

UNIVERSITÉ DE BRETAGNE OCCIDENTALE

DOCTORAL THESIS

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# Tomographic Image Reconstruction with Neural Networks

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*A thesis submitted in fulfillment of the requirements  
for the degree of Doctor of Philosophy*

*in the*

LATIM  
Biologie Santé

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# Declaration of Authorship

I, Venkata Sai Sundar KANDARPA, declare that this thesis titled, “Tomographic Image Reconstruction with Neural Networks” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

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Date:

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*“Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism.”*

Dave Barry



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*Abstract*

Biologie Santé

Biologie Santé

Doctor of Philosophy

**Tomographic Image Reconstruction with Neural Networks**

by Venkata Sai Sundar KANDARPA

Neural Networks are extensively used in the field of medical imaging for biomedical image segmentation, cancer diagnosis, image analysis, etc. The advancements in computation power (GPUs) and efficient memory utilization have propelled the spread of deep neural networks into various domains. The main motivation behind the use of neural network approaches is faster prediction (compared to traditional methods) without compromising on the quality of the result. Tomographic image reconstruction has also benefited from the development of neural networks. Medical image reconstruction involves the task of mapping raw measurement data collected by the detector to images that are comprehensible to a radiologist. A medical image reconstruction algorithm essentially approximates this mapping to predict the best possible image. There are established analytical and iterative reconstruction algorithms which have over the years proven to be effective in producing the best image possible. Convolutional neural networks (CNN) specifically have proven to be exceptional in tasks related to images such as denoising, deblurring, and super-resolution. The use of neural networks in Positron Emission Tomography (PET) and Computed Tomography (CT) reconstruction has been explored in this thesis. Novel frameworks called DUG-RECON (Double U-Net Generator) for PET, CT image reconstruction, and LRR-CED (Low-Resolution Reconstruction aware Convolutional Encoder-Decoder) for Sparse-view CT image reconstruction and Total-Body PET image reconstruction are proposed in this manuscript. Quantitative analysis of the images reconstructed with the proposed methods indicated that image quality was either better or on par with standard reconstruction algorithms.





# *Acknowledgements*

The acknowledgments and the people to thank go here, don't forget to include your project advisor. . .



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# List of Abbreviations

**LAH** List Abbreviations **Here**  
**WSF** What (it) **Stands For**



# Physical Constants

Speed of Light  $c_0 = 2.997\,924\,58 \times 10^8 \text{ m s}^{-1}$  (exact)



# List of Symbols

$a$	distance	m
$P$	power	W (J s <sup>-1</sup> )
$\omega$	angular frequency	rad



*For/Dedicated to/To my...*





# Chapter 1

## Introduction

### 1.1 Motivation

The use of deep learning in medical imaging has been on the rise over the last few years. It has widely been used in various tasks across medical imaging such as image segmentation (Ronneberger, Fischer, and Brox, 2015; Guo et al., 2019; Sinha and Dolz, 2019; Dolz et al., 2018; Hatt et al., 2018), image denoising (Kadimesetty et al., 2018; Li et al., 2020; Chen et al., 2017; Yang et al., 2018), image analysis (Litjens et al., 2017; Amyar et al., 2019; Cui et al., 2018). Deep learning based algorithms produce faster results along with best possible quality in accordance with existing state of the art methods (Leuschner et al., 2021). Medical Image reconstruction too has benefited hugely with the advancement of deep learning (Reader et al., 2020; Zhang and Dong, 2020). Medical Image reconstruction corresponds to the task of mapping raw projection data retrieved from the detector to image domain data. During the course of this thesis, the focus has been specific to positron emission tomography (PET) and computed tomography (CT) image reconstruction. Both these modalities present a unique set of challenges for image reconstruction. There are many standard analytical and model-based methods for the task of medical image reconstruction. Some of the challenges in PET image reconstruction are scatter, attenuation and difficulty in identifying the exact annihilation point of the electron-positron. Analytical algorithms for PET often result in very noisy image realizations. In the specific case of CT image reconstruction, there has been active interest in sparse-view and low-dose reconstruction scenarios. In both cases, severe artifacts are introduced in reconstructed images either due to incomplete projections or low counts. Many established model-based iterative methods account for the low-dose and sparse-view settings to remove artifacts and noise from the reconstruction (Nuyts et al., 1998; Elbakri and Fessler, 2002; Liu et al., 2013). However, these methods require the knowledge of the noise and artifacts

statistics and generally have longer reconstruction times (Kim, Ramani, and Fessler, 2014). Deep learning-based methods have proven to be effective in dealing with image denoising and image-to-image translation tasks making them suitable for tackling the difficulties posed in medical image reconstruction. (add citations here) This thesis aims to explore novel deep learning approaches for PET and CT image reconstruction. The proposed methods are also compared with standard reconstruction algorithms and existing deep learning algorithms appropriate to the particular case.

### 1.1.1 Subsection 1

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### 1.1.2 Subsection 2

Morbi rutrum odio eget arcu adipiscing sodales. Aenean et purus a est pulvinar pellentesque. Cras in elit neque, quis varius elit. Phasellus fringilla, nibh eu tempus venenatis, dolor elit posuere quam, quis adipiscing urna leo nec orci. Sed nec nulla auctor odio aliquet consequat. Ut nec nulla in ante ullamcorper aliquam at sed dolor. Phasellus fermentum magna in augue gravida cursus. Cras sed pretium lorem. Pellentesque eget ornare odio. Proin accumsan, massa viverra cursus pharetra, ipsum nisi lobortis velit, a malesuada dolor lorem eu neque.

## 1.2 Thesis Organization

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sit amet nulla pulvinar id facilisis ligula mollis. Nam elit libero, tincidunt ut aliquam at, molestie in quam. Aenean rhoncus vehicula hendrerit.

## **1.3 Image Reconstruction Model**

### **1.3.1 PET**

### **1.3.2 CT**



## Appendix A

# Frequently Asked Questions

### A.1 How do I change the colors of links?

The color of links can be changed to your liking using:

```
\hypersetup{urlcolor=red}, or  
\hypersetup{citecolor=green}, or  
\hypersetup{allcolor=blue}.
```

If you want to completely hide the links, you can use:

```
\hypersetup{allcolors=.}, or even better:  
\hypersetup{hidelinks}.
```

If you want to have obvious links in the PDF but not the printed text, use:

```
\hypersetup{colorlinks=false}.
```



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