Contribution of class activation map on PET deep features for primary tumor classification

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MOTIVATIONS & OBJECTIVES

- The first step in a PET radiomic analysis[1] is to locate pathological uptakes.
- Deep learning applications require important databases for each type of cancer as well as the segmentation of each uptake (pathological or physiological).
- The goal of this study is to classify the type of cancer and locate uptakes in various cancer pathologies with weakly supervised learning.

OUTLINE

- CAM: computation of class activation map
- Development of a computational model classifying and detecting tumors in PET images: GECHB design.

EXPERIMENTAL BACKGROUND

PET images

We consider a database of 1362 FDG-PET whole body pre-therapeutic exams.

Type of cancer	Nb of patient
Lung	156
Esophagus	97
Head & Neck	264
Lymphomas	209
Normal exams	636

MIP of a PET image used to train the neural network, The black area at the head, the kidneys and the bladder are physiological (normal). The balck area within the lungs are pathological (cancer).

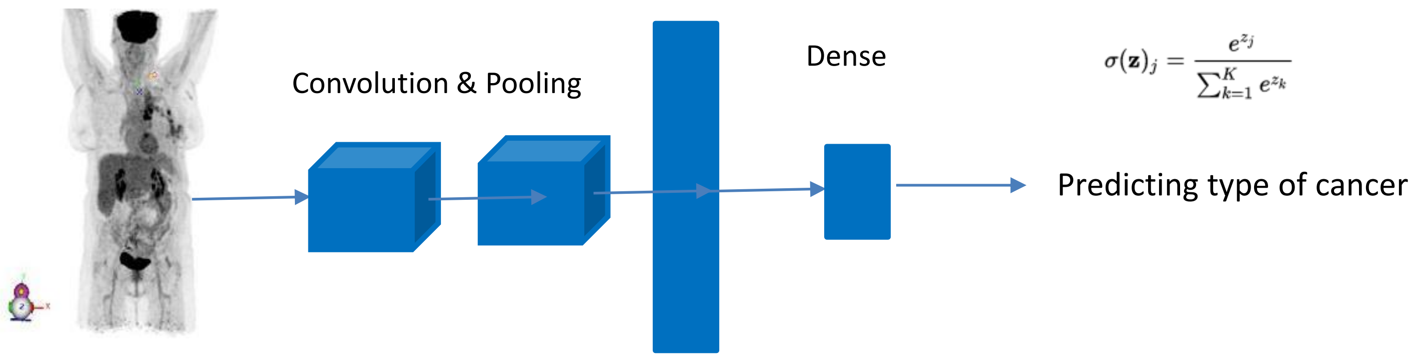
Pre-TREATMENTS

- Spatial normalization: All exams were normalized to have an isotropic resolution of 2 mm³
- Intensity normalization: 0 to 5 SUV translated between 0 and 1
- MIP generation: Maximum intensity projection was applied to enhance the 3D nature of uptakes fixation

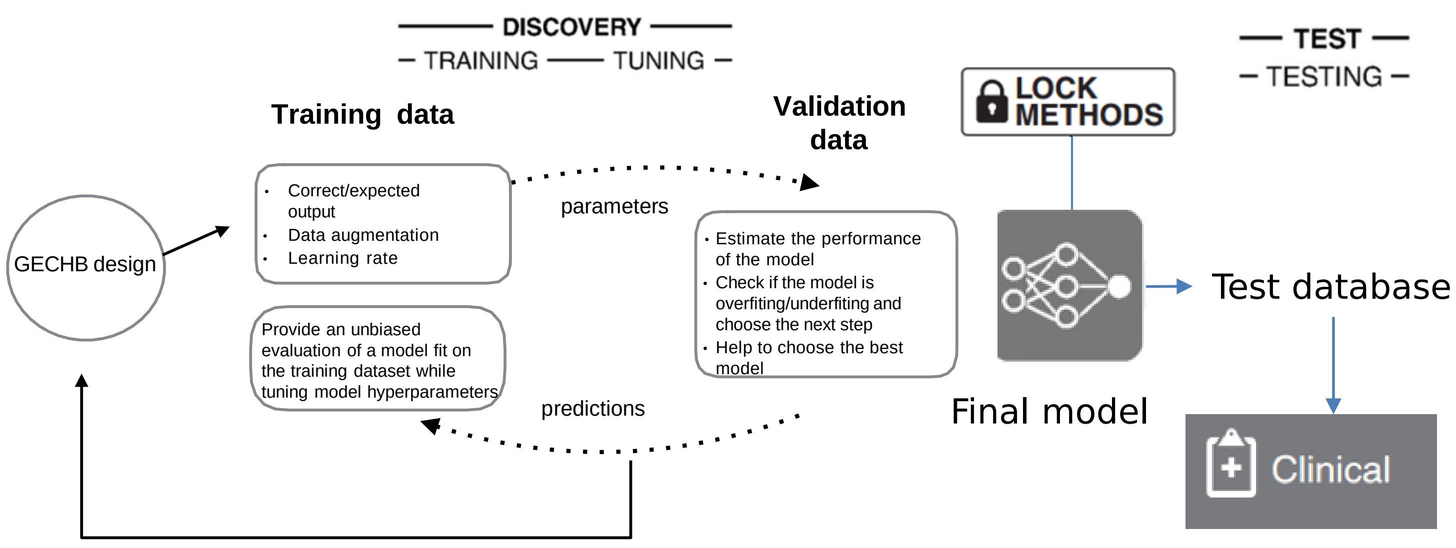
- The patients underwent FDG PET with CT before treatment
- Head & Neck and Lung databases are public obtained at TCIA
- The Other databases are local

METHODS

- Testing the ability of a deep learning framework based CNN to classify the type of cancer and to localize the 18F-Fluorodeoxyglucose (FDG) PET uptakes.
- Evaluating the ability of fully convolutional network (FCN) for the same purpose.
- The database was divided into training (60%), validation (20%) and testing (20%) subsets with the same ratio of cancer types in each category



- CAM to generate class activation map to detect pathological uptakes



PRELIMINARY RESULTS

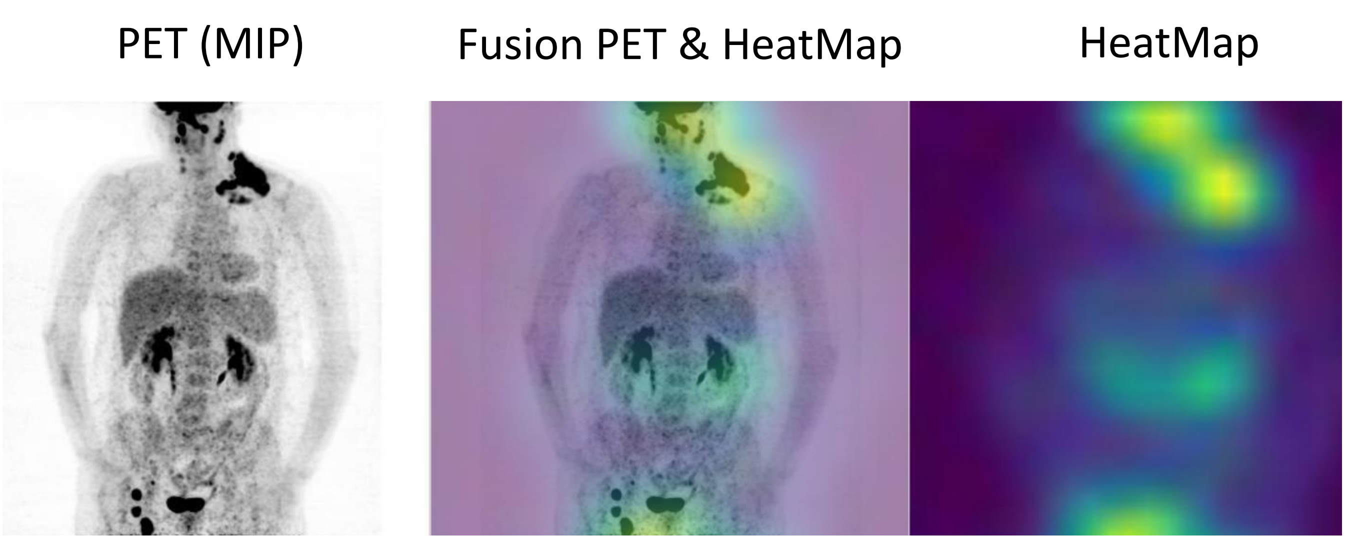
Pathology Classification

- The best result was achieved using 9 layers CNN with an accuracy of 86%.
- CAM allowed to localize the pathologies and/or confounding factors for the missed diseases.

Class	Accuracy
Lung	72%
Esophagus	40%
Head & Neck	73%
Lymphomas	73%
Normal exams	95%
Global	86%

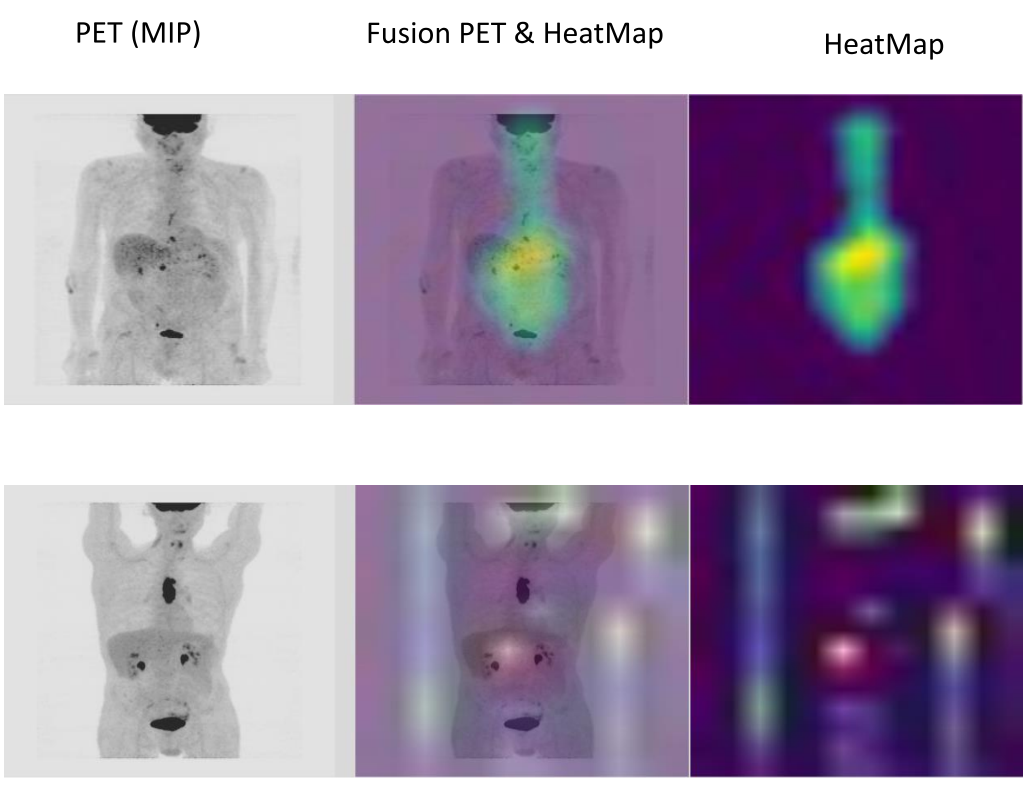
CNN was excellent in classifying normal patients with only physiological uptakes, and performed poorly on the esophagus.
On the other hand, FCN was excellent for classifying lymphomas and esophagus and not for Normal exams.

CAM to localize the pathologies



Class activation map obtained using a 9 layers convolutional neural network: On the left a MIP of a patient with lumphoma, On the right the activation map of the CNN, and in the model the fusion of the two images, We notice that the CNN is hilighting the importance of the tumor on the top left and the bottom right,

The obtention of correct heatmap

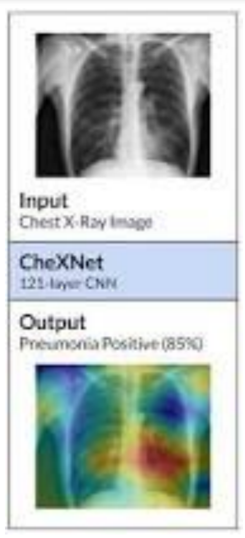


Prediction of the pathology is correct: esophageal cancer. The decision is taken inside the body

Prediction of the pathology is correct: esophageal cancer. The decision is taken outside the body

Conclusion & Perspectives

- Deep learning network can distinguish tumor from other organs and develop tumor-specific signature when its guided by normal patient in weakly supervised learning.
- The methodoly presented allows a CNN to develop its own definition of a PET tumor.
- CAM is a promising tool for physicians to verify the decision of a CNN



CheXNet is a 121-layer convolutional neural net-work that takes a chest X-ray image as input, and outputsthe probability of a pathology. On this example, CheXnetcorrectly detects pneumonia and also localizes areas in theimage most indicative of the pathology. [2]

1 AMYAR, A., et al. 3-D RPET-NET: Development of a 3-D PET Imaging Convolutional Neural Network for Radiomics Analysis and Outcome Prediction. IEEE Transactions on Radiation and Plasma Medical Sciences, 2019, vol. 3, no 2, p. 225-231.
2 RAJPURKAR, P et al. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225, 2017.