Documentation

Objective:

Design and develop an efficient deep CNN for solving Single Image Super Resolution Task. Multi Image Feature Fusion Generative adversarial Network (MFFGAN) has been implemented and trained and tested on DIV2K dataset.

Tools Used:

- Tensorflow-gpu, Tensorlayer python libraries were used for running standard deep-learning models.
- NumPy , Opencv tools were used for processing images for training and validation dataset.

Experimental Setup:

The experiments were carried out on a 64 bit PC with 16 GB RAM and CPU Intel core i7 and Ubuntu 16 OS installed , also carried out on Google Colaboratory environment as well.

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