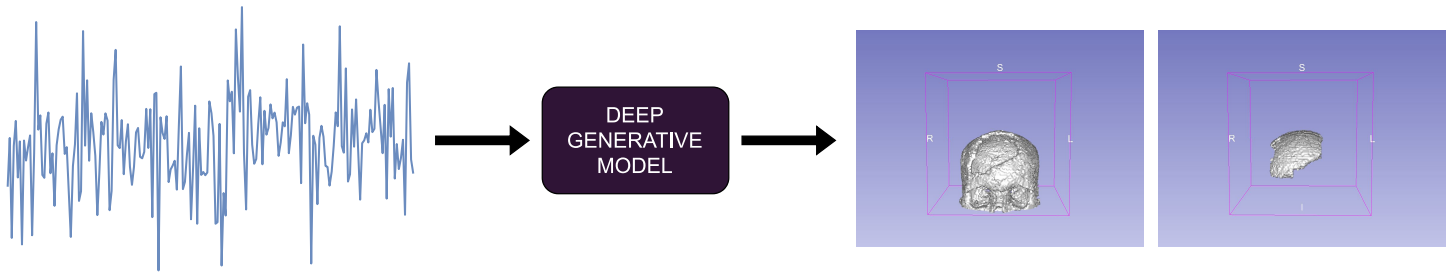
Deep generative networks for heterogeneous augmentation of cranial defects

Kamil Kwarciak



The cranial implant design is a very complex process that is crucial for performing proper surgical reconstruction of a cranial defect. In recent years, deep learning algorithms have become state-of-the-art approaches to this matter, however, the main bottleneck is that they require huge amounts of data. Thus, many different techniques of augmentation are being applied. This work explores a very novel one that is based on generative artificial intelligence and adapts its concepts from 2D computer vision to a volumetric modality of skull data. Different deep generative networks are used for enlarging the original dataset, with the main objective of providing both, highly realistic and also heterogeneous and diversified types of defects. In the scope of this work it is shown that basic generative networks presented in the literature such as Deep Convolutional Generative Adversarial Network are not suitable for volumetric medical data and to properly capture all the details and dynamics, more sophisticated algorithms are required. Hence, models such as Wasserstein Generative Adversarial Network, Variational Autoencoder and Introspective Variational Autoencoder are used for generating defective skulls with their compatible defects. These methods are evaluated quantitatively and qualitatively to show that they enable data generation that fulfills mentioned requirements. The quantitative part of the analysis is focused on using synthetically generated skulls in real-life clinical tasks and qualitative analysis targets the reproduction of the real data distribution. With the use of techniques such as t-SNE it is shown that synthetic skulls capture real skulls' distribution. The key takeaway of this work is that with the use of proposed models, it is possible to generate hundreds of thousands of realistic skulls with highly diversified types of defects that can be further used in real medical use cases.