**Appendix 3:**

Table 2: Details of Included articles

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| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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 | AUC: 0.957 |
| 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: 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 | Acuuracy93.2% |
| 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 |

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

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