry vision impairment can be detected more accurately than wet vision impairment. It is also demonstrated that the eighteen-layer ResNet model outperforms the AlexNet model in classifications. The area under the ResNet model's receiver operating characteristic curve for each AMD stage is 94% and 63%, respectively. L. Fang et al. [17] propose an IFCNN method for automatic retinal OCT image classification. Different convolutional layers in a CNN contain feature information at various scales. As a result, the proposed network employs an iterative fusion strategy that iteratively combines features from the current convolutional layer with those from all previous layers in the CNN network, allowing it to use the features of different convolutional layers to achieve accurate classification of OCT images. The proposed method outperforms the traditional CNN and several well-known OCT classification methods in experiments on a real retinal OCT dataset and a musculoskeletal radiograph dataset.

3. PRE-TRAINED MODEL RESNET-50

ResNet-50 is a convolutional neural network with 50 layers (48 convolutional layers, one MaxPool layer, and one average pool layer). Residual neural networks are an ANN type that builds networks by stacking residual blocks. The following elements are included in the 50-layer ResNet architecture, as shown in the table below:

- A convolution of 77 kernels and 64 other kernels with a 2-sized stride.
- A maximum pooling layer with two strides.
- 9 more layers—33, 64 kernel convolution, 11,64 kernel convolution, and 11,256 kernel convolution. These three layers are repeated three times.
- Iterated 12 more layers with 11,128 kernels, 33,128 kernels, and 11,512 kernels.
- Iterated 6 times on 18 more layers with 11,256 cores and 2 cores 33,256 and 11,1024.

- 9 more layers with 11,512, 33,512, and 11,2048 cores iterated three times

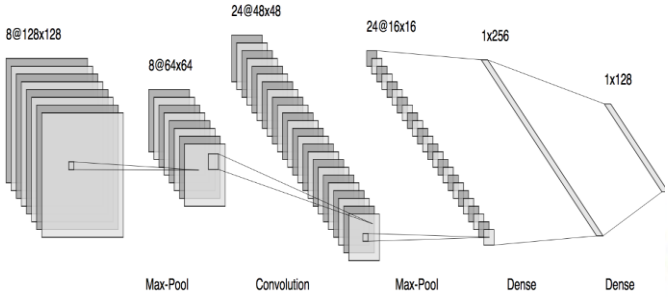

Figure 2: RESNET 50 Architecture

Lee filter: This filter mainly used to remove the noise from the input OCT gray-scale images and smoothing the low variance region. However, this cannot be applied on high variance region that is near edges. This filter estimates that the input OCT image is predicted by using linear model initialized by Eq. (1).

$$Y_{ij} = \overline{K} + W * (C - \overline{K}) \quad (1)$$

Where Y_{ij} represents the gray scale value of the pixel at (i, j) after filtering

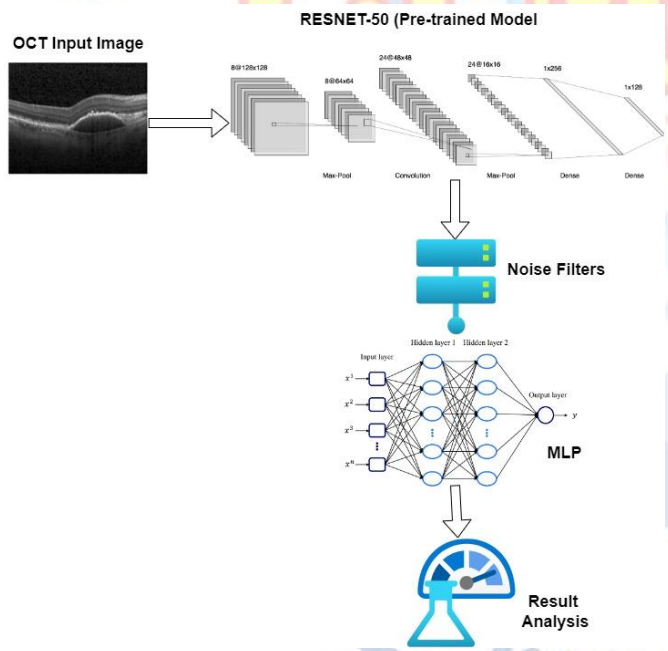

Figure 3: Step-by-Step process of Rapid and Automated System (RAS)

Multilayer Perceptrons (MLPs)

Multilayer Perceptrons (MLPs) are a type of artificial neural network that can be used for classification tasks. Age-related macular degeneration (AMD) is a common eye condition that affects millions of people worldwide, and MLPs have been used to classify images of the retina to help diagnose and monitor the progression of the disease. One approach to using MLPs for AMD classification is to train the network on a large dataset of retinal images labeled with AMD status (e.g., healthy, early-stage AMD, intermediate-stage AMD, advanced-stage AMD). The MLP can then be used to classify new retinal images based on the features it has learned from the training data. To improve the performance of the MLP, various techniques can be used, such as regularization, early stopping, and dropout. Regularization helps prevent overfitting, early stopping helps prevent the network from memorizing the training data, and dropout helps prevent the network from relying too heavily on any one feature. In addition, other types of neural networks, such as CNNs, have also been used for AMD classification with promising results. However, MLPs remain a useful tool for this task, especially when the dataset size is relatively small. Overall, MLPs can be an effective tool for classifying retinal images for AMD diagnosis and monitoring. However, as with any machine learning approach, it is important to carefully evaluate the performance of the network on new data and to consider potential biases in the dataset used for training.

$$a^{(in)} = \begin{matrix} a_0^{(in)} \\ a_1^{(in)} \\ a_2^{(in)} \end{matrix} = \begin{matrix} 1 \\ x_{10}^{(in)} \\ x_{m0}^{(in)} \end{matrix} \quad (2)$$

- $ai^{(in)}$ initializes i^{th} value in the input layer
- $ai^{(h)}$ initializes i^{th} unit in the hidden layer
- $ai^{(out)}$ initializes ith unit in the output layer
- $ao^{(in)}$ initializes bias unit and is equal to 1; it will have the corresponding weight w0

4. DATASET DESCRIPTION

The Kermany [18] dataset, available on Kaggle, was used to train the proposed model in this study. The dataset's two classes, DRUSEN and CNV (Choroidal Neovascularisation), each containing 32,931 images, were used to differentiate between dry and wet AMD. There are 23,792 images in the training dataset, 4,199 images in the validation dataset, and 4940 in the test dataset. This study classified dry and wet AMD using

the architecture of ResNet50 convolutional neural networks pre-trained on the ImageNet dataset. The ImageNet dataset is an online dataset with over one million images and one thousand classes, allowing the network parameters to be well estimated.

Performance Metrics

The confusion matrix is used to analyze the classification algorithm performance. Measuring the performance with a confusion matrix gives a better for find the accurate errors. It is also used to solve several classification issues. This can be applied for classification of binary issues and also for multiclass classification issues. The count values are based on various attributes such as

TP: In this the actual value of true (disease present) and predicted value is true (disease present).

TN: The actual value is true (disease present) and predicted value is false (No disease).

FP: The actual value is false (No disease) and predicted value is true (disease present).

FN: The actual value is false (No disease) and predicted value is false (No disease).

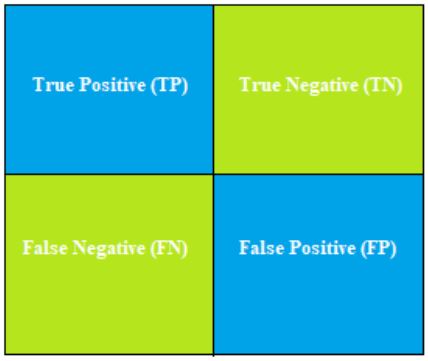

Figure 4: Confusion Matrix

Sensitivity (S_n): Sensitivity, recall, or the TP rate (TPR) is the fraction of positive values out of the total actual positive instances (i.e., the proportion of actual positive cases that are correctly identified):

$$S_n = \frac{TP}{TP + FN}$$

Specificity (S_p): Specificity gives the fraction of negative values out of the total actual negative instances. In other words, it is the proportion of actual negative cases that are correctly identified. The FP rate is given by (1 – specificity):

$$S_p = \frac{TN}{TN + FP}$$

Precision (P): Precision or the positive predictive value, is the fraction of positive values out of the total predicted positive instances. In other words, precision is the proportion of positive values that were correctly identified:

$$P = \frac{TP}{TP + FP}$$

Accuracy (Acc): Accuracy shows the total number of prediction that is correct. Actual and predicted values are correct. It is represented with below formula.

$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

F1-Score (F1S): The F1-score combines the precision and recall of a classifier into a single metric by taking their harmonic mean.

$$F1S = 2 * \frac{P * S_n}{P + S_n}$$

Table 1 Performance of Existing and Proposed Algorithms for detection of Dry AMD

	AlexNet	ResNet 50	RAS
Sensitivity (SE)	77.22	86.76	98.98
Specificity (SP)	81.54	85.76	98.56
Precision (PE)	80.65	85.43	98.34
Accuracy (ACC)	81.66	87.52	97.76
F1-Score	82.12	87.53	97.58

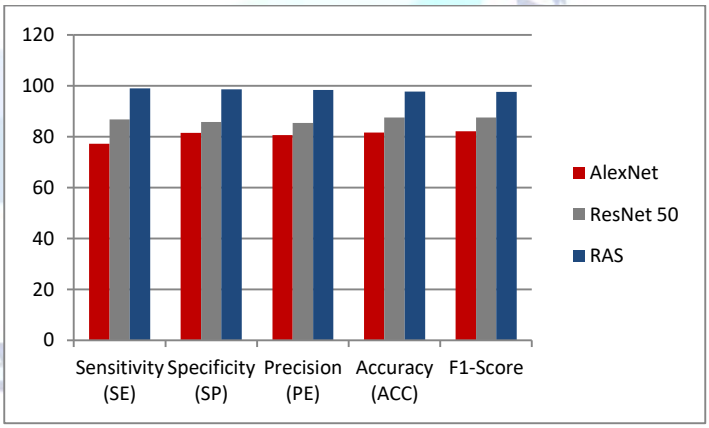

Figure 5: Performance of Existing and Proposed Algorithms for detection of Dry AMD

Table 2 Shows the Performance of Existing and Proposed Algorithms for detection of WET AMD

	AlexNet	ResNet 50	RAS
Sensitivity (SE)	77.22	86.76	98.98
Specificity (SP)	81.54	85.76	98.56
Precision (PE)	80.65	85.43	98.34
Accuracy (ACC)	81.66	87.52	97.76
F1-Score	82.12	87.53	97.58

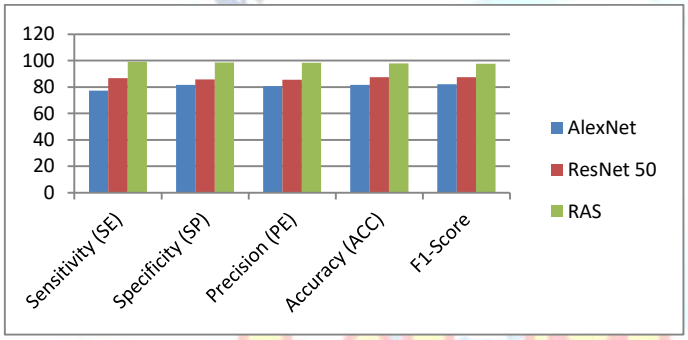

Figure 6: Performance of Existing and Proposed Algorithms for detection of Wet AMD

5. CONCLUSION

Two deep learning based methods, namely AlexNet and ResNet 50, compare with rapid and automated system (RAS) are used to automatically classify OCT images for dry and wet AMD diseases. The performances of these methods are evaluated by simulating two classification tasks. In both cases the RAS outperforms the ResNet model and AlexNet model. When the RAS model is further evaluated, it is observed that it indeed does a more accurate classification of dry AMD than wet AMD. Therefore, it should be the choice between the two models if and when an automated deep learning classification is needed for AMD vision impairment.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1]] S. Apostolopoulos, C. Ciller, S. De Zanet, S. Wolf, and R. Sznitman, "Retinet: Automatic amd identification in OCT volumetric data," Investigative. Ophthalmol. Visual. Sci., vol. 58, no. 8, pp. 387–387, 2017.

[2] F. Grassmann et al., "A deep learning algorithm for prediction of agerelated eye disease study severity scale for age-related macular degeneration from color fundus photography," Ophthalmology, vol. 125, no. 9, pp. 1410–1420, 2018.

[3] S. P. K. Karri, D. Chakraborty, and J. Chatterjee, "Transfer learning based classification of optical coherence tomography images with diabetic macular edema and dry age-related macular degeneration," Biomed. Opt. Exp., vol. 8, no. 2, pp. 579–592, 2017.

[4] D. S. Kermany et al., "Identifying medical diagnoses and treatable diseases by image-based deep learning," Cell, vol. 172, no. 5, pp. 1122–1131, 2018.

[5] S. Farsiu et al., "Quantitative classification of eyes with and without intermediate age-related macular degeneration using optical coherence tomography," Ophthalmology, vol. 121, no. 1, pp. 162–172, 2014.

[6] P. P. Srinivasan et al., "Fully automated detection of diabetic macular edema and dry age-related macular degeneration from optical coherence tomography images," Biomed. Opt. Exp., vol. 5, no. 10, pp. 3568–3577, 2014.

[7] S. J. Chiu, M. J. Allingham, P. S. Mettu, S. W. Cousins, J. A. Izatt, and S. Farsiu, "Kernel regression based segmentation of optical coherence tomography images with diabetic macular edema," Biomed. Opt. Exp., vol. 6, no. 4, pp. 1172–1194, 2015

[8] D. S. Ting et al., "Deep learning in ophthalmology: the technical and clinical considerations," Progress. Retinal. Eye. Res., vol. 72, 2019, Art. no. 100759.

[9] . S. W. Ting et al., "Artificial intelligence and deep learning in ophthalmology," Brit. J. Ophthalmol., vol. 103, no. 2, pp. 167–175, 2019.

[10] U. S-Erfurth, A. Sadeghipour, B. S. Gerendas, S. M. Waldstein, and H. Bogunovi´c, "Artificial intelligence in retina," Progress. Retinal. Eye. Res., vol. 67, pp. 1–29, 2018.

[11] S. G. Zadeh et al.,"CNNs enable accurate and fast segmentation of drusen in optical coherence tomography," in Deep. Learn. in Medical. Image. Analysis. and Multimodal. Learn. for Clinical. Decision. Support.. Berlin, Germany: Springer, 2017, pp. 65–73.

[12] G. An et al., "Deep Learning Classification Models Built with Two-step Transfer Learning for Age Related Macular Degeneration Diagnosis," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, pp. 2049–2052, 2019, doi:10.1109/EMBC.2019.8857468.

[13] C. S. Lee, D. M. Baughman, and A. Y. Lee, "Deep Learning Is Effective for Classifying Normal versus Age-Related Macular Degeneration OCT Images," Kidney Int. Reports, vol. 2, no. 4, pp.322–327, 2017.

[14] F. Li and H. Chen, "Fully automated detection of retinal disorders by image-based deep learning," Graefes Arch Clin Exp Ophthalmol, vol. 257, no. 3, pp. 495–505, 2019.

[15] S. Kaymak and A. Serener, "Automated age-related macular degeneration and diabetic macular edema detection on OCT images using deep learning," in 2018 IEEE 14th International Conference on Intelligent Computer Communication and Processing, ICCP 2018, 2018, pp. 265–269.

[16] A. Serener and S. Serte, "Dry and Wet Age-Related Macular Degeneration Classification Using OCT Images and Deep Learning," 2019 Sci. Meet. Electr. Biomed. Eng. Comput. Sci., pp. 1–4,2019.

[17] L. Fang, Y. Jin, L. Huang, S. Guo, G. Zhao, and X. Chen, "Iterative fusion convolutional neural networks for classification of optical coherence tomography images," J. Vis. Commun. Image Represent., vol. 59, pp. 327–333, 2019.

[18] 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, 2018, doi: 10.1016/j.cell.2018.02.010.