|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Author | Year | Aim | Number of Patients | Type of Image | Application | Deep Learning Method | DR Severity | Performance: AUC |
| Pooja Bidwai (1) | 2024 | Detect 1DR in geriatric patients using OCTA images and deep learning algorithms. | 179 | 2OCTA | Staging | Inception V3 ResNet-50 ResNet50V2 VGGNet-16 VGGNet-19 DenseNet121 DenseNet201 EfficientNetV2 | NO DR Mild DR Moderate DR. | AUC  0.86 to 1 |
| Zhi-Yuan Li (2) | 2024 | Evaluate OCTA changes in subzones of peripapillary atrophy among type 2 diabetes patients with or without DR | 90 | OCTA | Object Detection | 3YOLO-V8 | 4NDR  5NPDR | Accuracy 90.13% |
| Fei Ma (3) | 2024 | Develop a lightweight deep learning model for fine-grained DR grading using OCTA images. | 611 training images and 386 test images for DR grading task | OCTA | Staging | 6CSANet | Normal 6NPDR  7PDR | Accuracy  97.41% |
| Fei Ma (4) | 2024 | Develop a text-controlled deep learning model to evaluate multiple factors related to DR using UWFA. | More than 5000 DR patients | UWFA | Staging | Proposed deep learning | Normal NPDR  PDR | Accuracy 93.98% |
| Lisa Toto (5) | 2024 | To detect hard exudates (HE) and classify 8DRIL on 9OCT images of eyes with DME using deep learning. | 442 OCT images | OCT | Diagnosis | Ensemble learning using YOLOv7  Conv-NeXt Reg-NetXt | Presence or absence of DRIL | Accuracy to 91% |
| Dan Zhang (6) | 2024 | To develop a multi-level feature fusion network using graph-based methods for DR grading with UWF images | 1234 (in-house dataset) 3662 (public dataset) | 11UWF | Staging | Multi-level feature fusion with graph convolution | Mild to Proliferative DR | Accuracy: 81% |
| Behrouz Ebrahimi (7) | 2023 | Evaluate different layer fusion options for deep learning classification of OCTA images | - | OCTA | Staging | EfficientNetV2 | No DR NPDR | Accuracy: 92.65% |
| Yihao Li (8) | 2023 | Investigate a deep learning algorithm to classify DR severity using high-resolution SS-OCTA and UWF-SS-OCTA acquisitions. | 444 patients; 875 eyes | OCTA | Staging | Hierarchical fusion with ResNet DenseNet backbones | Absence of DR  mild NPDR moderate NPDR severe NPDR  PDR and PRP | - |
| Philipp Matten (9) | 2023 | Develop a multiple instance learning based network capable of detecting DR biomarkers in an OCTA dataset without pixel-level annotations. | 102 diabetic patients; 40 healthy volunteers; 352 OCTA images | OCTA | Diagnosis | 16ResNet | Presence of DR | - |
| Mohamed Elsharkawy(10) | 2022 | Develop an OCT-based computer-aided diagnosis (CAD) method to detect DR early using structural 3D retinal scans | 188 | OCT s | Staging | Proposed deep learning | Mild and moderate NPDR | Accuracy: 96.88% |
| Rafael Gelman(11) | 2022 | Analyze the effect of transfer learning (TL) for DR classification using Fundus photography and for classification of other retinal diseases using SD-OCT | - | Fundus  OCT | Diagnosis | AlexNet DenseNet Inception ResNet  VGG | DR for Fundus photographs other retinal diseases for SD-OCT | - |
| Qiaoyu Li (12) | 2022 | Develop a deep learning framework that fuses multilevel information in OCTA images for DR diagnosis. | 301 (57 DR 244 normal) | OCTA | Diagnosis | U-Net for segmentation combined with a deep learning framework incorporating isolated concatenated blocks (ICBs) for multilevel information fusion. | DR vs. normal | AUC: 0.92 |
| Jakob Grauslund (13) | 2022 | Detect moderate or worse DR | 128175 | OCTA | Staging | CNN | Moderate or worse DR | - |
| Bowen Dong (14) | 2022 | Develop a deep learning method for screening and staging DR using OCTA images | 410 | OCTA | Staging | Multi-Branch CNN | Mild to Proliferative DR | AUC:  0.92. |
| Zhiyuan Gao (15) | 2022 | To develop a clinically usable multilevel classification deep learning model for Fundus fluorescein angiography (FFA) images including prediagnosis assessment and lesion classification. | 15,599 | 12FFA | Staging | ResNet18 LeNet-5 VGG16 | Absence of DR  mild NPDR moderate NPDR severe NPDR  PDR | AUC: 0.81 |
| Jie Xu(16) | 2022 | To present a generalizable DR grading system by incorporating causality into the training pipeline to learn invariant features across multiple domains. | 5082 | Fundus | Staging | Proposed deep learning | Absence of DR  mild NPDR moderate NPDR severe NPDR  PDR | - |
| Toshihiko Nagasawa (17) | 2021 | To investigate the Accuracy of a deep learning method in identifying NDR and DR using multimodal images UWF, Fundus ophthalmoscopy and OCTA. | 491 multimodal images | UWF  Fundus ophthalmoscopy  OCTA | Staging | 17DCNN | NDR  DR  NDR  PDR | AUC: 0.847 for NDR vs. DR and AUC: 0.964 for NDR vs. PDR. |
| Jinwook Oh (18) | 2021 | To develop a deep learning model for early detection of DR using transfer learning | 10529 images | Fundus | Triage | ResNet50 | Referable DR | AUC:  0.982 |
| Xiaoling Wang (19) | 2021 | To develop a diagnostic technology to automatically grade DR severity using UWFA and ETDRS 7-SF. | 280 diabetic patients and 119 normal patients | UWFA | Staging | Optimized CycleGAN and CNN model classifier | NPDR  PDR | AUC:  0.885 |
| Chen Zang(20) | 2021 | To develop a novel deep learning framework called DcardNet for the classification and lesion detection of DR using OCTA images. | 399 OCTA volumes (95 NPDR 199 PDR 85 no DR) | OCTA | Staging | ResNet-18 | No DR NPDR  PDR | Accuracy: 95.7% |
| Pengxiao Zang (21) | 2021 | To introduce a novel biomarker activation map (BAM) framework based on generative adversarial learning that allows clinicians to verify and understand classifiers’ decision-making. | 355 | OCTA | Triage | U-Shape ResNet | Referable non-referable DR | AUC:  0.97 |
| Cam-Hao Hua (22) | 2020 | Improve DR severity recognition using Fundus and wide-field SS-OCTA images | KHUMC dataset: Not specified Messidor dataset: 1200 | Fundus  OCTA | Triage | TFA-Net with ResNet-18 backbone | Referable vs. non-referable DR |  |
| Mohamed Shaban (23) | 2020 | Develop a deep CNN for DR screening and staging | Dataset of 2950 Fundus images split into 3 categories | Fundus | Staging | 18 convolutional layers and 3 fully connected layers | No DR moderate DR  mild  moderate NPDR  severe DR  severe NPDR  PDR | AUC\_over all: 0.95 |
| Ali J. Abidalkareem (24) | 2020 | Classify DR severity levels using an ensemble of multi-inception CNNs | 3650 | Fundus | Staging | Ensemble of multi-inception CNNs | No DR  Mild Moderate Severe Proliferative | Accuracy: 93.2% |
| Rui-Peng Wang (25) | 2020 | Develop an automated system with artificial intelligence algorithms to comprehensively identify pathologic retinal cases and make urgent referrals. | 2254 | OCT | Object Detection | 14FPN  15RF | Various retinal diseases | Accuracy: 98.12% |
| David Le (26) | 2020 | Test the feasibility of using deep learning for OCTA detection of DR6 | 177 (131 for training and cross-validation 46 for external validation) | OCTA | Diagnosis | VGG16 | NoDR  DR | Accuracy: 87.27% |
| Miriam Heisler (27) | 2020 | Evaluate the role of ensemble learning techniques in conjunction with deep learning to classify DR in OCTA images and their corresponding co-registered structural images | 380 eyes from 242 subject | OCT and OCTA | Triage | CNNs with transfer learning and ensemble learning | Non referable DR  referable DR | Accuracy: 91.88% |
| Bing Li (28) | 2019 | To explore and evaluate an appropriate deep learning system for the detection of 12 major Fundus diseases using color Fundus photograph | 5390 | Fundus | Diagnosis | Se-ResNext50 | 12 binary classification models | AUC:  0.950-0.996 |

1DR: Diabetic Retinopathy, 2OCTA: optical coherence tomography angiography,3YOLO: You Only Look Ones

4NDR No Diabetic Retinopathy,5NPDR Non Proliferative DR,6CSANet: lightweight channel and spatial attention network,7PDR: Proliferative DR, 9OCT: Optical Coherence Tomography,10DRIL: Disorganization of the Retinal Inner Layers,12UWF:Ultra-Widefield, 12FFA: Fundus AutoFuorescence,13UWFA: Ultra-Wide field Fundus Auto fluorescence,14 FPN: Adapted feature pyramid network, 15RF: Random forest,16Res-Net: Residual Convolutional Neural Network, 17DCN: NDeep convolutional neural network

# **References:**

1. Bidwai P, Gite S, Pradhan B, Gupta H, Alamri A. Harnessing deep learning for detection of diabetic retinopathy in geriatric group using optical coherence tomography angiography-OCTA: A promising approach. MethodsX. 2024;13:102910.

2. Li Y, Hu X, Guo X, Ye X, Wang D, Zhang J, et al. Unveiling the hidden: a deep learning approach to unraveling subzone-specific changes in peripapillary atrophy in type 2 diabetes. Frontiers in Cell and Developmental Biology. 2024;12.

3. Ma F, Liu X, Wang S, Li S, Dai C, Meng J. CSANet: a lightweight channel and spatial attention neural network for grading diabetic retinopathy with optical coherence tomography angiography. Quant Imaging Med Surg. 2024;14(2):1820-34.

4. Ma X, Ji Z, Chen Q, Ge L, Wang X, Chen C, et al. Controllable editing via diffusion inversion on ultra-widefield fluorescein angiography for the comprehensive analysis of diabetic retinopathy. Biomed Opt Express. 2024;15(3):1831-46.

5. Toto L, Romano A, Pavan M, Degl'Innocenti D, Olivotto V, Formenti F, et al. A deep learning approach to hard exudates detection and disorganization of retinal inner layers identification on OCT images. Sci Rep. 2024;14(1):16652.

6. Zhang D, Liu M, Chen F, Lu Q, Zhao Y. Graph-based multi-level feature fusion network for diabetic retinopathy grading using ultra-wide-field images. Biomedical Signal Processing and Control. 2024;93.

7. Ebrahimi B, Le D, Abtahi M, Dadzie AK, Lim JI, Chan RVP, et al. Optimizing the OCTA layer fusion option for deep learning classification of diabetic retinopathy. Biomed Opt Express. 2023;14(9):4713-24.

8. Li Y, El Habib Daho M, Conze PH, Zeghlache R, Le Boité H, Bonnin S, et al. Hybrid Fusion of High-Resolution and Ultra-Widefield OCTA Acquisitions for the Automatic Diagnosis of Diabetic Retinopathy. Diagnostics (Basel, Switzerland). 2023;13(17).

9. Matten P, Scherer J, Schlegl T, Nienhaus J, Stino H, Niederleithner M, et al. Multiple instance learning based classification of diabetic retinopathy in weakly-labeled widefield OCTA en face images. Sci Rep. 2023;13(1):8713.

10. Elsharkawy M, Sharafeldeen A, Soliman A, Khalifa F, Ghazal M, El-Daydamony E, et al. A Novel Computer-Aided Diagnostic System for Early Detection of Diabetic Retinopathy Using 3D-OCT Higher-Order Spatial Appearance Model. Diagnostics. 2022;12(2).

11. Gelman R, Fernandez-Granda C. ANALYSIS of TRANSFER LEARNING for SELECT RETINAL DISEASE CLASSIFICATION. Retina. 2022;42(1):174-83.

12. Li Q, Zhu XR, Sun G, Zhang L, Zhu M, Tian T, et al. Diagnosing Diabetic Retinopathy in OCTA Images Based on Multilevel Information Fusion Using a Deep Learning Framework. Computational and Mathematical Methods in Medicine. 2022;2022.

13. Grauslund J. Diabetic retinopathy screening in the emerging era of artificial intelligence. Diabetologia. 2022;65(9):1415-23.

14. Dong B, Wang X, Qiang X, Du F, Gao L, Wu Q, et al. A Multi-Branch Convolutional Neural Network for Screening and Staging of Diabetic Retinopathy Based on Wide-Field Optical Coherence Tomography Angiography. IRBM. 2022;43(6):614-20.

15. Gao Z, Pan X, Shao J, Jiang X, Su Z, Jin K, et al. Automatic interpretation and clinical evaluation for fundus fluorescein angiography images of diabetic retinopathy patients by deep learning. British Journal of Ophthalmology. 2023;107(12):1852-8.

16. Wei H, Shi P, Miao J, Zhang M, Bai G, Qiu J, et al. CauDR: A causality-inspired domain generalization framework for fundus-based diabetic retinopathy grading. Computers in Biology and Medicine. 2024;175.

17. Nagasawa T, Tabuchi H, Masumoto H, Morita S, Niki M, Ohara Z, et al. Accuracy of Diabetic Retinopathy Staging with a Deep Convolutional Neural Network Using Ultra-Wide-Field Fundus Ophthalmoscopy and Optical Coherence Tomography Angiography. Journal of Ophthalmology. 2021;2021.

18. Oh K, Kang HM, Leem D, Lee H, Seo KY, Yoon S. Early detection of diabetic retinopathy based on deep learning and ultra-wide-field fundus images. Scientific Reports. 2021;11(1).

19. Wang X, Ji Z, Ma X, Zhang Z, Yi Z, Zheng H, et al. Automated Grading of Diabetic Retinopathy with Ultra-Widefield Fluorescein Angiography and Deep Learning. Journal of Diabetes Research. 2021;2021.

20. Zang P, Gao L, Hormel TT, Wang J, You Q, Hwang TS, et al. DcardNet: Diabetic Retinopathy Classification at Multiple Levels Based on Structural and Angiographic Optical Coherence Tomography. IEEE Transactions on Biomedical Engineering. 2021;68(6):1859-70.

21. Zang P, Hormel TT, Wang J, Guo Y, Bailey ST, Flaxel CJ, et al. Interpretable Diabetic Retinopathy Diagnosis Based on Biomarker Activation Map. IEEE Transactions on Biomedical Engineering. 2024;71(1):14-25.

22. Hua CH, Kim K, Huynh-The T, You JI, Yu SY, Le-Tien T, et al. Convolutional Network with Twofold Feature Augmentation for Diabetic Retinopathy Recognition from Multi-Modal Images. IEEE Journal of Biomedical and Health Informatics. 2021;25(7):2686-97.

23. Shaban M, Ogur Z, Mahmoud A, Switala A, Shalaby A, Abu Khalifeh H, et al. A convolutional neural network for the screening and staging of diabetic retinopathy. PLoS One. 2020;15(6):e0233514.

24. Abidalkareem AJ, Abd MA, Ibrahim AK, Zhuang H, Altaher AS, Muhamed Ali A. Diabetic Retinopathy (DR) Severity Level Classification Using Multimodel Convolutional Neural Networks. Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Annual International Conference. 2020;2020:1404-7.

25. Wang L, Wang G, Zhang M, Fan D, Liu X, Guo Y, et al. An Intelligent Optical Coherence Tomography-based System for Pathological Retinal Cases Identification and Urgent Referrals. Translational vision science & technology. 2020;9(2):46.

26. Le D, Alam M, Yao CK, Lim JI, Hsieh YT, Chan RVP, et al. Transfer learning for automated octa detection of diabetic retinopathy. Translational Vision Science and Technology. 2020;9(2):1-9.

27. Heisler M, Karst S, Lo J, Mammo Z, Yu T, Warner S, et al. Ensemble deep learning for diabetic retinopathy detection using optical coherence tomography angiography. Translational Vision Science and Technology. 2020;9(2):1-11.

28. Li B, Chen H, Zhang B, Yuan M, Jin X, Lei B, et al. Development and evaluation of a deep learning model for the detection of multiple fundus diseases based on colour fundus photography. The British journal of ophthalmology. 2022;106(8):1079-86.