

MDBrain | MDProstate

- 1.1 Akhondi-Asl, A., and Warfield. S. K. (2013). Simultaneous truth and performance level estimation through fusion of probabilistic segmentations. *IEEE Trans. Med. Imaging* 32, 1840-1852. doi: 10.1109/TMI.2013.2266258
- 1.2 Allay, E. E.. Fisher. E.. Jones. S. E., Hara-Cleaver, G, Lee, L-G, and Rudick, R. A. (2013). Reliability of classifying multiple sclerosis disease activity using magnetic resonance imaging in a multiple sclerosis clinic. *JAMA Neurol.* 70, 338-344. doi: 10.1001/2013.jamaneuroL211
- 1.3 Battaglini, M.. Rossi, F.» Grove, R. A., Stromillo, M. L, Whitcher, B., Matthews, P. M.. et al. (2014). Automated identification of brain new lesions in multiple sclerosis using subtraction images. *I. Magn. Reson. Imaging* 39, 1543-1549. doi: 10.1002/jmri .24293
- 1.4 Baur, G, Denner, S., Wiestler, B., Navab, N., and Albarqouni, S. (2021). Autoencoders for unsupervised anomaly segmentation in brain MR images: a comparative study. *Med. Image Anal.* 69:101952. doi: 10.1016/j.media.2020.101952
- 1.5 Bose, M., Heitz. F.» Armspach, J.-P.» Namer, L, Gounot, D., and Rumbach. L (2003). Automatic change detection in multimodal serial MRI: application to multiple sclerosis lesion evolution. *NeuroImage* 20, 643-656. doi: 10.1016/ZS1053-8119(03)00406 3
- 1.6 Brownlee, W. J., Altmann. D. R.. Prados, F., Miszkiel, K. A.. Eshaghi, A., Gandini Wheeler-Kingshott, Q A., et aL (2019). Early imaging predictors of long-term outcomes in relapse-onset multiple sclerosis. *Brain* 142, 2276-2287. doi: !0.1093/brain/awz156
- 1.7 Carass, A., Roy, log. A., Cuzzocreo. J. L, Magrath, E., Gherman, A., et al. (2017). Longitudinal multiple sclerosis lesion segmentation: resource and challenge. *NeuroImage* 148,77-102. doi: 10.1016/j.neuroimage2016.12.064
- 1.8 Qtek, O., Abdulkadir, A., Iienkamp, S. S.. Brox, T.» and Ronneberger, O. (2016). "3D U-Net learning dense volumetric segmentation from sparse annotation." in International Conference on Medical Image Computing and Computer-Assisted Intervention (Athens: Springer), 424-432.
- 1.9 Commowick, O.. Istace, A.. Kain, M.» Laurent. B.. Leray, F., Simon, M.. et al. (2018). Objective evaluation of multiple sclerosis lesion segmentation using a data management and processing infrastructure. *Sci. Rep.* 8, 1-17. doi: 10.1038/S41598-018-31911-7
- 1.10 Egger, G, Opfer, R., Wang, C.» Kepp, T.» Sormani, M. P.. Spies, L, et aL (2017). MRI FLAIR lesion segmentation in multiple sclerosis: does automated segmentation hold up with manual annotation? *NeuroImage Clin.* 13, 264-270. doi: 10.1016/j.nicl.2016.11.020

- 1.11 Fartaria, M. I., Kober, T., Granziera, G., and Cuadra, M. B. (2019). Longitudinal analysis of white matter and cortical lesions in multiple sclerosis. *NeuroImage Clin.* 23:101938. doi: 10.1016/j.nid.2019.101938
- 1.12 Filippi, M., Preziosa, P., Banwell, B. L., Barkhof, F., Ciccarelli, O., De Stefano, N., et al. (2019). Assessment of lesions on magnetic resonance imaging in multiple sclerosis: practical guidelines. *Brain* 142, 1858–1875. doi: 10.1093/brain/awz144
- 1.13 Ganiler, O., Oliver, A., Diez, Y., Freixenet, L., Vilanova, J. G., Beltran, B., et al. (2014). A subtraction pipeline for automatic detection of new appearing
- 1.14 multiple sclerosis lesions in longitudinal studies. *Neuroradiology* 56, 363–374. doi: 10.1007/s00234-014-1343-1
- 1.15 Garcia-Lorenzo, D., Francis, S., Narayanan, S., Arnold, D. L., and Collins, D. L. (2013). Review of automatic segmentation methods of multiple sclerosis white matter lesions on conventional magnetic resonance imaging. *Med. Image Anal.* 17, 1–18. doi: 10.1016/j.media.2012.09.004
- 1.16 Gessert, N., Bengs, M., Kruger, J., Opfer, R., Ostwaldt, A.-G., Manogaran, P., et al. (2020a). 4D deep learning for multiple sclerosis lesion activity segmentation. *arXivpreprint arXiv:2004.09216*. doi: 10.48550/arXiv.2004.09216
- 1.17 Gessert, N., Krüger, J., Opfer, R., Ostwaldt, A.-G., Manogaran, P., Kitzler, H. H., et al. (2020b). Multiple sclerosis lesion activity segmentation with attention-guided two-path CNNs. *Comput. Med. Imaging Graph.* 84:101772. doi: 10.1016/j.compmedimag.2020.101772
- 1.18 Henschel, L., Conjeti, S., Estrada, S., Diers, K., Fischl, B., and Reuter, M. (2020). FastSurfer-a fast and accurate deep learning based neuroimaging pipeline. *NeuroImage* 219:117012. doi: 10.1016/j.neuroimage.2020.117012
- 1.19 Isensee, F., Laeger, P. F., Kohl, S. A., Petersen, J., and Maier-Hein, K. H. (2021). nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. *Nat. Methods* 18, 203–211. doi: 10.1038/s41592-020-01008-z
- 1.20 Kruger, J., Opfer, R., Gessert, N., Ostwaldt, A.-G., Manogaran, P., Kitzler, H. H., et al. (2020). Fully automated longitudinal segmentation of new or enlarged multiple sclerosis lesions using 3D convolutional neural networks. *NeuroImage Clin.* 28:102445. doi: 10.1016/j.nid.2020.102445
- 1.21 Kuhlmann, T., Ludwin, S., Prat, A., Antel, J., Bruck, W., and Lassmann, H. (2017). An updated histological classification system for multiple sclerosis lesions. *Acta Neuropathol.* 133, 13–24. doi: 10.1007/s00401-016-1653-y

- 1.22 Lao, Z., Shen, D., Liu, D., Jawad, A. F., Melhem, E. R., Launer, L. L. et al. (2008). Computer-assisted segmentation of white matter lesions in 3D MR images using support vector machine. *Acad. Radiol.* 15:300-313. doi: 10.1016/j.acra~2007.10.012
- 1.23 Ma, I. (2021). Cutting-edge 3D medical image segmentation methods in 2020: are happy families all alike? *arXiv preprint arXiv.2101.00232*. doi: 10.48550/arXiv.2101.00232
- 1.24 Ma, Y., Zhang, G., Cabezas, M., Song, Y., Tang, Z., Liu, D., et al. (2022). Multiple sclerosis lesion analysis in brain magnetic resonance images: techniques and clinical applications. *IEEE Trans. Biomed. Health Inform.* doi: 10.1109/JBHI2022.3151741
- 1.25 McKinley, R., Wepfer, R., Grander, L., Aschwanden, F., Fischer, T., Friedli, G., et al. (2020). Automatic detection of lesion load change in multiple sclerosis using convolutional neural networks with segmentation confidence. *NeuroImage Clin.* 25:102104. doi: 10.1016/j.nicd2019.102104
- 1.26 McKinley, R., Wepfer, R., Gundersen, T., Wagner, F., Chan, A., Wiest, R., et al. (2016). "Nabia-net: A deep dag-like convolutional architecture for biomedical image segmentation," in International Workshop on Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries (Athens: Springer), 119-128.
- 1.27 Mortazavi, D., Kouzani, A. Z., and Soltanian-Zadeh, H. (2012). Segmentation of multiple sclerosis lesions in MR images: a review. *Neuroradiology* 54, 299-320. doi: 10.1007/s00234-011-0886-7
- 1.28 Ronneberger, O., Fischer, P., and Brox, T. (2015). "U-Net: convolutional networks for biomedical image segmentation," in International Conference on Medical Image Computing and Computer-Assisted Intervention (Munich: Springer), 234-241. doi: 10.1007/978-3-319-24574-4_28
- 1.29 Roy, A. G., Conjeti, S., Navab, N., Wachinger, C., Initiative, A. D. N., et al. (2019). QuickNAT: a fully convolutional network for quick and accurate segmentation of neuroanatomy. *NeuroImage* 186, 713-727. doi: 10.1016/j.neuroimage.2018.11.042
- 1.30 Salem, M., Cabezas, M., Valverde, S., Pareto, D., Oliver, A., Salvi, J., et al. (2018). A supervised framework with intensity subtraction and deformation field features for the detection of new T2-w lesions in multiple sclerosis. *NeuroImage Clin.* 17, 607-615. doi: 10.1016/j.nicd2017.11.015
- 1.31 Salem, M., Valverde, S., Cabezas, M., Pareto, D., Oliver, A., Salvi, J., et al. (2020). A fully convolutional neural network for new T2-w lesion detection in multiple sclerosis. *NeuroImage Clin.* 25:102149. doi: 10.1016/j.nicd2019.102149
- 1.32 Schmidt, P., Gaser, Q., Arsic, M., Buck, D., Forschler, A., Berthele, A., et al. (2012). An automated tool for detection of flair-hyperintense

- white-matter lesions in multiple sclerosis. *Neuroimage* 59, 3774-3783. doi: 10.1016/j.neuroimage2011.11.032
- 1.33 Schmidt, P., Pongratz, V., Küster, P., Meier, D., Wuerfel, J., Lukas, Q., et al (2019). Automated segmentation of changes in flair-hyperintense white matter lesions in multiple sclerosis on serial magnetic resonance imaging. *NeuroImage Clin.* 23:101849. doi: 10.1016/j.nic.2019.101849
- 1.34 Shiee, N., Bazin, P.-L., Ozturk, A., Reich, D. S., Calabresi, P. A., and Pham, D. L (2010). A topology-preserving approach to the segmentation of brain images with multiple sclerosis lesions. *NeuroImage* 49, 1524-1535. doi: 10.1016/j.neuroimage.2009.09.005
- 1.35 Sormani, M. P., Gasperini, C., Romeo, M., Rio, J., Calabrese, M., Cocco, E., et al (2016). Assessing response to interferon-/? in a multicenter dataset of patients with MS. *Neurology* 87, 134-140. doi: 10.1212/WNL.00000000000002830
- 1.36 Sundaresan, V., Zamboni, G., Rothwell, P. M., Jenkinson, M., and Griffanti, L (2021). Triplanar ensemble U-Net model for white matter hyperintensities segmentation on MR images. *Med. Image Anal.* 73:102184. doi: 10.1016/j.mediaJ2021.102184
- 1.37 Thompson, A. J., Banwell, B. L., Barkhof, F., Carroll, W. M., Coetze, T., Comi, G., et al (2018). Diagnosis of multiple sclerosis: 2017 revisions of the McDonald criteria. *Lancet Neurol.* 17, 162-173. doi: 10.1016/S1474-4422(17)30470-2
- 1.38 Van Leemput, K., Maes, F., Vandermeulen, D., Colchester, A., and Suetens, P. (2001). Automated segmentation of multiple sclerosis lesions by model outlier detection. */EEE Trans. Med. Imaging* 20, 677-688. doi: 10.1109/42.938237
- 1.39 Walker, E., and Nowacki, A. S. (2011). Understanding equivalence and noninferiority testing. */. Gen. Intern. Med.* 26, 192-196. doi: 10.1007/s11606-010-1513-8
- 1.40 Wu, Z., Shen, C., and Hengel, A. v. d. (2016). Bridging category-level and instance-level semantic image segmentation. *arXiv preprint arXiv:1605.06885*. doi: 10.48550/arXiv.1605.06885
- 1.41 Zhang, H., and Oguz, I. (2020). “Multiple sclerosis lesion segmentation-a survey of supervised CNN-based methods,” in *International MICCAI Brainlesion Workshop* (Lima: Springer), 11-29.
- 1.42 Kuijf, H. J., Biesbroek, J. M., De Bresser, J., Heinen, R., Andermatt, S., Bento, M.,... & Biessels, G. J. (2019). Standardized assessment of automatic segmentation of white matter hyperintensities and results of the WMH segmentation challenge. *IEEE transactions on medical imaging*, 38(11), 2556-2568.
- 1.43 Mazurowski, M. A., Buda, M., Saha, A., & Bashir, M. R. (2019). Deep learning in radiology: An overview of the concepts and a survey of

- the state of the art with focus on MRI. *Journal of magnetic resonance imaging*, 49(4), 939-954.
- 1.44 Fiani, B., Pasko, K. B. D., Sarhadi, K., & Covarrubias, C. (2021). Current uses, emerging applications, and clinical integration of artificial intelligence in neuroradiology. *Reviews in the Neurosciences*.
- 1.45 Mann, P., Ziener, C., Michaely, H., Ferrera Bertrán, P., Fenchel, M., Opalka, J., & Lemke, A. (2020). mdbrain vs. FreeSurfer: Reproduzierbarkeits- und Performancemessungen in der Hirnvolumetrie. <https://doi.org/10.1055/S-0040-1703406>
- 1.46 Diekmeyer, M., Roy, A. G., Senapati, J., Wachinger, C., Grundl, L., Dbpfert, J.,... & Hedderich, D. M. (2021). Effect of MRI acquisition acceleration via compressed sensing and parallel imaging on brain volumetry. *Magnetic Resonance Materials in Physics, Biology and Medicine*, 1-11.
- 1.47 Rudolph, J., Rückel, J., Dbpfert, J., Ling, X., Opalka, J., Brem, C., et al. (2021). Artificial intelligence substantially improves differential diagnosis of dementia-added diagnostic value of rapid brain volumetry. *Clinical Neuroradiology*, 31 (Supplement 1), 21-22.
- 1.48 Rakic, M., Vercruyssen, S., Van Eynghoven, S., de la Rosa, E., Jain, S., Van Huffel, S & Sima, D. M. (2021). icobrain ms 5.1: Combining unsupervised and supervised approaches for improving the detection of multiple sclerosis lesions. *NeuroImage: Clinical*, 31, 102707.
- 1.49 Bash, S., Wang, L., Airriess, C., Zaharchuk, G., Gong, E., Shankaranarayanan, A., & Tanenbaum, L. N. (2021). Deep Learning Enables 60% Accelerated Volumetric Brain MRI While Preserving Quantitative Performance: A Prospective, Multicenter, Multireader Trial. *American Journal of Neuroradiology*, 42(12), 2130-2137.
- 1.50 Pemberton, H. G., Zaki, L. A., Goodkin, O., Das, R. K., Steketee, R. M., Barkhof, F., & Vernooij, M. W. (2021). Technical and clinical validation of commercial automated volumetric MRI tools for dementia diagnosis—a systematic review. *Neuroradiology*, 63(11), 1773-1789.
- 1.51 van Leeuwen, K. G., Schalekamp, S., Rutten, M. J., van Ginneken, B., & de Rooij, M. (2021). Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. *European radiology*, 31 (6), 3797-3804.
- 1.52 Zaki, L. A., Vernooij, M. W., Smits, M., Tolman, C., Papma, J. M., Visser, J. J., & Steketee, R. M. (2022). Comparing two artificial intelligence software packages for normative brain volumetry in memory clinic imaging. *Neuroradiology*, 1-8.12. Sima, D., Wilms, G., Vyvere, T. V., Van Hecke, W., & Smeets, D. (2020, January). On the use of icobrain's prepopulated radiology reporting template for multiple sclerosis follow-up. European Congress of Radiology-ECR 2020.

- 1.53 van Winkel, S. L., Rodríguez-Ruiz, A., Appelman, L., Gubern-Mérida, A., Karssemeijer, N., Teuwen, J., ... & Mann, R. M. (2021). Impact of artificial intelligence support on accuracy and reading time in breast tomosynthesis image interpretation: a multi-reader multi-case study. *European Radiology*, 1-10.
- 1.54 Martini, K., Blüthgen, C., Eberhard, M., Schbnenberger, A. L. N., De Martini, I., Huber, F. A & Frauenfelder, T. (2021). Impact of vessel suppressed-CT on diagnostic accuracy in detection of pulmonary metastasis and reading time. *Academic radiology*, 28(7), 988-994.
- 1.55 McDonald, W. I., Compston, A., Edan, G., Goodkin, D., Hartung, H. P., Lublin, F. D & Wolinsky, J. S. (2001). Recommended diagnostic criteria for multiple sclerosis: guidelines from the International Panel on the diagnosis of multiple sclerosis. *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society*, 50(1), 121-127.
- 1.56 Polman, C. H., Reingold, S. C., Banwell, B., Clanet, M., Cohen, J. A., Filippi, M & Wolinsky, J. S. (2011). Diagnostic criteria for multiple sclerosis: 2010 revisions to the McDonald criteria. *Annals of neurology*, 69(2), 292-302.
- 1.57 Filippi, M., Rocca, M. A., Ciccarelli, O., De Stefano, N., Evangelou, N., Kappos, L., ... & MAGNIMS Study Group. (2016). MRI criteria for the diagnosis of multiple sclerosis: MAGNIMS consensus guidelines. *The Lancet Neurology*, 15(3), 292-303.
- 1.58 Meissner, J.E., Fritz, T., Opalka, J., Michaely, H. & Mann, P. (2020) Characterization of MS lesions: Comparison of a new deep learning based solution with academic standard. Presentation EAN 2020
- 1.59 Zidan, M., Mann, P., Gnirs, R., Meissner, J.E., Paech, D., Opalka, J. & Jesser, J. (2020) Automated volumetry measurements for different field strengths – a feasibility study. Presentation EAN 2020.
- 1.60 Döpfert, J. & Opalka, J. (2020) mdbrain – Deep Learning in der Radiologie . Med Engineering 3: 12-13.
- 1.61 Notohamiprodjo, M., Krause, L., Lummel, N., Baum, T., Röttinger, M. & Kleiter, I (2021) Vergleich von zwei Software-Lösungen zur automatisierten Quantifizierung des Hirn- und Läsionsvolumens bei Multiple-Sklerose-Patienten. *Fortschr Röntgenstr*; 193: S25.
- 1.62 Meissner, J.E., Mann, P., Michaely, H., Opalka, J. & Lemke, A. Application of Deep Learning for a reliable MRI-based diagnosis for Progressive Supranuclear Palsy (PSP). Presentation ECR 2021.
- 1.63 Hock, S.W., Marterstock, D., Mayer, A.L., Betray, C., Huhn, K., Rothhammer, V., Dörfler, A., Schmidt, M. (2021) Latest Artificial Intelligence Provides Fast, Accurate and Consistent Detection of Multiple Sclerosis Lesions Clinical Neuroradiology, 31(Supplement 1), 41-42.

- 1.64 Mayer, A.L., Mennecke, A., Hock, S.W., Marterstock, D., Rösch, J., Hamer, H., Kasper, B., Dörfler, A., Schmidt, M. (2021) KI-basierte Volumetriealgorithmen zur Unterstützung bei der bildgebenden Epilepsiediagnostik. *Clinical Neuroradiology*, 31(Supplement 1), 29-30.
- 1.65 Aruci, M., Dünnwald, M., Schreiber, F., Sciarra, A., Maass, A., Schreiber, S., Oeltze-Jafra, S. (2021) Challenging cases for WMH segmentation comparatively processed by seven automated methods. *Clinical Neuroradiology*, 31(Supplement 1), 40-41.
- 1.66 Mittenentzwei, S., Sciarra, A., Lüsebrink, F., Aruci, M., Ulbrich, P., Schreiber, F., Lemke, A., Meuschke, A., Preim, B., Schreiber, S., Oeltze-Jafra, S. (2021) Visual analysis of brain lesion load in patients with cerebral small vessel disease. *Clinical Neuroradiology*, 31(Supplement 1), 41-42.
- 1.67 Klail T., Radojewski P. (Inselspital Bern): AI-Assistant in the MRI-based Diagnostics of Small Intracranial Aneurysms. Poster@SCR2022
- 1.68 Dalbis T, Grilo J, Hitziger S, Ling WX, Opalka JR, Lemke A: Deep learning-based detection and segmentation of new MS lesions using optimized merging of orientations. iPoster@ECR2022
- 1.69 Opalka J, Ferrera Bertran P, Lemke A: mdbrain vs. FreeSurfer & SPM: Repeatability and performance of different methods for brain volumetry. Presentation@ECR2022
- 1.70 Dalbis T, Grilo J, Hitziger S, Ling WX, Opalka JR, Lemke A: Segmentation of MS Lesions Accuracy of mdbrain 4.5 versus a pool of human experts. Presentation@ECR2022
- 1.71 Albert J, Fernandez M, Thauerer M, Egger K, Gärtner F, Peters S, Hock S, Trautmann D, Opalka J: Real-life evaluation of the AI-based neuroradiology suite mdbrain. Presentation@ECR2022
- 1.72 Dalbis T, Albert J, Fernandez M, Thauerer M, Egger K, Gärtner F, Peters S, Hock S, Schmidt MA, Trautmann D, Opalka J, Zahn T: Evaluation of the AI-based neuroradiology system mdbrain in a real-life setting. Submitted to European Radiology 10/2022
- 1.73 Dalbis T, Fritz T, Grilo J, Hitziger S, Ling WX (2022) Triplanar U-Net with Lesion-wise Voting for the Segmentation of New Lesions on Longitudinal MRI Studies. *Front. Neurosci.* 16:964250
- 1.74 Lehn NC, Haase R, Schmeel C, Dorn D, Radbruch A, Paech D (2022) Automated Detection of Cerebral Aneurysms on TOF-MRA Using a Deep Learning Approach: An External Validation Study. *American Journal of Neuroradiology* 43 (12) 1700-1705
- 1.75 Kromrey ML, Grothe S, Nell C, Rosenberg B (2022): Künstliche Intelligenz in der Radiologie. *Radiologie up2date*. 22 (2): 121-136
- 1.76 Rudolph, J.; Rueckel, J.; Döpfert, J.; Ling, W.; Opalka, J.; Brem, C. ; Hesse, N.; Ingenerf, M.; Koliogiannis, V.; Solyanik, O.; Zimmermann,

- H.; Flatz, W.; Forbrig, R.; Patzig, M.; Rauchmann, B.; Perneczky, R., ; Peters, O.; Priller, J.; Schneider, A.; Fliessbach, K.; Hermann, A.; Wiltfang, J.; Jessen, F.; Dützel, E.; Bürger, K.; Teipel, S.; Laske, C.; Synofzik, M.; Spottke, A.; Ewers, M.; Dechent, P.; Haynes, J. D.; Liebig, T.; Ricke, J.; Ingrisch, M.; Stoeöcklein, S.: Artificial intelligence substantially improves differential diagnosis of dementia – Added diagnostic value of rapid brain volumetry. To be submitted 12/2022
- 1.77 Lehnen NC, Haase R, Schmeel C, Dorn D, Radbruch A, Paech D (2022) Automatisierte Detektion zerebraler Aneurysmen mit einer KI-Software. Clin Neuroradiol (2022) (Suppl 1) 32:S53.
- 1.78 Fagotti, C.; Caldarelli, G.; Mancini, S.; Bellini, M.; Bruno, F.; Spendiani, A.; Masciocchi, M.: Concordanza tra segmentazione manuale e segmentazione automatica delle placche de sclerosi multipla effettuata da diversi lettori su immagini die risonanza magnetica ache tramite l'utilizzo die un software die intelligenza artificiale. Poster@AINR2022
- 1.79 Fagotti, C.; Caldarelli, G.; Borea, F.; Martino, S.; Bruno, A.; Catalucci, A.; Spendiani, A.; Masciocchi, M.: Analisi delle volumetrie cerebrali in pazienti con tremore essentiale (TE) e Parkinson tremorigeno (PD) sottoposti ad ablazione del VIM con MRgFUS. Poster@AINR2022
- 1.80 Bruno, F. et al. (2023) Evaluation of Cerebral Volume Changes in Patients with Tremor Treated by MRgFUS Thalamotomy. Life. 13, 16
- 1.81 Haase, R. et al. (2023) Quantitative Neuroimaging: Automated Brain Volumetry in Patients with Huntington's Disease submitted 12/2022 to Neurology
- 1.82 Bendella Z, Widmann CN, Layer JP, Layer YL, Haase R, Sauer M, Bieler L, Lehnen NC, Paech D, Heneka MT, Radbruch A, Schmeel FC. Brain Volume Changes after COVID-19 Compared to Healthy Controls by Artificial Intelligence-Based MRI Volumetry. Diagnostics. 2023; 13(10):1716.
- 1.83 Rechtman, A., Brill, L., Zveik, O., Uliel, B., Haham, N., Bick, A. S., Levin, N., & Vaknin Dembinsky, A. (2022). Volumetric Brain Loss Correlates With a Relapsing MOGAD Disease Course. Frontiers in Neurology, 13(March), 1–11. <https://doi.org/10.3389/fneur.2022.867190>
- 1.84 Veronika Purrer, Emily Pohl, Julia M Lueckel, Valeri Borger, Malte Sauer, Alexander Radbruch, Ullrich Wüllner, Frederic Carsten Schmeel, Artificial-intelligence-based MRI brain volumetry in patients with essential tremor and tremor-dominant Parkinson's disease, Brain Communications, Volume 5, Issue 6, 2023, fcad271, <https://doi.org/10.1093/braincomms/fcad271>
- 1.85 Changes in MRI Workflow of Multiple Sclerosis after Introduction of an AI-software: a qualitative study

- 1.86 Lehnen, N.C., Schievelkamp, AH., Gronemann, C. et al. Impact of an AI software on the diagnostic performance and reading time for the detection of cerebral aneurysms on time of flight MR-angiography. *Neuroradiology* (2024).
<https://doi.org/10.1007/s00234-024-03351-w>
- 1.87 Winkel, D. J., Tong, A., Lou, B., Kamen, A., Comaniciu, D., Disselhorst, J. A & Boll, D. T. (2021). A novel deep learning based computer-aided diagnosis system improves the accuracy and efficiency of radiologists in reading biparametric magnetic resonance images of the prostate: results of a multireader, multicase study. *Investigative Radiology*, 56(10), 605-613.
- 1.88 Development, multi-institutional external validation, and algorithmic audit of an artificial intelligence-based Side-specific Extra-Prostatic Extension Risk Assessment tool for patients undergoing radical prostatectomy: a retrospective cohort study. *The Lancet Digital Health* Vol 5, No. 7, e445, Published May 19, 2023
Jetro CC Kwong, Adree Khondker, Eric Meng, Nicholas Taylor, Cynthia Kuk, Nathan Perlis, and others.
- 1.89 An integrated nomogram combining deep learning, Prostate Imaging-Reporting and Data System (PI-RADS) scoring, and clinical variables for identification of clinically significant prostate cancer on biparametric MRI: a retrospective multicentre study. *The Lancet Digital Health*, Vol 3, No 7, e445-e454, Published July, 2021.
Amogh Hiremath, Rakesh Shiradkar, Pingfu Fu, Amr Mahran, Adeshir R Rastinehad, Ashutosh Tewari
- 1.90 Application os a novel machine learning framework for predicting non-metastatic prostate cancer-specific mortality in men using the Surveillance, Epidemiology, and End Results database. *The Lancet Digital Health*, Vol 3, No 3, e158-e165, Published February 3, 2021.
Changhee Lee, Alexander Light, Ahmed Alaa, David Thurtle, Mihaela van der Schaar, Vincent Gnanapragasam
- 1.91 An artificial intelligence algorithm for prostate cancer diagnosis in whole slide images of core needle biopsies: a blinded clinical validation and deployment study. *The Lancet Digital Health*, Vol 2, No 8, e407-e416, Published August, 2020. Liron Pantanowitz, Gabriel M Quiroga-Garza, Lilach Bien, Ronen Heled, Daphna Laifenfeld, Chaim Linhart.
- 1.92 Clinical Deployment of AI for prostate cancer diagnosis. *The Lancet Digital Health*, Vol 2, No 8, e383-e384, Published August, 2020.
Andrew Janowczyk, Patrick Leo, Mark A Rubin