In recent years, the classical computer vision problem of super-resolution has been approached with deep learning technologies, e.g., convolutional neural networks (CNNs). These new techniques such as SRCNN have vastly surpassed traditional example-based methods such as sparse-coding. High resolution medical images significantly improve the performance of detection, segmentation, and diagnosis of abnormalities. Unfortunately, the quality of medical images is critically dependent on both practical and physical limitations. First, the quality of imaging is directly proportional to the radiative dosage received by the patient. Furthermore, the extended time in cramped machines leaves the patient prone to anxiety, which may result in motion artifacts. Finally, high-powered machines are necessary to produce high-resolution scans, but they are expensive.

We propose a novel context-aware CNN architecture, C-SRCNN, as a superior solution to super-resolution, particularly regarding medical imaging. Our novel model employs a multi-channel input to a deep CNN to learn an end-to-end mapping from low-resolution to high-resolution images. Unlike previous techniques, our model is context-aware, having the ability to utilize surrounding patches of an input image patch for increased performance. The addition of contextual information is apt for medical imaging due to self-similarity between anatomical structures and allows our model to train with more information on a deep and wider network. The model is built using the modern deep learning framework of Tensorflow and Python. Our model has clearly superior performance compared to existing work on benchmark datasets as well as on medical images in similar experimental conditions.