**Multimedia Appendix 7 Deep Learning Models Characteristics.**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Study**  **ID** | **Author** | **Input Training Data** | **Main deep learning architecture** | **Specific deep learning architecture** | **DL algorithm Type pf validation** | **Performance metrics** |
| 1 | Abbasi [1] | Image features | CNN | Unspecified CNN | K-fold | ACC, PREC, REC, Jaccard-Index |
| 2 | Abbasi [2] | Image features | CNN | ResNet | K-fold | ACC, PREC, REC, Jaccard-Index |
| 3 | Ahlstrom [3] | Image features | CNN | I3D | hold-out | AUC-ROC |
| 4 | Bamford [4] | Image features, demographics, clinical and reproductive history, ART parameters , male data | DNN | MLP | K-fold | SENS, SPES,FPR, AUC-ROC, ACC,PREC,F1 |
| 5 | Benchaib [5] | Image features, demographics , ART parameters | DNN, RNN | MLP, LSTM | K-fold | AUC-ROC, ACC, PREC,REC,F1 |
| 6 | Berntsen [6] | Image features | CNN | I3D | K-fold | AUC-ROC |
| 7 | Bori [7] | Image features | DNN | MLP | hold-out | AUC-ROC |
| 8 | Bormann [8] | Image features | CNN | CNNg | hold-out | AUC-ROC |
| 9 | Boucret [9] | Image features | NA | NA | hold-out | AUC-ROC |
| 10 | Chavez-Badiola [10] | Image features | DNN | Unspecified DNN | K-fold | AUC-ROC |
| 11 | Chen [11] | Image features , demographics, Clinical and reproductive history | CNN | AMSNet, AMCFNet | hold-out | AUC-ROC |
| 12 | Cimadomo [12] | Image features | CNN | I3D | hold-out | AUC-ROC |
| 13 | Cimadomo [13] | Image features | NA | NA | K-fold | p-value |
| 14 | Cimadomo [14] | Image features | NA | NA | K-fold | p-value |
| 15 | Coticchio [15] | Image features | RNN | LSTM | K-fold | SENS, SPES, ACC,PREC,F1 |
| 16 | Danardono [16] | Image features | CNN | Inception, EfficientNet, MobileNet, ResNet | hold-out | ACC |
| 17 | Danardono [17] | Image features | CNN | VGG, DenseNet | hold-out | REC, ACC,PREC,F1 |
| 18 | Dehkordi [18] | Image features | CNN | ResNet, Unet | hold-out | ACC, PREC, REC |
| 19 | Diakiw [19] | Image features, demographics | CNN | R-CNN, ResNet | K-fold | ACC,AUC-ROC,SENS |
| 20 | Diakiw [20] | Image features | CNN | ResNet, DeneNet | hold-out | ROC,AUC-ROC,ACC |
| 21 | Dirvanauskas [21] | Image features | CNN | AlexNet | hold-out | ACC |
| 22 | Duval [22] | Image features, demographics, clinical and reproductive history , ART parameters , male data | CNN | ResNet | K-fold | AUC-ROC,ACC,ROC,SENS |
| 23 | Eastick [23] | Image features | DNN | Unspecified DNN | hold-out | p-value |
| 24 | Einy [24] | Image features | CNN, RNN | LBCNN, LSTM | hold-out | ACC, AUC-ROC,PREC, F1 |
| 25 | Ezoe [25] | Image features | CNN | I3D | hold-out | p-value |
| 26 | Ferrick [26] | Image features | CNN | I3D | K-fold | p-value |
| 27 | Fukunaga [27] | Image features | NA | NA | hold-out | ACC,SENS |
| 28 | Gomez [28] | Image features | CNN, RNN | LSTM, ResNet | K-fold | r, ACC |
| 29 | Hammer [29] | Image features | CNN | Xception, ResNet | K-fold | ACC |
| 30 | Hori [30] | Image features | DNN | Unspecified DNN | K-fold | NA |
| 31 | Huang [31] | Image features, demographics | CNN | ResNet | K-fold | AUC-ROC,ACC |
| 32 | Huang [32] | Image features | CNN | ResNet | hold-out, K-fold | AUC-ROC |
| 33 | Huang [33] | Image features | CNN | Unet | hold-out | p-value |
| 34 | Johansen [34] | Image features | CNN | I3D | hold-out | AUC-ROC |
| 35 | Kallipolitis [35] | Image features | CNN | EfficientNet, Unet, ResNet | K-fold | ACC,AUC-ROC |
| 36 | Kanakasabapathy [36] | Image features | CNN | Xception | hold-out | AUC-ROC,ACC |
| 37 | Kato [37] | Image features | CNN | I3D | hold-out | AUC-ROC |
| 38 | Khan [38] | Image features | CNN | Unspecified CNN | K-fold | ACC |
| 39 | Khosravi [39] | Image features | CNN | Inception | hold-out | ACC, AUC-ROC |
| 40 | Kragh [40] | Image features | CNN,RNN | Xception, LSTM | hold-out | ACC,MSE, AUC-ROC |
| 41 | Kragh [41] | Image features | CNN | I3D | K-fold | AUC-ROC |
| 42 | Lassen [42] | Image features, demographics | CNN | I3D | hold-out | AUC-ROC |
| 43 | Leahy [43] | Image features | CNN | R-CNN, ResNet | hold-out | ACC,PREC |
| 44 | Lee [44] | Image features | CNN | I3D | hold-out | AUC-ROC,PREC |
| 45 | Liao [45] | Image features | CNN, RNN | DenseNet, LSTM | hold-out | AUC-ROC, ACC |
| 46 | Liu [46] | Image features | CNN | ResNet | hold-out | AUC-ROC,ACC |
| 47 | Liu [47] | Image features | CNN | ResNet, AlexNet | hold-out | MSE, ACC |
| 48 | Lockhart [48] | Image features | CNN | Unet | K-fold | ACC |
| 49 | Lukyanenko [49] | Image features | CNN,RNN | ResNet, LSTM | hold-out | ACC |
| 50 | Mapstone [50] | Image features | CNN | MobileNet | hold-out | AUC-ROC, ACC |
| 51 | Marsh [51] | Image features | CNN | ResNet, DenseNet | hold-out | AUC-ROC |
| 52 | Milewski [52] | Image features, demographics | DNN | MLP | hold-out | AUC-ROC |
| 53 | Nagaya [53] | Image features | CNN | ResNet | k-fold | AUC-ROC,PREC,FPR,NPV |
| 54 | Nguyen [54] | Image features | CNN | ResNet | K-fold | AUC-ROC,PREC,ACC |
| 55 | Ou [55] | Image features | CNN, Transformer | AlexNet, EfficientNet, Swin-T | hold-out | ACC,SENS,PPV,NPV,SPES |
| 56 | Papamentzelopoulou [56] | Image features | CNN | I3D | hold-out | AUC-ROC, p-value |
| 57 | Patil [57] | Image features | CNN | Unspecified CNN | hold-out | SPES,SENS,ACC |
| 58 | Paya [58] | Image features | CNN | ResNet, VGG, MLP | hold-out | ACC,PREC,SENS,SPES,F1,AUC-ROC |
| 59 | Rajendran [59] | Image features, demographics | CNN, RNN | LSTM, VGG | K-fold | AUC-ROC,MAE,ACC |
| 60 | Raudonis [60] | Image features | CNN | AlexNet, VGG | K-fold | ACC,PREC |
| 61 | Rocha [61] | Image features | DNN | Unspecified DNN | hold-out | ACC |
| 62 | Sawada [62] | Image features | CNN | ABN | K-fold | AUC-ROC |
| 63 | Sharma [63] | Image features | CNN, Transformer | DETR,YOLO | hold-out | PREC,AUPRC, SPES,ACC,F1, MCC |
| 64 | Thirumalaraju [64] | Image features | CNN | Iception, ResNet , NASNet, Xception | hold-out | AUC-ROC, ACC,SENS,SPES |
| 65 | Tran [65] | Image features | DNN | Unspecified DNN | K-fold, hold-out | AUC-ROC |
| 66 | Tran [66] | Image features | CNN | YOLO | hold-out | ACC,PREC |
| 67 | Ueno [67] | Image features | CNN | I3D | hold-out | AUC-ROC |
| 68 | Uysal [68] | Image features | CNN | Unet | K-fold | Jaccard-index,Dice,ACC,PREC |
| 69 | Vaidya [69] | Image features | CNN,RNN | LSTM, VGG, Xception,Inception, MobileNet, DenseNet, GRU | hold-out | MSE,ACC |
| 70 | Vergos [70] | Image features | CNN | AlexNet ,VGG | hold-out | PREC,F1,ACC |
| 71 | Wang [71] | Image features | CNN | DeepLab | hold-out | p-value |
| 72 | Wang [72] | Image features | CNN, Transformer | BYOL, IVFormer | k-fold | AUC-ROC, SPES |
| 73 | Xie [73] | Image features | CNN | AMSNet, TSM,MFS,ResNet | hold-out | AUC-ROC, ACC |
| 74 | Yuan [74] | Image features, demographics, ART parameters | CNN | Unspecified CNN | hold-out | AUC-ROC,SEN, SPEC, p-value |
| 75 | Zhao [75] | Image features | CNN | Unspecified CNN | K-fold | PREC,ACC |
| 76 | Zhu [76] | Image features, Clinical and reproductive history | CNN | I3D | hold-out | AUC-ROC |
| 77 | Zou [77] | Image features, demographics, ART parameters, male data | RNN | LSTM | K-fold | AUC-ROC,ACC,F1,PREC, AUPRC |

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