Automated quality assurance of deep learning contours in head-and-neck radiotherapy

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>
> Sir Isaac Newton

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Curriculum Vitae

Prerak was born in Mumbai, Maharashtra province, India in 1993. He finished his high school studies at Arya Vidya Mandir, Mumbai, India in 2011. He obtained a Bachelors of Technology (B.Tech) degree in Computer Science and Enginering at Vellore Institute of Technology (VIT), India in 2015. His masters studies (MSc) in Computer Science was done at Technical University (TU) Delft, Netherlands from 2018-2020. The topic of the masters thesis at Philips, Netherlands was on 3D human pose estimation in privacy preserving settings (for e.g. using point cloud images).

Shortly after he started his PhD at Division of Image Processing (LKEB), Radiology, Leiden University Medical Center with a focus on human-centered techniques for contouring in radiotherapy. Since 2025 he works at Medis Medical Imaging building software solutions to detect coronary structures within CT scans using deep learning.