

# Depth Reconstruction in Gamma Camera Imaging using AI - Whole Image Regression from Hybrid UNet-Deep Networks



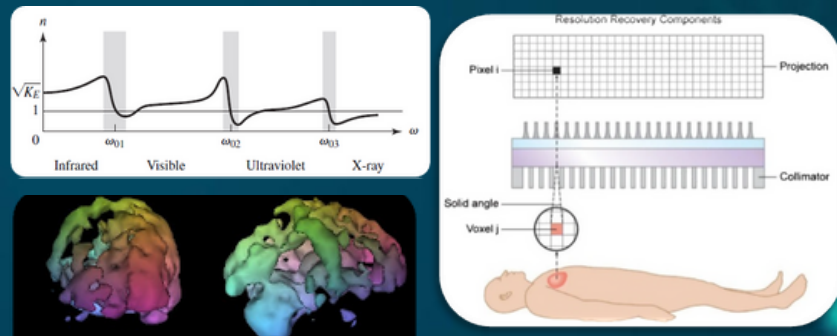
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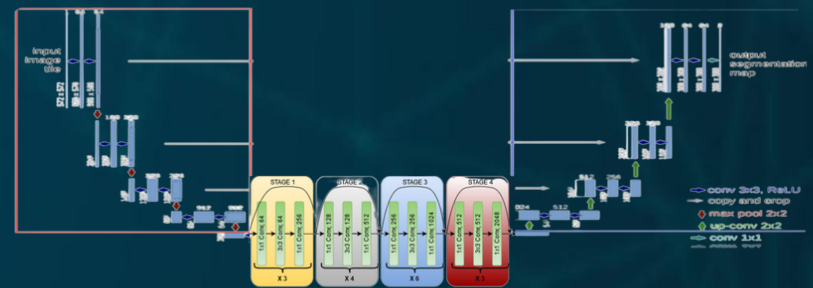
## INTRODUCTION

Gamma cameras currently used for medical imaging involve a trade-off between image quality and patient safety. The latter seeks to minimize patient intake of radioactive material and exposure time. Yet in the absence of lenses for gamma rays, projection images are formed from photons propagating in a small range of angles.



Finally a deep neural network (DNN) was employed in regression mode to directly reconstruct the image of the source. The network was designed with a hybrid U-Net architecture, in which a pretrained DNN – Resnet50 – was embedded in the bridge. This allowed exploitation of the power of the DNN, including transfer learning, together with the capabilities demonstrated by UNet for fully two-dimensional output.

## SCHEME OF UNET WITH RESNET AS BRIDGE



## OBJECTIVES

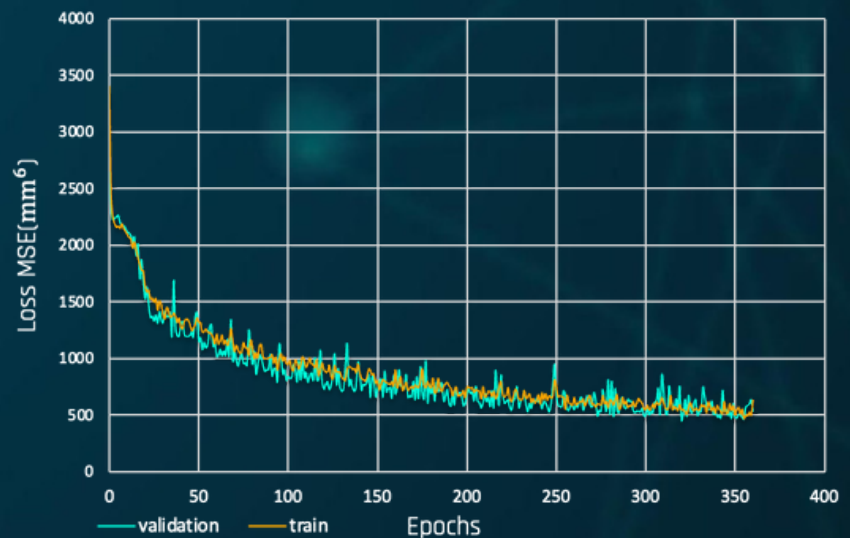
This work presents a new type of gamma-ray camera, which achieves a high resolution without compromising patient safety or long acquisition time. Only a small portion of the incoming photons are blocked, and the spatial location of the light source is determined using artificial intelligence.

## PRELIMINARY RESULTS

## MATERIALS & METHODS

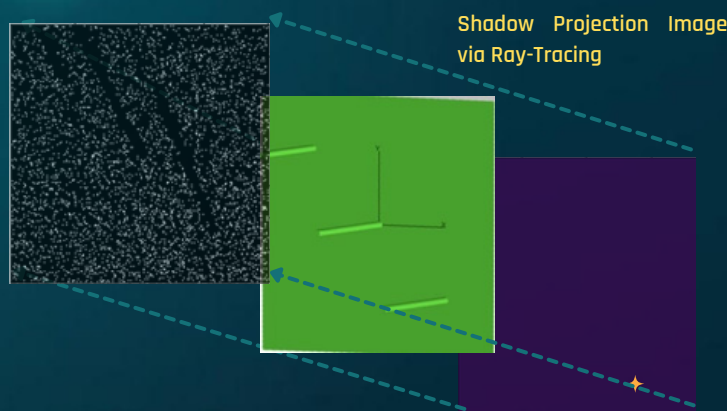
- Using a shadow template placed on the detector, a collection of images from different locations was generated by ray-tracing simulations, to serve as a training set for artificial intelligence algorithms. These seek to reconstruct the original source locations of new images – the test set – generated from different locations in space.
- Several methods of classical machine learning – including pseudoinverse, and Regression Support Vector Machines – were employed and compared to the performance of deep convolutional neural networks (CNN) – e.g. Resnet18.

### Step B: Training ResNet on simulation with tags as [3X1] vector



## CONCLUSIONS

This work demonstrates that it is possible to determine the location of a single light source that created the shadow pattern with good accuracy, even in the presence of moderate noise levels. Partial success was also achieved in identifying the location of two different sources that together contribute to a single shadow pattern. Using the UNET-DNN model, an error was attained of ~22.35 cubic millimeters – an error of about 2.817 millimeters per coordinate. The jumps in the locations of the samples of the dataset images are 37.5 millimeters – an error of 7.5 percent relative to the resolution of the jumps of the dataset. Evidently, the higher the density of the jumps – the smaller the relative error will be. This suggests that the required resolution may be attained by increasing the density of the jumps.



Shadow Projection Image via Ray-Tracing



Classification: Categories = Source Locations

Two Sources: Each image represents a different z-plane. Grey scale indicates probability.

## REFERENCES

- Image 1 - <https://www.cedars-sinai.org/programs/imaging-center/exams/nuclear-medicine.html>
- Image 2 - <https://link.springer.com/article/10.1007/s12350-018-1283-y>
- Image 3 - Hecht, Optics p.74