References

[1] T. Zhou, S. Ruan, and S. Canu, “A review: Deep learning for medical image segmentation using multi-modality fusion,” *Array*, vol. 3–4, p. 100004, Sep. 2019, doi: 10.1016/j.array.2019.100004.

[2] L. Cai, J. Gao, and D. Zhao, “A review of the application of deep learning in medical image classification and segmentation,” *Ann Transl Med*, vol. 8, no. 11, pp. 713–713, Jun. 2020, doi: 10.21037/atm.2020.02.44.

[3] W. G. Bradley, “History of Medical Imaging,” *Proceedings of the American Philosophical Society*, vol. 152, no. 3, pp. 349–361, 2008.

[4] G. J. Bansal, “Digital radiography. A comparison with modern conventional imaging,” *Postgraduate Medical Journal*, vol. 82, no. 969, pp. 425–428, Jul. 2006, doi: 10.1136/pgmj.2005.038448.

[5] C. Thion Ming, Z. Omar, N. H. Mahmood, and S. Kadiman, “A Literature Survey of Ultrasound and Computed Tomography-Based Cardiac Image Registration,” *Jurnal Teknologi*, vol. 74, no. 6, May 2015, doi: 10.11113/jt.v74.4672.

[6] P. Blake, B. Johnson, and J. W. VanMeter, “Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT): Clinical Applications:,” *Journal of Neuro-Ophthalmology*, vol. 23, no. 1, pp. 34–41, Mar. 2003, doi: 10.1097/00041327-200303000-00009.

[7] L. J. Lee, C. S. Kidwell, J. Alger, S. Starkman, and J. L. Saver, “Impact on Stroke Subtype Diagnosis of Early Diffusion-Weighted Magnetic Resonance Imaging and Magnetic Resonance Angiography,” *Stroke*, vol. 31, no. 5, pp. 1081–1089, May 2000, doi: 10.1161/01.STR.31.5.1081.

[8] R. Kumar *et al.*, "Magnetic resonance imaging and positron emission tomography-computed tomography evaluation of soft tissue sarcoma with surgical and histopathological correlation," *Indian J Nucl Med*, vol. 27, no. 4, p. 213, 2012, doi: 10.4103/0972-3919.115390.

[9] M. Kransdorf *et al.*, "Soft-tissue masses: diagnosis using MR imaging," *American Journal of Roentgenology*, vol. 153, no. 3, pp. 541–547, Sep. 1989, doi: 10.2214/ajr.153.3.541.

[10] R. Bitar *et al.*, "MR Pulse Sequences: What Every Radiologist Wants to Know but Is Afraid to Ask," *RadioGraphics*, vol. 26, no. 2, pp. 513–537, Mar. 2006, doi: 10.1148/rg.262055063.

[11] I. Despotović, B. Goossens, and W. Philips, "MRI Segmentation of the Human Brain: Challenges, Methods, and Applications," *Computational and Mathematical Methods in Medicine*, vol. 2015, pp. 1–23, 2015, doi: 10.1155/2015/450341.

[12] E.-S. A. El-Dahshan, H. M. Mohsen, K. Revett, and A.-B. M. Salem, "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm," *Expert Systems with Applications*, vol. 41, no. 11, pp. 5526–5545, Sep. 2014, doi: 10.1016/j.eswa.2014.01.021.

[13] J. Mohan, V. Krishnaveni, and Y. Guo, "A survey on the magnetic resonance image denoising methods," *Biomedical Signal Processing and Control*, vol. 9, pp. 56–69, Jan. 2014, doi: 10.1016/j.bspc.2013.10.007.

[14] S. V. Mohd Sagheer and S. N. George, "A review on medical image denoising algorithms," *Biomedical Signal Processing and Control*, vol. 61, p. 102036, Aug. 2020, doi: 10.1016/j.bspc.2020.102036.

[15] L. Gondara, “Medical image denoising using convolutional denoising autoencoders,” *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, pp. 241–246, Dec. 2016, doi: 10.1109/ICDMW.2016.0041.

[16] Y. Jin, L. M. Fayad, and A. F. Laine, “Contrast enhancement by multiscale adaptive histogram equalization,” San Diego, CA, Dec. 2001, pp. 206–213. doi: 10.1117/12.449705.

[17] M. Ganzetti, N. Wenderoth, and D. Mantini, “Intensity Inhomogeneity Correction of Structural MR Images: A Data-Driven Approach to Define Input Algorithm Parameters,” *Front. Neuroinform.*, vol. 10, Mar. 2016, doi: 10.3389/fninf.2016.00010.

[18] M. Bekiesińska-Figatowska, “Artifacts in Magnetic Resonance Imaging,” *Pol J Radiol*, vol. 80, pp. 93–106, 2015, doi: 10.12659/PJR.892628.

[19] J. N. Morelli *et al.*, “An Image-based Approach to Understanding the Physics of MR Artifacts,” *RadioGraphics*, vol. 31, no. 3, pp. 849–866, May 2011, doi: 10.1148/rg.313105115.

[20] J. Veraart, E. Fieremans, I. O. Jelescu, F. Knoll, and D. S. Novikov, “Gibbs ringing in diffusion MRI: Gibbs Ringing in Diffusion MRI,” *Magn. Reson. Med.*, vol. 76, no. 1, pp. 301–314, Jul. 2016, doi: 10.1002/mrm.25866.

[21] E. R. McVeigh, R. M. Henkelman, and M. J. Bronskill, “Noise and filtration in magnetic resonance imaging: Noise and filtration in magnetic resonance imaging,” *Med. Phys.*, vol. 12, no. 5, pp. 586–591, Sep. 1985, doi: 10.1118/1.595679.

[22] R. Maitra and D. Faden, “Noise Estimation in Magnitude MR Datasets,” *IEEE Trans. Med. Imaging*, vol. 28, no. 10, pp. 1615–1622, Oct. 2009, doi: 10.1109/TMI.2009.2024415.

[23] S. Aja-Fernandez and A. Tristan-Vega, “A review on statistical noise models for Magnetic 1 Resonance Imaging,” p. 23.

[24] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor, “Review of brain MRI image segmentation methods,” *Artif Intell Rev*, vol. 33, no. 3, pp. 261–274, Mar. 2010, doi: 10.1007/s10462-010-9155-0.

[25] E. Miranda, M. Aryuni, and E. Irwansyah, “A survey of medical image classification techniques,” in *2016 International Conference on Information Management and Technology (ICIMTech)*, Bandung, Indonesia, Nov. 2016, pp. 56–61. doi: 10.1109/ICIMTech.2016.7930302.

[26] M. Angulakshmi and G. G. Lakshmi Priya, “Automated brain tumour segmentation techniques- A review,” *Int. J. Imaging Syst. Technol.*, vol. 27, no. 1, pp. 66–77, Mar. 2017, doi: 10.1002/ima.22211.

[27] T. Lei, R. Wang, Y. Wan, B. Zhang, H. Meng, and A. K. Nandi, “Medical Image Segmentation Using Deep Learning: A Survey,” *arXiv:2009.13120 [cs, eess]*, Dec. 2020, Accessed: May 05, 2021. [Online]. Available: http://arxiv.org/abs/2009.13120

[28] X. Zhuang *et al.*, “Evaluation of algorithms for Multi-Modality Whole Heart Segmentation: An open-access grand challenge,” *Medical Image Analysis*, vol. 58, p. 101537, Dec. 2019, doi: 10.1016/j.media.2019.101537.

[29] T. Magadza and S. Viriri, “Deep Learning for Brain Tumor Segmentation: A Survey of State-of-the-Art,” *J. Imaging*, vol. 7, no. 2, p. 19, Jan. 2021, doi: 10.3390/jimaging7020019.

[30] O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” *arXiv:1505.04597 [cs]*, May 2015, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1505.04597

[31] Changyang Li *et al.*, “A Likelihood and Local Constraint Level Set Model for Liver Tumor Segmentation from CT Volumes,” *IEEE Trans. Biomed. Eng.*, vol. 60, no. 10, pp. 2967–2977, Oct. 2013, doi: 10.1109/TBME.2013.2267212.

[32] A. Tsai *et al.*, “A shape-based approach to the segmentation of medical imagery using level sets,” *IEEE Trans. Med. Imaging*, vol. 22, no. 2, pp. 137–154, Feb. 2003, doi: 10.1109/TMI.2002.808355.

[33] M. Lalonde, M. Beaulieu, and L. Gagnon, “Fast and robust optic disc detection using pyramidal decomposition and Hausdorff-based template matching,” *IEEE Trans. Med. Imaging*, vol. 20, no. 11, pp. 1193–1200, Nov. 2001, doi: 10.1109/42.963823.

[34] D. Zikic, Y. Ioannou, M. Brown, and A. Criminisi, “Segmentation of Brain Tumor Tissues with Convolutional Neural Networks,” p. 5, 2014.

[35] K. Kamnitsas *et al.*, “Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation,” *Medical Image Analysis*, vol. 36, pp. 61–78, Feb. 2017, doi: 10.1016/j.media.2016.10.004.

[36] P. F. Christ *et al.*, “Automatic Liver and Lesion Segmentation in CT Using Cascaded Fully Convolutional Neural Networks and 3D Conditional Random Fields,” in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016*, vol. 9901, S. Ourselin, L. Joskowicz, M. R. Sabuncu, G. Unal, and W. Wells, Eds. Cham: Springer International Publishing, 2016, pp. 415–423. doi: 10.1007/978-3-319-46723-8_48.

[37] F. Milletari, N. Navab, S.-A. Ahmadi, and L.-M.-U. Munchen, “V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation,” p. 7.

[38] H. Fu, J. Cheng, Y. Xu, D. W. K. Wong, J. Liu, and X. Cao, “Joint Optic Disc and Cup Segmentation Based on Multi-Label Deep Network and Polar Transformation,” *IEEE Trans. Med. Imaging*, vol. 37, no. 7, pp. 1597–1605, Jul. 2018, doi: 10.1109/TMI.2018.2791488.

[39] Y. Onishi *et al.*, “Multiplanar analysis for pulmonary nodule classification in CT images using deep convolutional neural network and generative adversarial networks,” *Int J CARS*, vol. 15, no. 1, pp. 173–178, Jan. 2020, doi: 10.1007/s11548-019-02092-z.

[40] Y. Gao, J. M. Phillips, Y. Zheng, R. Min, P. T. Fletcher, and G. Gerig, "Fully convolutional structured LSTM networks for joint 4D medical image segmentation," in *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, Washington, DC, Apr. 2018, pp. 1104–1108. doi: 10.1109/ISBI.2018.8363764.

[41] H. Seo, C. Huang, M. Bassenne, R. Xiao, and L. Xing, "Modified U-Net (mU-Net) With Incorporation of Object-Dependent High Level Features for Improved Liver and Liver-Tumor Segmentation in CT Images," *IEEE Trans. Med. Imaging*, vol. 39, no. 5, pp. 1316–1325, May 2020, doi: 10.1109/TMI.2019.2948320.

[42] X. Chen, R. Zhang, and P. Yan, "Feature Fusion Encoder Decoder Network for Automatic Liver Lesion Segmentation," in *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*, Venice, Italy, Apr. 2019, pp. 430–433. doi: 10.1109/ISBI.2019.8759555.

[43] W. Tang, D. Zou, S. Yang, and J. Shi, "DSL: Automatic Liver Segmentation with Faster R-CNN and DeepLab," in *Artificial Neural Networks and Machine Learning – ICANN 2018*, vol. 11140, V. Kůrková, Y. Manolopoulos, B. Hammer, L. Iliadis, and I. Maglogiannis, Eds. Cham: Springer International Publishing, 2018, pp. 137–147. doi: 10.1007/978-3-030-01421-6_14.

[44] M. A. Al-antari, M. A. Al-masni, M.-T. Choi, S.-M. Han, and T.-S. Kim, "A fully integrated computer-aided diagnosis system for digital X-ray mammograms via deep learning detection, segmentation, and classification," *International Journal of Medical Informatics*, vol. 117, pp. 44–54, Sep. 2018, doi: 10.1016/j.ijmedinf.2018.06.003.

[45] Y. Yan *et al.*, "Cascaded multi-scale convolutional encoder-decoders for breast mass segmentation in high-resolution mammograms," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Berlin, Germany, Jul. 2019, pp. 6738–6741. doi: 10.1109/EMBC.2019.8857167.

[46] P. Kaur, G. Singh, and P. Kaur, “A Review of Denoising Medical Images Using Machine Learning Approaches,” *CMIR*, vol. 14, no. 5, pp. 675–685, Sep. 2018, doi: 10.2174/1573405613666170428154156.

[47] T. Higaki, Y. Nakamura, F. Tatsugami, T. Nakaura, and K. Awai, “Improvement of image quality at CT and MRI using deep learning,” *Jpn J Radiol*, vol. 37, no. 1, pp. 73–80, Jan. 2019, doi: 10.1007/s11604-018-0796-2.

[48] S. M. A. Sharif, R. A. Naqvi, and M. Biswas, “Learning Medical Image Denoising with Deep Dynamic Residual Attention Network,” *Mathematics*, vol. 8, no. 12, p. 2192, Dec. 2020, doi: 10.3390/math8122192.

[49] H. Gudbjartsson and S. Patz, “The rician distribution of noisy mri data,” *Magn. Reson. Med.*, vol. 34, no. 6, pp. 910–914, Dec. 1995, doi: 10.1002/mrm.1910340618.

[50] T. Wang *et al.*, “A review on medical imaging synthesis using deep learning and its clinical applications,” *J Appl Clin Med Phys*, vol. 22, no. 1, pp. 11–36, Jan. 2021, doi: 10.1002/acm2.13121.

[51] A. D. Missert, L. Yu, S. Leng, J. G. Fletcher, and C. H. McCollough, “Synthesizing images from multiple kernels using a deep convolutional neural network,” *Med. Phys.*, vol. 47, no. 2, pp. 422–430, Feb. 2020, doi: 10.1002/mp.13918.

[52] M. Kidoh *et al.*, “Deep Learning Based Noise Reduction for Brain MR Imaging: Tests on Phantoms and Healthy Volunteers,” *MRMS*, vol. 19, no. 3, pp. 195–206, 2020, doi: 10.2463/mrms.mp.2019-0018.

[53] D. Jiang, W. Dou, L. Vosters, X. Xu, Y. Sun, and T. Tan, “Denoising of 3D magnetic resonance images with multi-channel residual learning of convolutional neural network,” *arXiv:1712.08726 [cs]*, Dec. 2017, Accessed: Sep. 23, 2019. [Online]. Available: http://arxiv.org/abs/1712.08726

[54] J. V. Manjón and P. Coupe, “MRI denoising using Deep Learning and Non-local averaging,” p. 23.

[55] D. Eun, R. Jang, W. S. Ha, H. Lee, S. C. Jung, and N. Kim, “Deep-learning-based image quality enhancement of compressed sensing magnetic resonance imaging of vessel wall: comparison of self-supervised and unsupervised approaches,” *Sci Rep*, vol. 10, no. 1, p. 13950, Dec. 2020, doi: 10.1038/s41598-020-69932-w.

[56] M. Zhussip, S. Soltanayev, and S. Y. Chun, “Training Deep Learning Based Image Denoisers From Undersampled Measurements Without Ground Truth and Without Image Prior,” in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, Jun. 2019, pp. 10247–10256. doi: 10.1109/CVPR.2019.01050.

[57] A. Benou, R. Veksler, A. Friedman, and T. Riklin Raviv, “Ensemble of expert deep neural networks for spatio-temporal denoising of contrast-enhanced MRI sequences,” *Medical Image Analysis*, vol. 42, pp. 145–159, Dec. 2017, doi: 10.1016/j.media.2017.07.006.

[58] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, “Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising,” *IEEE Trans. on Image Process.*, vol. 26, no. 7, pp. 3142–3155, Jul. 2017, doi: 10.1109/TIP.2017.2662206.

[59] R. Wang, X. Xiao, B. Guo, Q. Qin, and R. Chen, “An Effective Image Denoising Method for UAV Images via Improved Generative Adversarial Networks,” *Sensors*, vol. 18, no. 7, p. 1985, Jun. 2018, doi: 10.3390/s18071985.

[60] G. Yang *et al.*, “DAGAN: Deep De-Aliasing Generative Adversarial Networks for Fast Compressed Sensing MRI Reconstruction,” *IEEE Trans. Med. Imaging*, vol. 37, no. 6, pp. 1310–1321, Jun. 2018, doi: 10.1109/TMI.2017.2785879.

[61] F. Agostinelli, M. R. Anderson, and H. Lee, “Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising,” p. 9.

[62] S. S. Yadav and S. M. Jadhav, “Deep convolutional neural network based medical image classification for disease diagnosis,” *J Big Data*, vol. 6, no. 1, p. 113, Dec. 2019, doi: 10.1186/s40537-019-0276-2.

[63] S. P. Singh, L. Wang, S. Gupta, H. Goli, P. Padmanabhan, and B. Gulyás, “3D Deep Learning on Medical Images: A Review,” *Sensors*, vol. 20, no. 18, p. 5097, Sep. 2020, doi: 10.3390/s20185097.

[64] Z. Lai and H. Deng, “Medical Image Classification Based on Deep Features Extracted by Deep Model and Statistic Feature Fusion with Multilayer Perceptron ,” *Computational Intelligence and Neuroscience*, vol. 2018, pp. 1–13, Sep. 2018, doi: 10.1155/2018/2061516.

[65] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[66] K. Simonyan and A. Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” *arXiv:1409.1556 [cs]*, Sep. 2014, Accessed: Sep. 23, 2019. [Online]. Available: http://arxiv.org/abs/1409.1556

[67] H.-C. Shin *et al.*, “Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning,” *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1285–1298, May 2016, doi: 10.1109/TMI.2016.2528162.

[68] A. Barbu, M. Suehling, Xun Xu, D. Liu, S. K. Zhou, and D. Comaniciu, “Automatic Detection and Segmentation of Lymph Nodes From CT Data,” *IEEE Trans. Med. Imaging*, vol. 31, no. 2, pp. 240–250, Feb. 2012, doi: 10.1109/TMI.2011.2168234.

[69] Q. Dou *et al.*, “Automatic Detection of Cerebral Microbleeds From MR Images via 3D Convolutional Neural Networks,” *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1182–1195, May 2016, doi: 10.1109/TMI.2016.2528129.

[70] T.-H. Chan, K. Jia, S. Gao, J. Lu, Z. Zeng, and Y. Ma, “PCANet: A Simple Deep Learning Baseline for Image Classification?,” *IEEE Trans. on Image Process.*, vol. 24, no. 12, pp. 5017–5032, Dec. 2015, doi: 10.1109/TIP.2015.2475625.

[71] R. Zeng *et al.*, “Color image classification via quaternion principal component analysis network,” *Neurocomputing*, vol. 216, pp. 416–428, Dec. 2016, doi: 10.1016/j.neucom.2016.08.006.

[72] C. Szegedy *et al.*, “Going Deeper with Convolutions,” *arXiv:1409.4842 [cs]*, Sep. 2014, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1409.4842

[73] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” *arXiv:1801.04381 [cs]*, Mar. 2019, Accessed: Oct. 22, 2020. [Online]. Available: http://arxiv.org/abs/1801.04381

[74] F. Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions,” *arXiv:1610.02357 [cs]*, Apr. 2017, Accessed: Mar. 22, 2021. [Online]. Available: http://arxiv.org/abs/1610.02357

[75] S. J. Pan and Q. Yang, “A Survey on Transfer Learning,” *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, Oct. 2010, doi: 10.1109/TKDE.2009.191.

[76] A. Magotra and J. Kim, “Improvement of Heterogeneous Transfer Learning Efficiency by Using Hebbian Learning Principle,” *Applied Sciences*, vol. 10, no. 16, p. 5631, Aug. 2020, doi: 10.3390/app10165631.

[77] M. Oquab, L. Bottou, I. Laptev, and J. Sivic, “Learning and Transferring Mid-level Image Representations Using Convolutional Neural Networks,” in *2014 IEEE*

Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, Jun. 2014, pp. 1717–1724. doi: 10.1109/CVPR.2014.222.

[78] Y. Yu, H. Lin, J. Meng, X. Wei, H. Guo, and Z. Zhao, “Deep Transfer Learning for Modality Classification of Medical Images,” *Information*, vol. 8, no. 3, p. 91, Jul. 2017, doi: 10.3390/info8030091.

[79] H. Chougrad, H. Zouaki, and O. Alheyane, “Deep Convolutional Neural Networks for breast cancer screening,” *Computer Methods and Programs in Biomedicine*, vol. 157, pp. 19–30, Apr. 2018, doi: 10.1016/j.cmpb.2018.01.011.

[80] A. Jaiswal, N. Gianchandani, D. Singh, V. Kumar, and M. Kaur, “Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning,” *Journal of Biomolecular Structure and Dynamics*, pp. 1–8, Jul. 2020, doi: 10.1080/07391102.2020.1788642.

[81] R. K. Samala, H.-P. Chan, L. Hadjiiski, M. A. Helvie, J. Wei, and K. Cha, “Mass detection in digital breast tomosynthesis: Deep convolutional neural network with transfer learning from mammography: DBT mass detection using deep convolutional neural network,” *Med. Phys.*, vol. 43, no. 12, pp. 6654–6666, Nov. 2016, doi: 10.1118/1.4967345.

[82] N. Tajbakhsh *et al.*, “Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?,” *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1299–1312, May 2016, doi: 10.1109/TMI.2016.2535302.

[83] D. Abler, R. C. Rockne, and P. Büchler, “Evaluating the Effect of Tissue Anisotropy on Brain Tumor Growth Using a Mechanically Coupled Reaction–Diffusion Model,” in *New Developments on Computational Methods and Imaging in Biomechanics and Biomedical Engineering*, vol. 33, J. M. R. S. Tavares and P. R. Fernandes, Eds. Cham: Springer International Publishing, 2019, pp. 37–48. doi: 10.1007/978-3-030-23073-9_3.

[84] A. Işın, C. Direkoğlu, and M. Şah, “Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods,” *Procedia Computer Science*, vol. 102, pp. 317–324, 2016, doi: 10.1016/j.procs.2016.09.407.

[85] N. Kampa *et al.*, “EFFECT OF REGION OF INTEREST SELECTION AND UPTAKE MEASUREMENT ON GLOMERULAR FILTRATION RATE MEASURED BY 99mTc-DTPA SCINTIGRAPHY IN DOGS,” *Veterinary Radiology & Ultrasound*, vol. 43, no. 4, pp. 383–391, Jul. 2002, doi: 10.1111/j.1740-8261.2002.tb01022.x.

[86] A. Hamamci, N. Kucuk, K. Karaman, K. Engin, and G. Unal, “Tumor-Cut: Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications,” *IEEE Trans. Med. Imaging*, vol. 31, no. 3, pp. 790–804, Mar. 2012, doi: 10.1109/TMI.2011.2181857.

[87] “Brain Tumor Detection and Segmentation using Histogram and Optimization Algorithm,” *IJITEE*, vol. 8, no. 10S, pp. 125–129, Sep. 2019, doi: 10.35940/ijitee.J1023.08810S19.

[88] Jin Liu, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, and Yi Pan, “A survey of MRI-based brain tumor segmentation methods,” *Tinshhua Sci. Technol.*, vol. 19, no. 6, pp. 578–595, Dec. 2014, doi: 10.1109/TST.2014.6961028.

[89] Y. LeCun, L. Bottou, Y. Bengio, and P. Ha, “Gradient-Based Learning Applied to Document Recognition,” p. 46, 1998.

[90] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” *arXiv:1512.03385 [cs]*, Dec. 2015, Accessed: Sep. 23, 2019. [Online]. Available: http://arxiv.org/abs/1512.03385

[91] D. C. Ciresan, L. M. Gambardella, and A. Giusti, “Deep Neural Networks Segment Neuronal Membranes in Electron Microscopy Images,” p. 9.

[92] E. Shelhamer, J. Long, and T. Darrell, “Fully Convolutional Networks for Semantic Segmentation,” *arXiv:1605.06211 [cs]*, May 2016, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1605.06211

[93] P. V. Tran, “A Fully Convolutional Neural Network for Cardiac Segmentation in Short-Axis MRI,” *arXiv:1604.00494 [cs]*, Apr. 2017, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1604.00494

[94] V. Badrinarayanan, A. Kendall, and R. Cipolla, “SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation,” *arXiv:1511.00561 [cs]*, Oct. 2016, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1511.00561

[95] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, “Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation,” in *Computer Vision – ECCV 2018*, vol. 11211, V. Ferrari, M. Hebert, C. Sminchisescu, and Y. Weiss, Eds. Cham: Springer International Publishing, 2018, pp. 833–851. doi: 10.1007/978-3-030-01234-2_49.

[96] M. Drozdzal, E. Vorontsov, G. Chartrand, S. Kadoury, and C. Pal, “The Importance of Skip Connections in Biomedical Image Segmentation,” *arXiv:1608.04117 [cs]*, Sep. 2016, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1608.04117

[97] J. L. Ba, J. R. Kiros, and G. E. Hinton, “Layer Normalization,” *arXiv:1607.06450 [cs, stat]*, Jul. 2016, Accessed: Sep. 23, 2019. [Online]. Available: http://arxiv.org/abs/1607.06450

[98] H. K. Vydana and A. K. Vuppala, “Investigative study of various activation functions for speech recognition,” in *2017 Twenty-third National Conference on Communications (NCC)*, Chennai, India, Mar. 2017, pp. 1–5. doi: 10.1109/NCC.2017.8077043.

[99] D. R. Martin, C. C. Fowlkes, and J. Malik, "Learning to detect natural image boundaries using local brightness, color, and texture cues," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 26, no. 5, pp. 530–549, May 2004, doi: 10.1109/TPAMI.2004.1273918.

[100] K. Duan, S. S. Keerthi, W. Chu, S. K. Shevade, and A. N. Poo, "Multi-category Classification by Soft-Max Combination of Binary Classifiers," in *Multiple Classifier Systems*, vol. 2709, T. Windeatt and F. Roli, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 125–134. doi: 10.1007/3-540-44938-8_13.

[101] B. Gao and L. Pavel, "On the Properties of the Softmax Function with Application in Game Theory and Reinforcement Learning," p. 11.

[102] K. Janocha and W. M. Czarnecki, "On Loss Functions for Deep Neural Networks in Classification," *arXiv:1702.05659 [cs]*, Feb. 2017, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1702.05659

[103] *Kaggle dataset*. [Online]. Available: https://kaggle.com/mateuszbuda/lgg-mri-segmentation.

[104] *Figshare dataset*. [Online]. Available: http://dx.doi.org/10.6084/m9.figshare.1512427

[105] D. Valsesia, S. M. Fosson, C. Ravazzi, T. Bianchi, and E. Magli, "Analysis of SparseHash: an efficient embedding of set-similarity via sparse projections," *arXiv:1909.01802 [cs]*, Sep. 2019, Accessed: Nov. 17, 2019. [Online]. Available: http://arxiv.org/abs/1909.01802

[106] G. Csurka, D. Larlus, and F. Perronnin, "What is a good evaluation measure for semantic segmentation?," in *Procedings of the British Machine Vision Conference 2013*, Bristol, 2013, p. 32.1-32.11. doi: 10.5244/C.27.32.

[107] E. Fernandez-Moral, R. Martins, D. Wolf, and P. Rives, "A New Metric for Evaluating Semantic Segmentation: Leveraging Global and Contour Accuracy," in *2018*

IEEE Intelligent Vehicles Symposium (IV), Changshu, Jun. 2018, pp. 1051–1056. doi: 10.1109/IVS.2018.8500497.

[108] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, “Densely Connected Convolutional Networks,” *arXiv:1608.06993 [cs]*, Jan. 2018, Accessed: Nov. 21, 2020. [Online]. Available: http://arxiv.org/abs/1608.06993

[109] Y. Li, H. Qi, J. Dai, X. Ji, and Y. Wei, “Fully Convolutional Instance-Aware Semantic Segmentation,” in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, Jul. 2017, pp. 4438–4446. doi: 10.1109/CVPR.2017.472.

[110] H. Chen, X. Qi, L. Yu, and P.-A. Heng, “DCAN: Deep Contour-Aware Networks for Accurate Gland Segmentation,” *arXiv:1604.02677 [cs]*, Apr. 2016, Accessed: Nov. 21, 2020. [Online]. Available: http://arxiv.org/abs/1604.02677

[111] N. Feng, X. Geng, and L. Qin, “Study on MRI Medical Image Segmentation Technology Based on CNN-CRF Model,” *IEEE Access*, vol. 8, pp. 60505–60514, 2020, doi: 10.1109/ACCESS.2020.2982197.

[112] H. Lu, H. Wang, Q. Zhang, D. Won, and S. W. Yoon, “A Dual-Tree Complex Wavelet Transform Based Convolutional Neural Network for Human Thyroid Medical Image Segmentation,” in *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, New York, NY, Jun. 2018, pp. 191–198. doi: 10.1109/ICHI.2018.00029.

[113] P. Naylor, M. Lae, F. Reyal, and T. Walter, “Segmentation of Nuclei in Histopathology Images by Deep Regression of the Distance Map,” *IEEE Trans. Med. Imaging*, vol. 38, no. 2, pp. 448–459, Feb. 2019, doi: 10.1109/TMI.2018.2865709.

[114] J. Guo, “Network Decoupling: From Regular to Depthwise Separable Convolutions,” p. 12.

[115] Y. Wu and K. He, “Group Normalization,” *arXiv:1803.08494 [cs]*, Jun. 2018, Accessed: Nov. 21, 2020. [Online]. Available: http://arxiv.org/abs/1803.08494

[116] A. F. Agarap, “Deep Learning using Rectified Linear Units (ReLU),” *arXiv:1803.08375 [cs, stat]*, Feb. 2019, Accessed: Oct. 22, 2020. [Online]. Available: http://arxiv.org/abs/1803.08375

[117] V. Thakkar, S. Tewary, and C. Chakraborty, “Batch Normalization in Convolutional Neural Networks — A comparative study with CIFAR-10 data,” in *2018 Fifth International Conference on Emerging Applications of Information Technology (EAIT)*, Jan. 2018, pp. 1–5. doi: 10.1109/EAIT.2018.8470438.

[118] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” *arXiv:1412.6980 [cs]*, Jan. 2017, Accessed: May 06, 2021. [Online]. Available: http://arxiv.org/abs/1412.6980

[119] Y. Yu and F. Liu, “Effective Neural Network Training With a New Weighting Mechanism-Based Optimization Algorithm,” *IEEE Access*, vol. 7, pp. 72403–72410, 2019, doi: 10.1109/ACCESS.2019.2919987.

[120] A. Maier, C. Syben, T. Lasser, and C. Riess, “A gentle introduction to deep learning in medical image processing,” *Zeitschrift für Medizinische Physik*, vol. 29, no. 2, pp. 86–101, May 2019, doi: 10.1016/j.zemedi.2018.12.003.

[121] F. Liu and M. Fang, “Semantic Segmentation of Underwater Images Based on Improved Deeplab,” *JMSE*, vol. 8, no. 3, p. 188, Mar. 2020, doi: 10.3390/jmse8030188.

[122] A. A. Taha, A. Hanbury, and O. A. J. del Toro, “A formal method for selecting evaluation metrics for image segmentation,” in *2014 IEEE International Conference on Image Processing (ICIP)*, Paris, France, Oct. 2014, pp. 932–936. doi: 10.1109/ICIP.2014.7025187.

[123] M. H. Hesamian, W. Jia, X. He, and P. Kennedy, “Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges,” *J Digit Imaging*, vol. 32, no. 4, pp. 582–596, Aug. 2019, doi: 10.1007/s10278-019-00227-x.

[124] C. Nwankpa, W. Ijomah, A. Gachagan, and S. Marshall, “Activation Functions: Comparison of trends in Practice and Research for Deep Learning,” *arXiv:1811.03378 [cs]*, Nov. 2018, Accessed: Feb. 06, 2021. [Online]. Available: http://arxiv.org/abs/1811.03378

[125] Y. Hu, A. Huber, J. Anumula, and S.-C. Liu, “Overcoming the vanishing gradient problem in plain recurrent networks,” *arXiv:1801.06105 [cs]*, Jul. 2019, Accessed: Mar. 22, 2021. [Online]. Available: http://arxiv.org/abs/1801.06105

[126] L. Chan, M. Hosseini, C. Rowsell, K. Plataniotis, and S. Damaskinos, “HistoSegNet: Semantic Segmentation of Histological Tissue Type in Whole Slide Images,” in *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, Seoul, Korea (South), Oct. 2019, pp. 10661–10670. doi: 10.1109/ICCV.2019.01076.

[127] J. Ker, L. Wang, J. Rao, and T. Lim, “Deep Learning Applications in Medical Image Analysis,” *IEEE Access*, vol. 6, pp. 9375–9389, 2018, doi: 10.1109/ACCESS.2017.2788044.

[128] Yu. Gordienko *et al.*, “Deep Learning with Lung Segmentation and Bone Shadow Exclusion Techniques for Chest X-Ray Analysis of Lung Cancer,” in *Advances in Computer Science for Engineering and Education*, vol. 754, Z. Hu, S. Petoukhov, I. Dychka, and M. He, Eds. Cham: Springer International Publishing, 2019, pp. 638–647. doi: 10.1007/978-3-319-91008-6_63.

[129] B. Ait Skourt, A. El Hassani, and A. Majda, “Lung CT Image Segmentation Using Deep Neural Networks,” *Procedia Computer Science*, vol. 127, pp. 109–113, 2018, doi: 10.1016/j.procs.2018.01.104.

[130] V. Vashishtha and D. Aju, “Nerve segmentation in ultrasound images,” in *2017 Innovations in Power and Advanced Computing Technologies (i-PACT)*, Vellore, Apr. 2017, pp. 1–5. doi: 10.1109/IPACT.2017.8244914.

[131] M. Khened, V. A. Kollerathu, and G. Krishnamurthi, “Fully convolutional multi-scale residual DenseNets for cardiac segmentation and automated cardiac diagnosis using ensemble of classifiers,” *Medical Image Analysis*, vol. 51, pp. 21–45, Jan. 2019, doi: 10.1016/j.media.2018.10.004.

[132] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, “DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs,” *arXiv:1606.00915 [cs]*, May 2017, Accessed: Mar. 24, 2021. [Online]. Available: http://arxiv.org/abs/1606.00915

[133] X. Zhou, R. Takayama, S. Wang, T. Hara, and H. Fujita, “Deep learning of the sectional appearances of 3D CT images for anatomical structure segmentation based on an FCN voting method,” *Med. Phys.*, vol. 44, no. 10, pp. 5221–5233, Oct. 2017, doi: 10.1002/mp.12480.

[134] I. Goodfellow *et al.*, “Generative Adversarial Nets,” p. 9.

[135] P. Luc, C. Couprie, S. Chintala, and J. Verbeek, “Semantic Segmentation using Adversarial Networks,” *arXiv:1611.08408 [cs]*, Nov. 2016, Accessed: Mar. 24, 2021. [Online]. Available: http://arxiv.org/abs/1611.08408

[136] Y. Xue, T. Xu, H. Zhang, R. Long, and X. Huang, “SegAN: Adversarial Network with Multi-scale L_1 Loss for Medical Image Segmentation,” *Neuroinform*, vol. 16, no. 3–4, pp. 383–392, Oct. 2018, doi: 10.1007/s12021-018-9377-x.

[137] N. Khosravan, A. Mortazi, M. Wallace, and U. Bagci, “PAN: Projective Adversarial Network for Medical Image Segmentation,” *arXiv:1906.04378 [cs, eess]*, Jun. 2019, Accessed: Mar. 24, 2021. [Online]. Available: http://arxiv.org/abs/1906.04378

[138] G. Klambauer, T. Unterthiner, A. Mayr, and S. Hochreiter, "Self-Normalizing Neural Networks," *arXiv:1706.02515 [cs, stat]*, Sep. 2017, Accessed: Mar. 24, 2021. [Online]. Available: http://arxiv.org/abs/1706.02515

[139] Z. Zhang and M. Sabuncu, "Generalized Cross Entropy Loss for Training Deep Neural Networks with Noisy Labels," p. 11.

[140] M. Everingham, S. M. A. Eslami, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, "The Pascal Visual Object Classes Challenge: A Retrospective," *Int J Comput Vis*, vol. 111, no. 1, pp. 98–136, Jan. 2015, doi: 10.1007/s11263-014-0733-5.

[141] D. Chicco and G. Jurman, "The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation," *BMC Genomics*, vol. 21, no. 1, p. 6, Dec. 2020, doi: 10.1186/s12864-019-6413-7.

[142] R. Meyes, M. Lu, C. W. de Puiseau, and T. Meisen, "Ablation Studies in Artificial Neural Networks," *arXiv:1901.08644 [cs, q-bio]*, Feb. 2019, Accessed: Mar. 24, 2021. [Online]. Available: http://arxiv.org/abs/1901.08644

[143] T. K. Kim, "T test as a parametric statistic," *Korean J Anesthesiol*, vol. 68, no. 6, p. 540, 2015, doi: 10.4097/kjae.2015.68.6.540.

[144] J. Concato and J. A. Hartigan, "P values: from suggestion to superstition," *J Investig Med*, vol. 64, no. 7, pp. 1166–1171, Oct. 2016, doi: 10.1136/jim-2016-000206.

[145] P. Griffiths and J. Needleman, "Statistical significance testing and p-values: Defending the indefensible? A discussion paper and position statement," *International Journal of Nursing Studies*, vol. 99, p. 103384, Nov. 2019, doi: 10.1016/j.ijnurstu.2019.07.001.

[146] K. Saneipour and M. Mohammadpoor, "Improvement of MRI Brain Image Segmentation Using Fuzzy Unsupervised Learning," *Iran J Radiol*, vol. In Press, no. In Press, Jan. 2019, doi: 10.5812/iranjradiol.69063.

[147] R. Boda, S. K. Yezerla, and B. R. Naik, “Performance analysis of image segmentation methods for noisy MRI images,” in *2016 International Conference on Communication and Signal Processing (ICCSP)*, Melmaruvathur, Tamilnadu, India, Apr. 2016, pp. 0942–0946. doi: 10.1109/ICCSP.2016.7754286.

[148] S. Konam and N. R. Narni, “Statistical analysis of image processing techniques for object counting,” in *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, Delhi, India, Sep. 2014, pp. 2464–2469. doi: 10.1109/ICACCI.2014.6968534.

[149] K. Zhang, W. Zuo, S. Gu, and L. Zhang, “Learning Deep CNN Denoiser Prior for Image Restoration,” *arXiv:1704.03264 [cs]*, Apr. 2017, Accessed: Nov. 05, 2020. [Online]. Available: http://arxiv.org/abs/1704.03264

[150] M. G. Pereza, A. Concib, A. Belen Morenoc, V. H. Andaluza, and J. A. Hernandezd, “Estimating the Rician noise level in brain MR image,” in *2014 IEEE ANDESCON*, Cochabamba, Bolivia, Oct. 2014, pp. 1–1. doi: 10.1109/ANDESCON.2014.7098539.

[151] I. I. Maximov, E. Farrher, F. Grinberg, and N. Jon Shah, “Spatially variable Rician noise in magnetic resonance imaging,” *Medical Image Analysis*, vol. 16, no. 2, pp. 536–548, Feb. 2012, doi: 10.1016/j.media.2011.12.002.

[152] A. Buades, B. Coll, and J.-M. Morel, “A Non-Local Algorithm for Image Denoising,” in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05)*, San Diego, CA, USA, 2005, vol. 2, pp. 60–65. doi: 10.1109/CVPR.2005.38.

[153] J. V. Manjón, P. Coupé, L. Martí-Bonmatí, D. L. Collins, and M. Robles, “Adaptive non-local means denoising of MR images with spatially varying noise levels: Spatially Adaptive Nonlocal Denoising,” *J. Magn. Reson. Imaging*, vol. 31, no. 1, pp. 192–203, Jan. 2010, doi: 10.1002/jmri.22003.

[154] H. M. Golshan and R. P. R. Hasanzadeh, "An Optimized LMMSE Based Method for 3D MRI Denoising," *IEEE/ACM Trans. Comput. Biol. and Bioinf.*, vol. 12, no. 4, pp. 861–870, Jul. 2015, doi: 10.1109/TCBB.2014.2344675.

[155] F. Baselice, G. Ferraioli, and V. Pascazio, "A 3D MRI denoising algorithm based on Bayesian theory," *BioMed Eng OnLine*, vol. 16, no. 1, p. 25, Dec. 2017, doi: 10.1186/s12938-017-0319-x.

[156] Y.-N. Chang and H.-H. Chang, "Automatic brain MR image denoising based on texture feature-based artificial neural networks," *BME*, vol. 26, no. s1, pp. S1275–S1282, Aug. 2015, doi: 10.3233/BME-151425.

[157] M. Martin-Fernandez and S. Villullas, "The EM Method in a Probabilistic Wavelet-Based MRI Denoising," *Comput Math Methods Med*, vol. 2015, p. 182659, 2015, doi: 10.1155/2015/182659.

[158] D. Yang and J. Sun, "BM3D-Net: A Convolutional Neural Network for Transform-Domain Collaborative Filtering," *IEEE Signal Process. Lett.*, vol. 25, no. 1, pp. 55–59, Jan. 2018, doi: 10.1109/LSP.2017.2768660.

[159] H. V. Tran and D. Jiang, "Automated background segmentation for Rician noise estimation of noisy MR images," in *2012 Cairo International Biomedical Engineering Conference (CIBEC)*, Giza, Egypt, Dec. 2012, pp. 150–153. doi: 10.1109/CIBEC.2012.6473333.

[160] B. Landman, P.-L. Bazin, and J. Prince, "Diffusion Tensor Estimation by Maximizing Rician Likelihood," in *2007 IEEE 11th International Conference on Computer Vision*, Rio de Janeiro, Brazil, 2007, pp. 1–8. doi: 10.1109/ICCV.2007.4409140.

[161] N. Mohajerin and S. L. Waslander, "Modular deep Recurrent Neural Network: Application to quadrotors," in *2014 IEEE International Conference on Systems, Man,*

and Cybernetics (SMC), San Diego, CA, USA, Oct. 2014, pp. 1374–1379. doi: 10.1109/SMC.2014.6974106.

[162] S. Gu, L. Zhang, W. Zuo, and X. Feng, “Weighted Nuclear Norm Minimization with Application to Image Denoising,” in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA, Jun. 2014, pp. 2862–2869. doi: 10.1109/CVPR.2014.366.

[163] X. Zhang *et al.*, “Denoising of 3D magnetic resonance images by using higher-order singular value decomposition,” *Medical Image Analysis*, vol. 19, no. 1, pp. 75–86, Jan. 2015, doi: 10.1016/j.media.2014.08.004.

[164] J. V. Manjón, P. Coupé, A. Buades, D. Louis Collins, and M. Robles, “New methods for MRI denoising based on sparseness and self-similarity,” *Medical Image Analysis*, vol. 16, no. 1, pp. 18–27, Jan. 2012, doi: 10.1016/j.media.2011.04.003.

[165] D. G. Pereira, A. Afonso, and F. M. Medeiros, “Overview of Friedman’s Test and Post-hoc Analysis,” *Communications in Statistics - Simulation and Computation*, vol. 44, no. 10, pp. 2636–2653, Nov. 2015, doi: 10.1080/03610918.2014.931971.

[166] J. Jurečková and J. Kalina, “Nonparametric multivariate rank tests and their unbiasedness,” *Bernoulli*, vol. 18, no. 1, pp. 229–251, Feb. 2012, doi: 10.3150/10-BEJ326.

[167] G. D. Leo, “Statistical significance: p value, 0.05 threshold, and applications to radiomics—reasons for a conservative approach,” p. 8, 2020.

[168] C. Tian, Y. Xu, L. Fei, and K. Yan, “Deep Learning for Image Denoising: A Survey,” *arXiv:1810.05052 [cs]*, Oct. 2018, Accessed: Feb. 06, 2021. [Online]. Available: http://arxiv.org/abs/1810.05052

[169] Y. Bengio, P. Simard, and P. Frasconi, “Learning long-term dependencies with gradient descent is difficult,” *IEEE Trans. Neural Netw.*, vol. 5, no. 2, pp. 157–166, Mar. 1994, doi: 10.1109/72.279181.

[170] H. Tan, H. Xiao, S. Lai, Y. Liu, and M. Zhang, “Pixelwise Estimation of Signal-Dependent Image Noise Using Deep Residual Learning,” *Computational Intelligence and Neuroscience*, vol. 2019, pp. 1–12, Sep. 2019, doi: 10.1155/2019/4970508.

[171] U. Sara, M. Akter, and M. S. Uddin, “Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study,” *JCC*, vol. 07, no. 03, pp. 8–18, 2019, doi: 10.4236/jcc.2019.73002.

[172] L. Gopal and M. L. Sim, “Performance Analysis of Signal-to-Noise Ratio Estimators in AWGN and Fading Channels,” in *2008 6th National Conference on Telecommunication Technologies and 2008 2nd Malaysia Conference on Photonics*, Putrajaya, Malaysia, Aug. 2008, pp. 300–304. doi: 10.1109/NCTT.2008.4814291.

[173] F. Lauer, “Error Bounds for Piecewise Smooth and Switching Regression,” *arXiv:1707.07938 [cs, stat]*, Jul. 2017, Accessed: Sep. 24, 2019. [Online]. Available: http://arxiv.org/abs/1707.07938

[174] D. S. Kim, M. Arsalan, M. Owais, and K. R. Park, “ESSN: Enhanced Semantic Segmentation Network by Residual Concatenation of Feature Maps,” *IEEE Access*, vol. 8, pp. 21363–21379, 2020, doi: 10.1109/ACCESS.2020.2969442.

[175] N. M. Zaitoun and M. J. Aqel, “Survey on Image Segmentation Techniques,” *Procedia Computer Science*, vol. 65, pp. 797–806, 2015, doi: 10.1016/j.procs.2015.09.027.

[176] M. J. Rawle, D. L. Bertfield, and S. E. Brill, “Atypical presentations of COVID-19 in care home residents presenting to secondary care: A UK single centre study,” *Aging. Med.*, p. agm2.12126, Sep. 2020, doi: 10.1002/agm2.12126.

[177] A. S. Manolis, T. A. Manolis, A. A. Manolis, D. Papatheou, and H. Melita, “COVID-19 Infection: Viral Macro- and Micro-Vascular Coagulopathy and Thromboembolism/Prophylactic and Therapeutic Management,” *J Cardiovasc Pharmacol Ther*, p. 107424842095897, Sep. 2020, doi: 10.1177/1074248420958973.

[178] A. T. Huang *et al.*, “A systematic review of antibody mediated immunity to coronaviruses: kinetics, correlates of protection, and association with severity,” *Nat Commun*, vol. 11, no. 1, p. 4704, Dec. 2020, doi: 10.1038/s41467-020-18450-4.

[179] M. Jamshidi *et al.*, “Artificial Intelligence and COVID-19: Deep Learning Approaches for Diagnosis and Treatment,” *IEEE Access*, vol. 8, pp. 109581–109595, 2020, doi: 10.1109/ACCESS.2020.3001973.

[180] X. Gu, L. Pan, H. Liang, and R. Yang, “Classification of Bacterial and Viral Childhood Pneumonia Using Deep Learning in Chest Radiography,” in *Proceedings of the 3rd International Conference on Multimedia and Image Processing - ICMIP 2018*, Guiyang, China, 2018, pp. 88–93. doi: 10.1145/3195588.3195597.

[181] Lin Li,Lixin Qin*2, Zeguo Xu1a, Youbing Yin3, Xin Wang3, Bin Kong3, Junjie Bai3, Yi Lu3, Zhenghan Fang3, Qi Song3, Kunlin Cao3, Daliang Liu4, Guisheng Wang5, Qizhong Xu6, Xisheng Fang1a, Shiqin Zhang1a, Juan Xia1a, Jun Xia, “Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT”, doi: https://doi.org/10.1148/radiol.2020200905.

[182] T. K. Ho and J. Gwak, “Multiple Feature Integration for Classification of Thoracic Disease in Chest Radiography,” *Applied Sciences*, vol. 9, no. 19, p. 4130, Oct. 2019, doi: 10.3390/app9194130.

[183] Ophir Gozes , Ma’ayan Frid-Adar , Hayit Greenspan, Patrick D. Browning, Huangqi Zhang, Wenbin Ji, Adam Bernheim, and Eliot Siegel, “Rapid AI Development Cycle

for the Coronavirus (COVID-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring using Deep Learning CT Image Analysis", doi: arXiv:2003.05037.

[184] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases," p. 20.

[185] Ali Narin1, Ceren Kaya, Ziynet Pamuk, "Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks", doi: arXiv:2003.10849.

[186] P. K. Sethy and S. K. Behera, "Detection of Coronavirus Disease (COVID-19) Based on Deep Features," ENGINEERING, preprint, Mar. 2020. doi: 10.20944/preprints202003.0300.v1.

[187] P. Lakhani and B. Sundaram, "Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks," *Radiology*, vol. 284, no. 2, pp. 574–582, Aug. 2017, doi: 10.1148/radiol.2017162326.

[188] Jin Huang and C. X. Ling, "Using AUC and accuracy in evaluating learning algorithms," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 3, pp. 299–310, Mar. 2005, doi: 10.1109/TKDE.2005.50.

[189] L. Wang and A. Wong, "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images," *arXiv:2003.09871 [cs, eess]*, May 2020, Accessed: Oct. 03, 2020. [Online]. Available: http://arxiv.org/abs/2003.09871

[190] M. M. Hoffman, "The MCC-F1 curve: a performance evaluation technique for binary classification," p. 17.

[191] T. Evgeniou and M. Pontil, "Support Vector Machines: Theory and Applications," in *Machine Learning and Its Applications*, vol. 2049, G. Paliouras, V. Karkaletsis, and C.

D. Spyropoulos, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2001, pp. 249–257. doi: 10.1007/3-540-44673-7_12.

[192] M.-J. Lian and C.-L. Huang, “Texture feature extraction of gray-level co-occurrence matrix for metastatic cancer cells using scanned laser pico-projection images,” *Lasers Med Sci*, vol. 34, no. 7, pp. 1503–1508, Sep. 2019, doi: 10.1007/s10103-018-2595-5.

[193] D. Huang, C. Shan, M. Ardabilian, Y. Wang, and L. Chen, “Local Binary Patterns and Its Application to Facial Image Analysis: A Survey,” *IEEE Trans. Syst., Man, Cybern. C*, vol. 41, no. 6, pp. 765–781, Nov. 2011, doi: 10.1109/TSMCC.2011.2118750.

[194] W. T. Aung, Y. Myanmar, and K. H. M. Saw Hla, “Random forest classifier for multi-category classification of web pages,” in *2009 IEEE Asia-Pacific Services Computing Conference (APSCC)*, Singapore, Singapore, Dec. 2009, pp. 372–376. doi: 10.1109/APSCC.2009.5394100.

[195] A. Humeau-Heurtier, “Texture Feature Extraction Methods: A Survey,” *IEEE Access*, vol. 7, pp. 8975–9000, 2019, doi: 10.1109/ACCESS.2018.2890743.

[196] P. Thanh Noi and M. Kappas, “Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery,” *Sensors*, vol. 18, no. 2, p. 18, Dec. 2017, doi: 10.3390/s18010018.

[197] *T. Rahman. (2020). COVID-19 Radiography Database*. [Online]. Available: https://www.kaggle.com/tawsifurrahman/covid19-radiography-database

[198] C. Goutte and E. Gaussier, “A Probabilistic Interpretation of Precision, Recall and F-Score, with Implication for Evaluation,” in *Advances in Information Retrieval*, vol. 3408, D. E. Losada and J. M. Fernández-Luna, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 345–359. doi: 10.1007/978-3-540-31865-1_25.

[199] S. Boughorbel, F. Jarray, and M. El-Anbari, “Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric,” *PLoS ONE*, vol. 12, no. 6, p. e0177678, Jun. 2017, doi: 10.1371/journal.pone.0177678.

[200] C. D. G. ˘aneanu Ioan T˘abus, “Cluster Structure Inference Based on Clustering Stability with Applications toMicroarray Data Analysis,” *EURASIP Journal on Applied Signal Processing*, vol. 2004:1, pp. 64–80, 2004.

[201] S. Jamal, V. Periwal, O. Consortium, and V. Scaria, “Computational analysis and predictive modeling of small molecule modulators of microRNA,” *J Cheminform*, vol. 4, no. 1, p. 16, Dec. 2012, doi: 10.1186/1758-2946-4-16.

[202] A. I. Khan, J. L. Shah, and M. M. Bhat, “CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images,” *Computer Methods and Programs in Biomedicine*, vol. 196, p. 105581, Nov. 2020, doi: 10.1016/j.cmpb.2020.105581.

[203] B. Sekeroglu and I. Ozsahin, “Detection of COVID-19 from Chest X-Ray Images Using Convolutional Neural Networks,” *SLAS TECHNOLOGY: Translating Life Sciences Innovation*, vol. 25, no. 6, pp. 553–565, Dec. 2020, doi: 10.1177/2472630320958376.

[204] T. D. Pham, “A comprehensive study on classification of COVID-19 on computed tomography with pretrained convolutional neural networks,” *Sci Rep*, vol. 10, no. 1, p. 16942, Dec. 2020, doi: 10.1038/s41598-020-74164-z.

[205] R. St. Laurent and P. Turk, “The Effects of Misconceptions on the Properties of Friedman’s Test,” *Communications in Statistics - Simulation and Computation*, vol. 42, no. 7, pp. 1596–1615, Aug. 2013, doi: 10.1080/03610918.2012.671874.

[206] F. Isensee, P. Jaeger, P. M. Full, I. Wolf, S. Engelhardt, and K. H. Maier-Hein, “Automatic Cardiac Disease Assessment on cine-MRI via Time-Series Segmentation

and Domain Specific Features," *arXiv:1707.00587 [cs]*, vol. 10663, 2018, doi: 10.1007/978-3-319-75541-0.

[207] A. G. Howard *et al.*, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv:1704.04861 [cs]*, Apr. 2017, Accessed: Oct. 22, 2020. [Online]. Available: http://arxiv.org/abs/1704.04861

[208] Y. Huang, C. Qiu, X. Wang, S. Wang, and K. Yuan, "A Compact Convolutional Neural Network for Surface Defect Inspection," *Sensors*, vol. 20, no. 7, p. 1974, Apr. 2020, doi: 10.3390/s20071974.

[209] *COVID-19 image data collection.* [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset

[210] *CT scans for covid-19 classification.* [Online]. Available: https://www.kaggle.com/azaemon/preprocessed-ct-scans-for-covid19

[211] T. Villmann, M. Kaden, M. Lange, P. Sturmer, and W. Hermann, "Precision-Recall-Optimization in Learning Vector Quantization Classifiers for Improved Medical Classification Systems," in *2014 IEEE Symposium on Computational Intelligence and Data Mining (CIDM)*, Orlando, FL, USA, Dec. 2014, pp. 71–77. doi: 10.1109/CIDM.2014.7008150.

[212] A. Ralescu, I. Díaz, and L. J. Rodríguez-Muñiz, "A classification algorithm based on geometric and statistical information," *Journal of Computational and Applied Mathematics*, vol. 275, pp. 335–344, Feb. 2015, doi: 10.1016/j.cam.2014.07.012.

[213] M. D. Ruopp, N. J. Perkins, B. W. Whitcomb, and E. F. Schisterman, "Youden Index and Optimal Cut-Point Estimated from Observations Affected by a Lower Limit of Detection," *Biom. J.*, vol. 50, no. 3, pp. 419–430, Jun. 2008, doi: 10.1002/bimj.200710415.

LIST OF PUBLICATION (ON PHD WORK)

A) Journal Publications

A.1) Published

1. **Sumit Tripathi**, Ashish Verma, Neeraj Sharma (2021). Automatic segmentation of brain tumor in MR images using an enhanced deep learning approach. **Computer Methods in Biomechanics and Biomedical Engineering,** Taylor & Francis, 9(2), 121-130.
2. **Sumit Tripathi**, Neeraj Sharma (2022). Denoising of Magnetic Resonance Images Using Discriminative Learning-Based Deep Convolutional Neural Network. **Technology and health care,** IoS press, 30, 145-160.
3. **Sumit Tripathi**, Taresh Sarvesh Sharan, Shiru Sharma, Neeraj Sharma (2021). An Augmented Deep Learning Network with Noise Suppression feature for Efficient Segmentation of Magnetic Resonance Images. **IETE Technical Reviews,** Taylor & Francis (DOI: 10.1080/02564602.2021.1937349).
4. **Sumit Tripathi**, Neeraj Sharma (2021). Computer-aided Automatic Approach for Denoising of Magnetic Resonance Images. **Computer Methods in Biomechanics and Biomedical Engineering,** Taylor & Francis, 9(6), 707-716.
5. **Sumit Tripathi**, Neeraj Sharma (2021). Computer Based Segmentation of Cancerous Tissues in Biomedical Images using Enhanced Deep Learning Model. **IETE Technical Reviews,** Taylor & Francis (DOI: 10.1080/02564602.2021.1994044).
6. **Sumit Tripathi**, Taresh Sarvesh Sharan, Shiru Sharma, Neeraj Sharma Encoder Modified U-Net and Feature Pyramid Network for Multi-class Segmentation of Cardiac Magnetic Resonance Images (2020). **IETE Technical Reviews,** Taylor & Francis (DOI: 10.1080/02564602.2021.1994044).

A.2) Articles submitted/under review

1. **Sumit Tripathi**, Neeraj Sharma Classification of Lung Infected Chest X-Ray Images by COVID-19 and Viral Pneumonia Using Deep Learning Based Approach. IETE Journal of Research. **Computer Methods in Biomechanics and Biomedical Engineering. Under Review.**
2. **Sumit Tripathi**, Neeraj Sharma, A Transfer Learning Based Classification Method for Efficient Identification of Covid-19 Infection in CT and X-ray Images. **Technology and health care**. **Under Review.**

B. Publications at Conference

1. **Sumit Tripathi**, Ashish Verma, Neeraj Sharma (2020). Augmented Deep Learning Architecture to Effectively Segment the Cancerous Regions in Biomedical Images. Conference: International Symposium on Sustainable Energy, Signal Processing & Cyber Security (IEEE-ISSSC 2020), IEEE, pp 1-6.
2. **Sumit Tripathi**, Neeraj Sharma (2021). Segmentation of Brain Tumour in MR Images Using Modified Deep Learning Network. International Conference on Smart Computing and Communication (IEEE-ICSSC 2021), IEEE, pp 1-5.