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Automatic analysis of chest CT in systemic sclerosis using deep learning

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Journal articles

Jia, Jingnan, Emiel R. Marges, Jeska K. De Vries-Bouwstra, Maarten K. Ninaber, Lucia JM Kroft, Anne A. Schouffoer, Marius Staring, and Berend C. Stoel. "Automatic Pulmonary Function Estimation From Chest CT Scans Using Deep Regression Neural Networks: The Relation Between Structure and Function in Systemic Sclerosis." *IEEE Access* 11 (2023): 135272-135282.

Jia, Jingnan, Irene Hernández-Girón, Anne A. Schouffoer, Jeska K. De Vries-Bouwstra, Maarten K. Ninaber, Julie C. Korving, Marius Staring, Lucia JM Kroft, and Berend C. Stoel. "Explainable fully automated CT scoring of systemic sclerosis related interstitial lung disease by cascaded regression neural networks and its comparison with experts." (*submitted*).

Jia, Jingnan, Bo Yu, Prerak Mody, Maarten K. Ninaber, Lucia JM Kroft, Anne A. Schouffoer, Marius Staring, and Berend C. Stoel. "Using 3D point cloud and graph-based neural networks to improve the estimation of pulmonary function tests from chest CT." (*submitted*).

Wen, Jingxuan, YongChang Jiao, YiXuan Zhang, and **Jingnan Jia**. "Wideband circularly polarized dielectric resonator antenna loaded with partially reflective surface." *International Journal of RF and Microwave ComputerAided Engineering* 29, no. 12 (2019): e21962.

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Jia, Jingnan, Zhiwei Zhai, M. Els Bakker, Irene Hernández-Girón, Marius Staring, and Berend C. Stoel. "Multi-task semi-supervised learning for pulmonary lobe segmentation." In *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, pp. 1329-1332. IEEE, 2021.

Jia, Jingnan, Marius Staring, Irene Hernández-Girón, Lucia JM Kroft, Anne A. Schouffoer, and Berend C. Stoel. "Prediction of lung CT scores of systemic sclerosis by cascaded regression neural networks." In *Medical Imaging 2022: ComputerAided Diagnosis*, vol. 12033, pp. 837-843. SPIE, 2022.

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Jia, Jingnan, Marius Staring, and Berend C. Stoel "seg-metrics: a Python package to compute segmentation metrics." *medRxiv*, 2024-02.

Open source software

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Curriculum Vitae

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