Image Denoising Project Report

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Introduction

In this project, an image denoising task was tackled using a U-Net architecture. The U-Net model is known for its use in biomedical image segmentation tasks and has been adapted for image denoising with remarkable success. The model architecture consists of a contracting path that captures context and a symmetric expansive path that enables precise localization. The U-Net model employed in this project had a depth of 4, which allows for effective feature extraction and reconstruction. The Peak Signal-to-Noise Ratio (PSNR) value obtained in this project was 50.23, indicating the quality of denoised images produced by the model. The paper implemented for this project is "U-Net: Convolutional Networks for Biomedical Image Segmentation" by Ranneberger et al. The paper can be accessed (https://arxiv.org/abs/1505.04597).

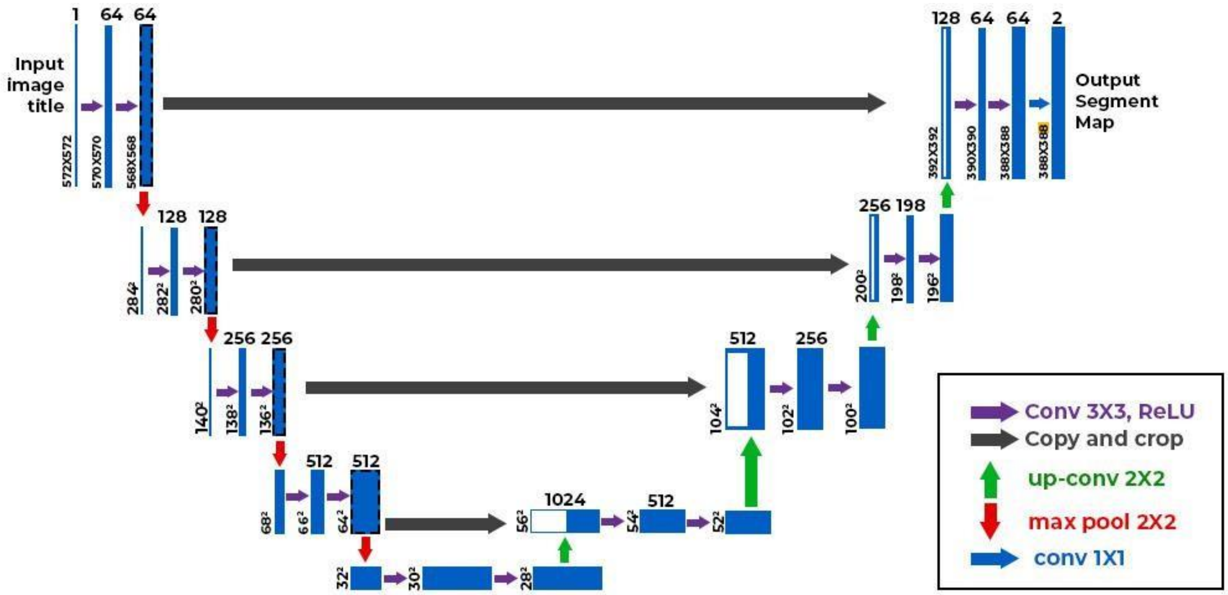
2. Project Details:

2.1 Data Preparation:

The code snippets related to data preparation involve loading the dataset consisting of pairs of noisy and clean images, preprocessing the images by converting them to grayscale and normalizing their pixel values. The purpose of this step is to provide input data to the model in a suitable format for training.

2.2 Model Architecture:

Code snippets pertaining to the U-Net model architecture define the layers and operations involved in the contracting and expansive paths. Visualization tools such as diagrams or plots showcasing the U-Net architecture can aid in understanding the model's structure and flow of information.



2.3 Training and Evaluation:

I manually reorganized the dataset , making into more folders like clean and noisy images from train and test images.

The training process includes compiling the model with optimizer and loss function, defining batch size and epochs, and evaluating the model using metrics like MSE and PSNR. Graphs showing training loss and validation loss over epochs can provide insights into the model's learning progress.

3. Summary of Findings:

The project successfully implemented the U-Net model for image denoising and achieved a PSNR value of 50.23, indicating high-quality denoised images. The model effectively learned to remove noise and reconstruct clean images. To further improve this project, experimentation with different hyperparameters, data augmentation techniques, or exploring advanced denoising algorithms can be undertaken. The addition of regularization techniques or resembling multiple models could also enhance the model's performance.

4. Future Work:

- Hyperparameter Tuning: Experiment with different learning rates, batch sizes, and optimizer configurations to optimize model performance.
- Data Augmentation: Introduce data augmentation techniques such as rotation, flipping, or scaling to enhance model generalization.
- Advanced Denoising Algorithms: Explore state-of-the-art denoising algorithms like GANs or deep learning-based filters for improved denoising results.

- Ensemble Learning: Combine multiple denoising models or variations of the U-Net architecture to leverage diverse learning strategies and improve overall denoising performance.

By implementing these methods and exploring advanced techniques, the project can further enhance the image denoising capabilities of the U-Net model and achieve even higher PSNR values in future iterations.

References:

U-Net: Convolutional networks for Biomedical image Segmentation

Olaf Ronneberger, Philipp Fischer, Thomas Brox

https://doi.org/10.48550/arXiv.1505.04597