Abstract—In this paper, we present a novel method for
tomographic image reconstruction in SPECT imaging with a
low number of projections. Deep convolutional neural networks
(CNN) are employed in the new reconstruction method. Projection
data from software phantoms were used to train the CNN
network. For evaluation of the efficacy of the proposed method,
software phantoms and hardware phantoms based on the FOV
SPECT system were used. The resulting tomographic images
are compared to those produced by the "Maximum Likelihood
Expectation Maximisation" (MLEM).

Index Terms—Convolutional Neural Networks (CNN), Recon-
struction, Single Photon Emission Computerized Tomography
(SPECT), SPECT angle interpolation

I. INTRODUCTION

Computed tomography (CT) techniques are useful nuclear
imaging techniques that are used most widely in medicine [1].
Single Photon Emission Computerized Tomography (SPECT)
[2]–[4] and Positron Emission Tomography (PET) [5], [6]
are two of the most used CT techniques for diagnosis and
monitoring of numerous diseases such as cancer [7] and car-
diac diseases [8]. SPECT image reconstructions have limited
spatial resolution and underperform when a low number of
projections is available or when the measurements are low
quality and noisy. These difficulties produce an ill-posed in-
verse problem for image reconstruction. In order to solve those
issues, alternative reconstruction algorithms were proposed and
developed, such as ordered subset expectation maximization
(OSEM) [9] and maximization likelihood expectation maxi-
mization (MLEM) [10]. Nevertheless, the improvement in the
reconstructions is not ideal in many cases. The reconstruction
accuracy improves with an increase in the number of iterations
but with the downside of also increasing the noise. The noise
increase in the reconstruction is challenging to measure and
may affect the final reconstruction as a false detection. There-
fore, a new method is needed to provide high spatial resolution
and handle high noise and a low number of projections. In this
paper, a novel method for tomographic image reconstruction
in SPECT imaging is proposed based on deep convolutional
neural networks (CNNR).

The paper is organised as follows: Section II-A presents the
data generated and used for training the proposed model, Section
II-B presents the proposed model. Section III presents the
results and discussions and finally Section IV is conclusions.

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B. Proposed Model

Artificial Neural networks and, more specifically, Convolutional neural network (CNN) have been used with great success in multiple domains to analyse visual representations. Initially, CNN’s were inspired by physiological and biological processes, and the connectivity model between neurons compares to the structure of the biological visual cortex [12]. CNN’s are designed and require relatively minimum pre-processing of data compared to other methodologies by employing multilayer perceptrons [13]. This minimum prior knowledge provision provides an essential advantage of CNN’s over other methodologies where prior knowledge and feedback from experts are required. CNN’s have already successfully implemented in medical image analysis [14], and classification [15], [16].

As shown in Figure 2, the proposed model structure consists of two parts, the encoder and the decoder. The encoder consists of five blocks. The first three blocks consist of two convolutional layers with 3x3 kernel and rectified nonlinear activation function (Leaky ReLU) [17], followed by a batch normalisation layer, and a 2x2 max pooling layer [18] and a Dropout layer of 30%. The fourth block consists of two convolutional layers with a 3x3 kernel, a batch normalisation layer, a Leaky ReLU activation function, a Dropout layer of 30% and a flatten layer. The fifth layer consists of a dense layer of 4096 neurons, a Leaky ReLU activation function, and a batch normalisation layer. The number of kernels increases for each block, beginning with 32 kernels for the first block, 64, 128 and 256 for the second, third and fourth blocks, respectively.

Before the data are passed to the decoder, the decoder’s output is transformed from 4096 features to a vector of 4x4x256. The decoder consists of six blocks. The first five blocks consist of two convolutional layers and a transposed convolutional layers, with a stride of 2, with a 3x3 kernel and Leaky ReLU activation function and a Dropout layer of 30%. The fourth block consists of two convolutional layers with a 3x3 kernel, a batch normalisation layer, a Leaky ReLU activation function, a Dropout layer of 30% and a flatten layer. The fifth layer consists of a dense layer of 4096 neurons, a Leaky ReLU activation function, and a flatten layer. The number of kernels increases for each block, beginning with 32 kernels for the first block, 64, 128 and 256 for the second, third and fourth blocks, respectively.

The results show and illustrated in Table I, the proposed methodology outperforms MLEM with 0.003 versus 0.006, 0.92 versus 0.77 and 0.96 versus 0.93 for MSE, SSIM and PCC respectively. The proposed method was also tested using hardware phantoms generated using a small FOV SPECT system [21] of three parallel pillars, as shown in Figure 3 with the activity of 21 $\mu$Ci and variant background activity of 190, 360 and 700 $\mu$Ci. The results are presented in figure 3.

IV. Conclusions

In this paper, we proposed a new method based on convolutional neural networks to reconstruct SPECT imaging and demonstrate its capability to reconstruct images with a limited number of projections. As the results show, the proposed method can significantly outperform existing methods such as MLEM. Although the results presented in this proposed work are appropriate for representing the proposed method’s capabilities, further experimentation is needed, as shown in Figure 3, were the size and shape of the reconstructed caterpillars were overestimated.

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Table I

| Methodology | MSE | SSIM | PCC |
|-------------|-----|------|-----|
| MLEM        | 0.006 | 0.77 | 0.93 |
| Proposed Model | 0.003 | 0.92 | 0.96 |
Fig. 2. Structure of the proposed model based on deep convolutional neural networks.

Fig. 3. Hardware phantoms of three parallel pillars, with activity of 21 $\mu$Ci and variant background activity of 190, 360 and 700 $\mu$Ci.

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Fig. 4. Evaluation of the proposed method results compared to the MLEM method using the Shepp Logan Phantom. The results achieved using the proposed method compare favourably to those obtained with the widely used MLEM method.

Fig. 5. Evaluation of the proposed method results compared to the MLEM method using the Hardware phantoms.