Deep learning-based synthetic post-contrast T1-weighted MR imaging of glioblastomas

Evan Calabrese, Javier Villanueva-Meyer, Soonmee Cha

Highlights:
This study presents a deep learning method for generating synthetic gadolinium enhanced T1-weighted brain MR images from a series of pre-contrast brain MR images of patients with glioblastoma. Synthetic images were both qualitatively and quantitatively similar to real gadolinium enhanced images.

Introduction:
Gadolinium enhanced T1-weighted MR imaging is an essential component of all MRI examinations of brain tumors and is particularly important for brain malignancies like glioblastoma. Despite their widespread use, gadolinium-based contrast agents have several potential drawbacks including additional scan time, adverse medication effects, and the theoretical risks associated with gadolinium deposition in the brain and bones. For these reasons, it would be particularly appealing to exclude post-contrast T1-weighted imaging from a brain tumor MRI study if it could be done without negatively impacting diagnostic accuracy. This study demonstrates a deep learning method that can generate accurate synthetic post-contrast T1-weighted brain MR images from pre-contrast images in patients with glioblastoma.

Materials and methods:
We analyzed preoperative brain MRIs from 131 patients with glioblastoma including pre and post-contrast T1, T2, T2-FLAIR, arterial spin labeling (ASL), susceptibility (SWI), and diffusion (DWI) weighted sequences. All images were spatially co-registered, intensity normalized, and skull stripped. Approximately 80% (n=105) of the datasets were used to train a deep convolutional neural network designed to infer post-contrast T1-weighted images from pre-contrast images. Network architecture was based on a modified U-net with decomposed 3D convolutions, long range skip connections, and bottleneck residual learning. The network was trained with all available pre-contrast images, and then separately after excluding each individual image series to determine its contribution to the final result. Synthetic post-contrast T1-weighted images were generated from the remaining 20% (n=26) of the datasets and were compared directly to real post-contrast images using mean absolute percentage error (MAPE).

Results:
Synthetic post-contrast T1-weighted images were both qualitatively and quantitatively similar to real post-contrast images (Figure 1). The average MAPE across the test set was $5.0 \pm 0.3\%$ for the whole brain and $5.8 \pm 1.4\%$ for the tumor region only. The largest increase in average synthetic image error was seen when pre-contrast T1-weighted images were excluded from the training set (0.24% increase in MAPE) followed by T2 FLAIR-weighted images (0.23% increase in MAPE) and then SWI images (0.19% increase in MAPE). In all three cases, these increased error rates were statistically significantly higher compared to the network trained with all pre-contrast images.

Conclusions:
We used a deep learning algorithm to generate synthetic post-contrast T1-weighted images of brain glioblastomas from a series of pre-contrast images. Synthetic post-contrast images were qualitatively and quantitatively similar to real post-contrast images. This relatively small retrospective study suggests that there may be a role for deep learning to help reduce the need for administration of gadolinium-based contrast agents in some cases. Future work will be

necessary for assessing the diagnostic accuracy of synthetic versus real post-contrast T1-weighted images, which was not addressed in this study.

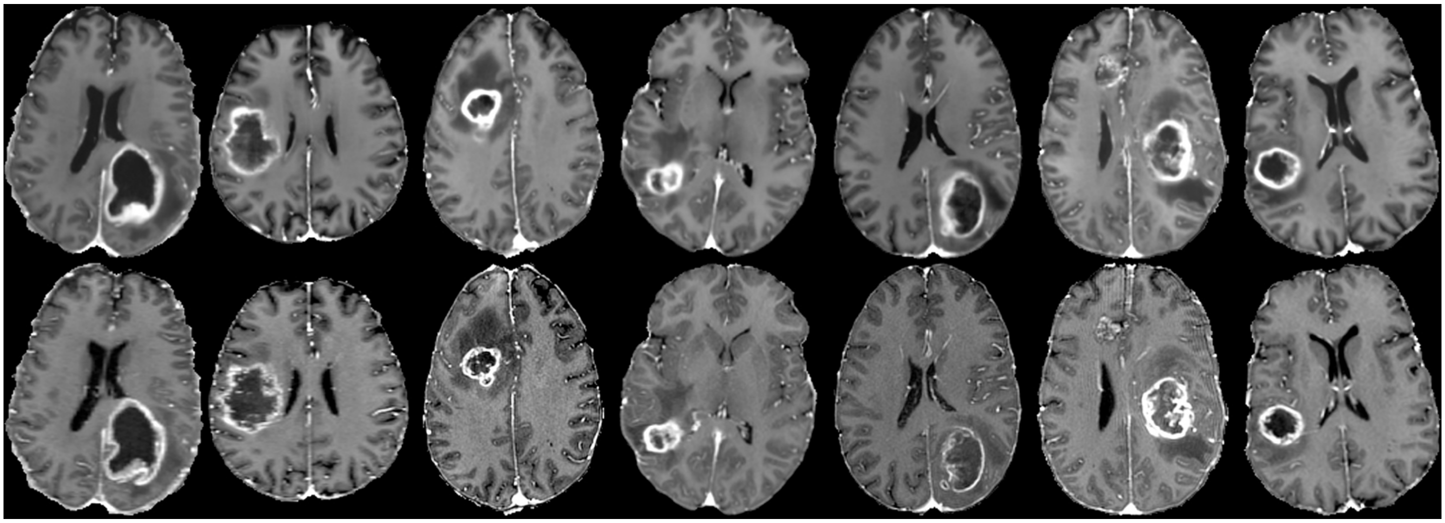

Figure 1 - Synthetic versus real post-contrast T1-weighted axial brain images of patients with glioblastoma. **Top row**: synthetic T1-weighted post-contrast imaging inferred from pre-contrast image series (T1, T2, T2 FLAIR, DWI, SWI, and ASL). **Bottom row**: corresponding real T1-weighted post-contrast axial images.