**Table 1** The deep learning-based models for single disease detection.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Authors** | **Imaging device** | **Dataset** | **Type of input** | **Type of deep learning networks** | **Data set up** | **Type of output** | **Data augmentation** | **AUROC** | **Sensitivity (Recall)** | **Specificity** | **Accuracy** |
| Treder M., et al. (2017) | Heiderberg Spectralis SDOCT | AMD / healthy = 751 / 361 scans | OCT B-scans | Inception-v3 | training + validation + test | AMD / healthy | NA | NA | 100% | 92.00% | 96.00% |
| Motozawa N., et al. (2019) | Heiderberg Spectralis SDOCT | AMD / normal = 197 / 74 eyes | OCT B-scans | CNN | training + test | AMD / normal, dry/wet AMD | flip, translation, rotation | AMD/normal 0.995 dry/wet AMD 0.991 | AMD/normal 100% dry/wet AMD 98.4% | AMD/normal 98.8% dry/wet AMD 91.1% | AMD/normal 99.0% dry/wet AMD 93.9% |
| Li X., et al. (2019) | SDOCT | mild DR / DM without DR / normal = 1,112/1,856/1,200 images | OCT B-scans | OCTD\_Net (modeified DenseNet, ReLayNet) | training + test | classification of mild DR/DM without DR/normal | random crop, zoom in, horizontal mirror | mild DR 0.970, DM without DR 0.990 | mild DR 87.0%, DM without DR 96.0%, trinary classification 90.0% | mild DR 97.0%, DM without DR 100%, trinary classification 95.0% | mild DR 95.0%, DM without DR 96.0%, trinary classification 92.0% |
| Le D., et al. (2020) | Optovue angiography OCT | NPDR/DM without DR/normal = 101/44/32 eyes | *En face* OCTA SCP images | transfer learning with VGG-16 | cross validation | classification of NPDR/DM without DR/normal | random flips, rotation, zoom | 0.965 | 83.80% | 90.80% | 87.30% |
| Heisler M., et al., 2020 | Zeiss Plex Elite | referable DR / non-referable DR = 224 / 156 eyes | *En face* OCT and OCTA SCP and DCP images | Ensemble learning with VGG, ResNet50, DenseNet | cross validation | Referable DR / Non-referable DR | random rotations, zoom, height and width shift, horizontal and vertical flipping | NA | 90.40% | 93.30% | 92% |
| Nagasato D., et al., 2019 | NA | RVO / normal = 174 / 148 images | *En face* OCTA SCP and DCP images | VGG-16 | cross validation | yes/no NPA | brightness adjustment, gamma correction, histogram equalization, noise addition and inversion | 0.986 | 93.70% | 97.30% | NA |
| Thompson A., et al. (2020) | Spectralis SDOCT | Glaucoma / normal = 612/542 eyes | OCT optic disc B-scans | CNN | training + validation + test | yes/no glaucoma | Random lighting, random horizontal flip, random rotation  | 0.960 | 95.0% | 80.0% | NA |
| Ran A., et al. (2019) | Cirrus HDOCT | GON/ normal = 2926/1951 volumes | OCT optic disc volumetric scans | 3D ResNet | training + validation + test | yes/no GON | Random cropping, random jittering, random flipping | 0.969 | 88.7% | 95.6% | 91.2% |
| Russakoff D., et al. (2020) | Zeiss Cirrus HDOCT | 2805 OCT volumes | OCT macula volumetric scans | CNN | cross validation | yes/no referable glaucoma | NA | 0.88 | NA | NA | NA |
| OCT = optical coherence tomography, OCTA = optical coherence tomography angiography, SDOCT = spectral domain OCT, HDOCT = high definition OCT, AMD = age-related macular degeneration, DR= diabetic retinopathy, NPDR = non-proliferative DR, DM = diabetes mellitus, RVO = retinal vein occlusion, GON = glaucomatous optic neuropathy, NPA = no-perfusion area, SCP = superficial capillary plexus, CNN = convolutional neural network, ResNet= residual neural network, VGG = visual geometry group, AUROC = area under the receiver operating characteristic curve |

**Table 2** The deep learning-based models for multiple diseases detection.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Authors** | **Imaging device** | **Dataset** | **Type of input** | **Type of deep learning networks** | **Data set up** | **Type of output** | **Data augmentation** | **AUROC** | **Sensitivity (Recall)** | **Specificity** | **Accuracy** |
| Kermany D., et al., 2018 | Heiderberg Spectralis SDOCT | CNV/DME/drusen/normal = 37,456/11,599/8,867/51,390 images | OCT B-scans | transfer learning + VGG-16 | training + test | urgent referral (CNV+DME) / non-urgent referral (drusen +normal) | NA | 0.999 | 97.80% | 97.40% | 96.60% |
| Li F., et al., 2019 | Heiderberg Spectralis SDOCT | CNV/DME/drusen/normal = 37,456/11,599/8,867/51,390 images | OCT B-scans | transfer learning + VGG-16 | training + test | urgent referral (CNV+DME) / non-urgent referral (drusen +normal) | NA | 1 | 97.80% | 99.40% | 98.60% |
| Alqudah A.,2019 | Public available dataset | CNV / DME/ AMD / drusen / normal = 37,705 / 11,826 / 27,150 / 9,116 / 51,640 images | OCT B-scans | Multi-task CNN | training + validation + test | CNV / DME /AMD / drusen / normal | NA | CNV 0.999, DME 0.999, AMD 1, drusen 0.993, normal 0.998 | overall 97.1% | overall 99.3% | overall 97.1% |
| Tsuji T., et al.,2020 | Heiderberg Spectralis SDOCT | CNV/DME/drusen/normal = 37,455/11,598/8,866/26,565 images | OCT B-scans | transfer learning + capsule network | training + validation + test | CNV/ DME/ drusen / normal | shift | NA | NA | NA | 99.60% |
| Zhang Q., et al.,2020 | Heiderberg Spectralis SDOCT | CNV / DME/ drusen / normal = 10,041 / 9,783 / 8,125 / 10,108 images | OCT B-scans | Multiscale transfer learning algorithm based on VGG-16 | training + test | CNV/ DME/ drusen / normal | NA | NA | 97.70% | 97.00% | 95% |
| De Fauw J., et al.,2018 | Heiderberg Spectralis SDOCT + Topcon 3D OCT | 15,877 Topcon OCT images | OCT B-scans / segmentation map | ensemble learning with U-Net, DenseNet | training + test | segmentation map, four referral decisions and ten diagnoses | affine and elastic transformations, intensity transformations | urgent referral 0.992 and 0.993, diagnoses over 0.960 |  | NA | NA |
| Wang X., et al.,2020 | Heiderberg Spectralis SDOCT + Triton SSOCT + Bioptigen SDOCT | SDOCT: DME / normal = 865/531 volumes, SS-OCT: DME / normal = 2045 / 1203 volumes, Bioptigen SDOCT: AMD / normal = 269/115 volumes | OCT B-scans | weakly supervised learning, uncertainty-driven deep multiple instance learning + RNN | cross validation | DME / AMD / normal | random horizontal flipping, vertical flipping | 0.975-0.987 | NA | NA | 93.3%-97.9% |

**Table 3** The deep learning-based models for treatment-related and visual function prediction.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Authors** | **Task** | **Imaging device** | **Dataset** | **Type of input** | **Type of deep learning networks** | **Data set up** | **Type of output** | **Data augmentation** | **AUROC** | **Sensitivity (Recall)** | **Specificity** | **Accuracy** | **Precision** | **Agreement** | **DSC** |
| Romo-Bucheli D., et al., 2020 | treatment-related prediction | NA | 350 nAMD patients | OCT B-scans | DenseNet, RNN | training + validation + test | low/intermediate/high treatment requirement | NA | low vs. the remaining 0.85, high vs. the remaining 0.81 | low 50.0%, intermediate 61.0%, high 82.0% | low 100%, intermediate 71.0%, high 69.0% | low 90.0%, intermediate 65.0%, high 72.0% | NA | 0.59 | NA |
| Rasti R., et al., 2020 | treatment-related prediction | Heiderberg Spectralis SDOCT | responsive/non-responsive DME subjects= 80/47 | pre-treatment OCT B-scans | modification of VGG | cross validation | differential retinal thickness | NA | 0.866 | 80.10% | 85.00% | NA | 85.50% | NA | NA |
| Kawczynski M., et al., 2020 | visual function prediction | Zeiss Cirrus HDOCT | 1071 nAMD patients | OCT volumetric scans | ResNet50 | cross validation | predicted BCVA and classification of poorer/better BCVA | NA | concurrent 0.92, 12-month 0.87 | NA | NA | NA | NA | 0.79 | NA |
| Kihara Y., et al., 2019 | visual function prediction | Heiderberg Spectralis SDOCT | 63 eyes with macular telangiectasia | OCT B-scans /microperimetry sensitivity | VGG-16 | training + validation + test | retinal sensitivity prediction | image translations, rotations, horizontal reflections | NA | NA | NA | NA | NA | 0.78 | NA |

**Table 4** The deep learning-based models for segmentation.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Authors** | **Imaging device** | **Dataset** | **Type of input** | **Type of deep learning networks** | **Data set up** | **Type of output** | **Data augmentation** | **AUROC** | **Sensitivity (Recall)** | **Specificity** | **Accuracy** | **Precision** | **Agreement** | **DSC** |
| Schlegl T., et al., 2018 | Zeiss Cirrus HDOCT and Heidelberg Spectralis SDOCT | AMD / DME / RVO = 400/400/400 images | OCT B-scans | CNN | cross validation | yes/no IRC/SRF | NA | IRC 0.94, SRF 0.92 | IRC 0.84 SRF 0.81 | NA | NA | IRC 0.91 SRF 0.61 | IRC 0.90, SRF 0.96 | NA |
| Pekala M., et al., 2019 | Heiderberg Spectralis SDOCT | 50 OCTA images | OCT B-scans | DenseNet | cross validation | retinal layers segmentation | random cropping, horizontal flipping, image blurring, image sharpening, brightness adjustments | NA | NA | NA | NA | NA | NA | NA |
| Masood S., et al., 2019 | Heiderberg Spectralis SDOCT | 475 OCT images | OCT B-scans | Cifar-10 | training + test | chroid segmentation | NA | NA | NA | NA | NA | NA | NA | 0.974 |
| Kugelman J., et al., 2019 | Heiderberg Spectralis SDOCT | 594 OCT images | OCT B-scans | Cifar CNN, complex CNN, RNN, U-net | training + validation + test | ILM, RPE, CSI boundary detection | NA | NA | NA | NA | NA | NA | NA | 0.992-0.994 |
| Alam M., et al., 2020 | Optovue angiography OCT | 50 OCTA images | *En face* OCT and OCTA SCP images | U-Net | cross validation | artery and vein segmentation | random flip, rotation, zooming, image shifting | NA | NA | NA | 86.75 | NA | NA | NA |
| Lo J., et al., 2020 | Zeiss Plex Elite | 76 OCTA images | *En face* OCTA SCP and DCP images | transfer learning + U-Net | training + test | vessels segmentation | NA | NA | NA | NA | SCP 86.0% DCP 79.9% | NA | NA | SCP 0.862 DCP 0.814 |
| Guo M., et al., 2019 | Zeiss Cirrus HDOCT 5000 with AngioPlex | 405 OCTA images | *En face* OCTA SCP images | U-net | cross validation | FAZ segmentation | rotation, flipping | NA | 97.20% | 99.90% | NA | NA | 0.997 | 0.976 |
| Mirshahi R., et al., 2021 | RTVue XR 100 Avanti | DR / normal = 131 / 22 eyes | *En face* OCTA images | ResNet50 | training + validation + test | FAZ segmentation | random flip | NA | NA | NA | NA | NA | 0.94±0.04 | NA |
| RNN = recurrent neural network, IRC = intraretinal cystoid fluid, SRF = subretinal fluid, DCP = deep capillary plexus, DSC = dice similarity coefficient |

**Table 5** The deep learning-based models for image quality control.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Authors** | **Imaging device** | **Dataset** | **Type of input** | **Type of deep learning networks** | **Data set up** | **Type of output** | **Data augmentation** | **AUROC** | **Sensitivity (Recall)** | **Specificity** | **Accuracy** |
| Ran A., et al., 2019 | Cirrus HDOCT | 5,599 OCT volumetric scans | OCT volumetric optic disc scans | SE-ResNeXt | training + test | Gradable/ungradable | random flipping, random rotation, random shifting | 0.954 | 86.2% | 92.6% | 89.7% |
| Kauer J., et al., 2019 | Heiderberg Spectralis SDOCT | 944 OCT volumetric scans | OCT A-scans | CNN | training + validation + test | good/bad/upper/lower | NA | NA | NA | NA | 99.50% |
| Lauermann J., et al., 2019 | RTVue XR Avanti | sufficient/insufficient OCTA images = 100/100 | *En face* OCTA SCP images | CNN | training + validation + test | IPS / SPS | NA | NA | 90.00% | 90.00% | 90.00% |
| Gao M., et al., 2020 | RTVue-XR, Optovue | DR/healthy = 248/50 eyes | paired 3x3mm and 6x6 mm *en face* OCTA images | CNN | training + test | Reconstructed 6x6 mm OCTA images | horizontal flipping, vertical flipping, transposition, 90-degree rotation | NA | NA | NA | NA |
| Kadomoto S., et al., 2020 | OCT HS-100 | 742 subjects | *En face* OCTA SCP images | U-Net | training + test | denoised images | NA | NA | NA | NA | NA |
| SE-ResNeXt = squeeze-and-excitation residual network next |