MAGIC: Multitask Automated Generation of Inter-modal CT Perfusion Maps via Generative Adversarial Network

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Introduction: Computed tomography perfusion (CTP) imaging requires injection of an intravenous contrast agent and increased exposure to ionizing radiation. This process can be lengthy, costly, and potentially dangerous to patients, especially in emergency settings. We propose MAGIC, a multitask, generative adversarial network-based deep learning model to synthesize an entire CTP series from only a non-contrasted CT (NCCT) input.

Materials and Methods: NCCT and CTP series were retrospectively retrieved from 493 patients at UF Health with IRB approval. The data were deidentified and all images were resized to 256x256 pixels. The collected perfusion data were analyzed using the RapidAI CT Perfusion analysis software (iSchemaView, Inc. CA) to generate each CTP map. For each subject, 10 CTP slices were selected. Each slice was paired with one NCCT slice at the same location and two NCCT slices at a predefined vertical offset, resulting in 4.3K CTP images and 12.9K NCCT images used for training. The incorporation of a spatial offset into the NCCT input allows MAGIC to more accurately synthesize cerebral perfusive structures, increasing the quality of the generated images. The studies included a variety of indications, including healthy tissue, mild infarction, and severe infarction.

The proposed MAGIC model incorporates a novel multitask architecture, allowing for the simultaneous synthesis of four CTP modalities: mean transit time (MTT), cerebral blood flow (CBF), cerebral blood volume (CBV), and time to peak (TTP). We propose a novel Physicians-in-the-loop module in the model's architecture, acting as a tunable layer that allows physicians to manually adjust the amount of anatomic detail present in the synthesized CTP series. Additionally, we propose two novel loss terms: multi-modal connectivity loss and extrema loss. The multi-modal connectivity loss leverages the multi-task nature to assert that the mathematical relationship between MTT, CBF, and CBV is satisfied. The extrema loss aids in learning regions of elevated and decreased activity in each modality, allowing for MAGIC to accurately learn the characteristics of diagnostic regions of interest. Corresponding NCCT and CTP slices were paired along the vertical axis. The model was trained for 100 epochs on a NVIDIA TITAN X GPU.

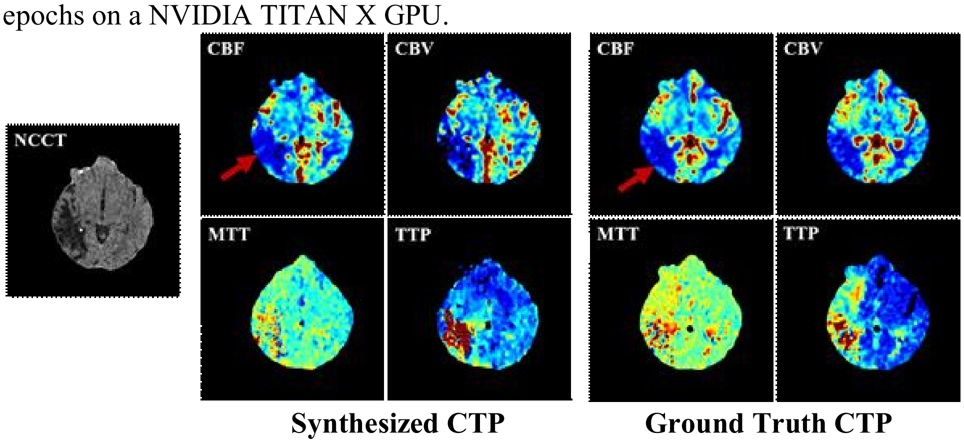

Figure 1. The MAGIC framework can synthesize high-quality CTP series to characterize cerebral tissue and identify infarcted regions of tissue from solely a NCCT input. From left-to-right: **(i)** NCCT slice input, **(ii)** synthesized CTP series generated by MAGIC, **(iii)** ground truth CTP series.

Results and Discussion: The MAGIC model's performance was evaluated on a sample of 40 patients from the UF Health dataset. Across all CTP modalities, MAGIC was able to accurately produce images with high structural agreement between the entire synthesized and clinical perfusion images ($SSIM_{mean}$=0.801 , UQI_{mean}=0.926). MAGIC was able to synthesize CTP images to accurately characterize cerebral circulatory structures and identify regions of infarct tissue, as shown in Figure 1. A blind binary evaluation was conducted to assess the presence of cerebral infarction in both the synthesized and clinical perfusion images, resulting in the synthesized images correctly predicting the presence of cerebral infarction with 87.5% accuracy.

Conclusions: We proposed a MAGIC model whose novel deep learning structures and loss terms enable high-quality synthesis of CTP maps and characterization of circulatory structures solely from NCCT images, potentially eliminating the requirement for the injection of an intravenous contrast agent and elevated radiation exposure during perfusion imaging. This makes MAGIC a beneficial tool in a clinical scenario increasing the overall safety, accessibility, and efficiency of cerebral perfusion and facilitating better patient outcomes.

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