TOWARD A MULTIMODAL DEEP LEARNING APPROACH FOR HISTOLOGICAL SUBTYPE CLASSIFICATION IN NSCLC

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Introduction

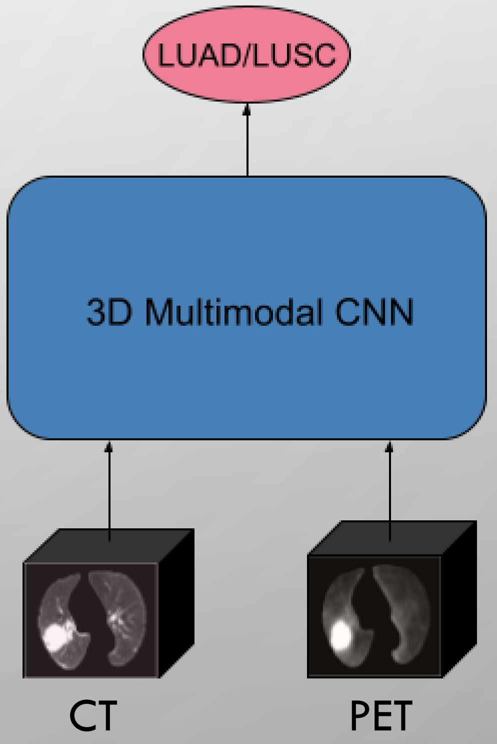
- Lunger cancer is one of the most common and deadly malignancies worldwide
- 85% of all lung cancers are NSCLC, with LUAD and LUSC as the most common subtypes
- Differentiating between LUAD and LUSC is crucial for effective, personalized treatment strategies
- Currently, invasive methods remain gold standard, but it is not always feasible and can lead to clinical complications

Credit: Echelon Health

Introduction

- CNNs have shown exceptional performance in various domains including medical image analysis
- Multimodal deep learning combines multiple data types for a comprehensive understanding
- PET and CT offers complementary metabolic and anatomical information

Therefore, we introduce a novel intermediate fusion approach to classify histological subtypes of NSCLC using PET and CT



Related Work

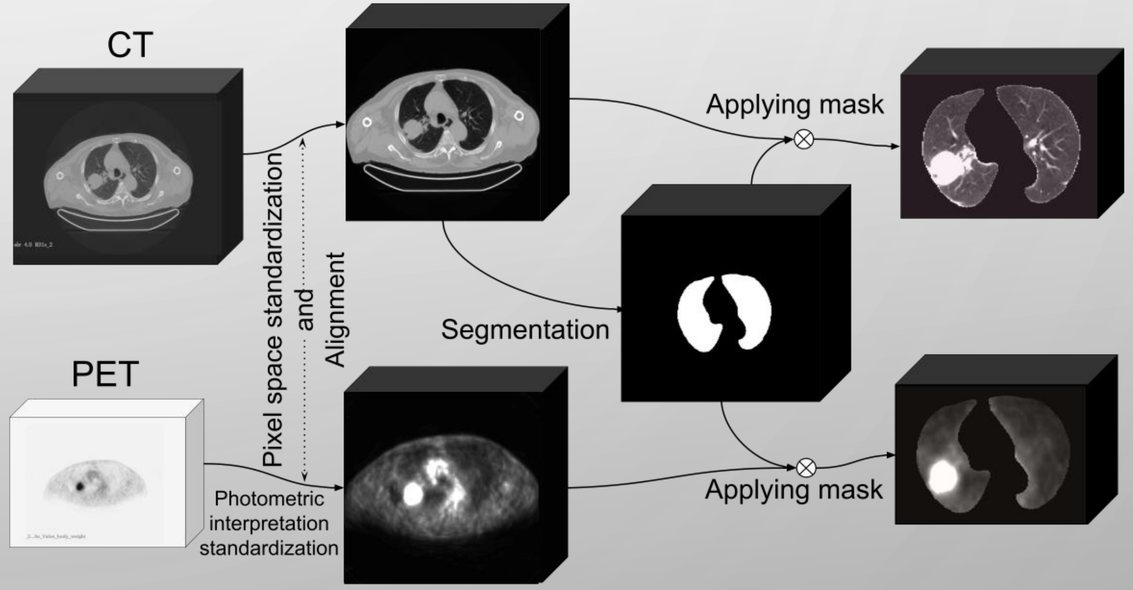
- Majority of the studies, particularly those using deep learning, utilize only CT images, either with:
  - 2D slices [1,2], or
  - 3D scans [3,4]
- Studies that employ both PET and CT typically use:
  - Radiomics features [5,6], or
  - Early fusion techniques [6,7]
- Only one study [8] applies intermediate fusion to PET and CT images; however, it is implemented for segmentation

Materials

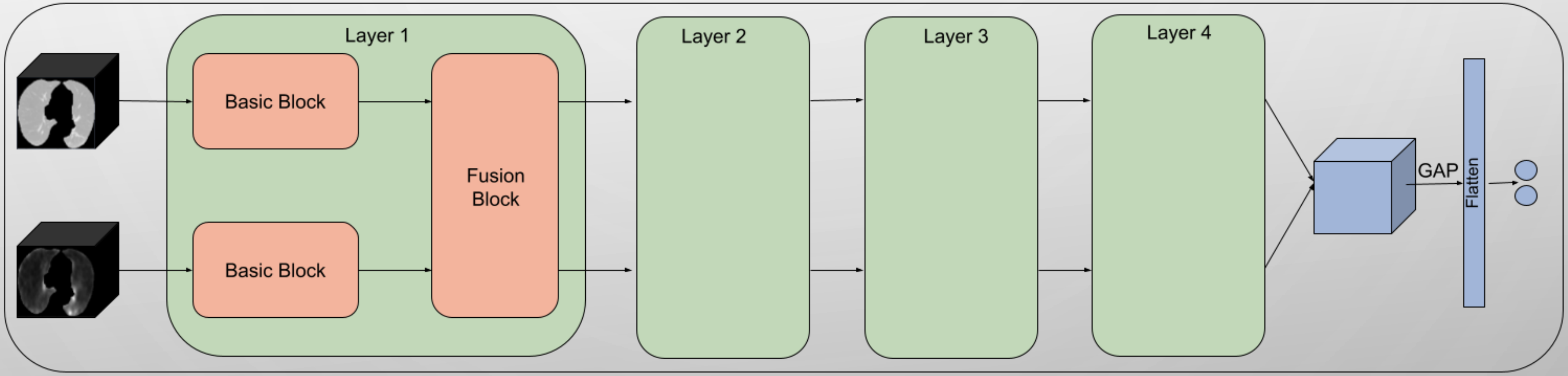
- Combination of 1 private and 2 public datasets
- Private dataset:
  - 423 patients from IRCCS Humanitas Research Hospital
- Public datasets from The Cancer Imaging Archive:
  - NSCLC Radiogenomics [9]: 193 patients
  - Lung-PET-CT-Dx [10]: 98 patients
- 714 patients in total with 546 LUAD and 168 LUSC cases

Pre-processing

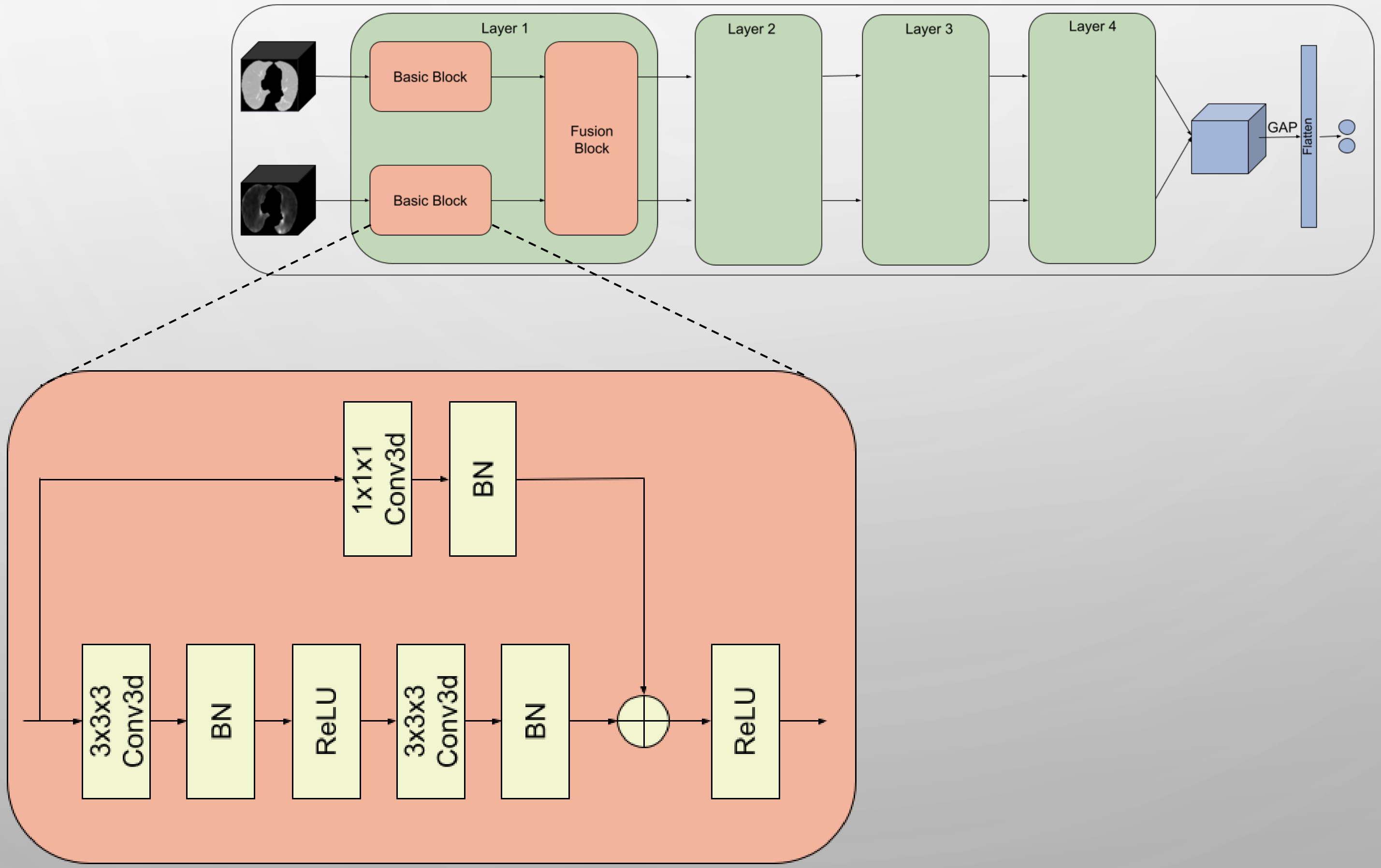
- Photometric interpretation standardization
- Hounsfield unit conversion
- Standard uptake values conversion
- Uniform pixel spacing and slice thickness
- PET – CT alignment
- Lung segmentation
- Clipping intensities
- Voxel value normalization



Network Architecture

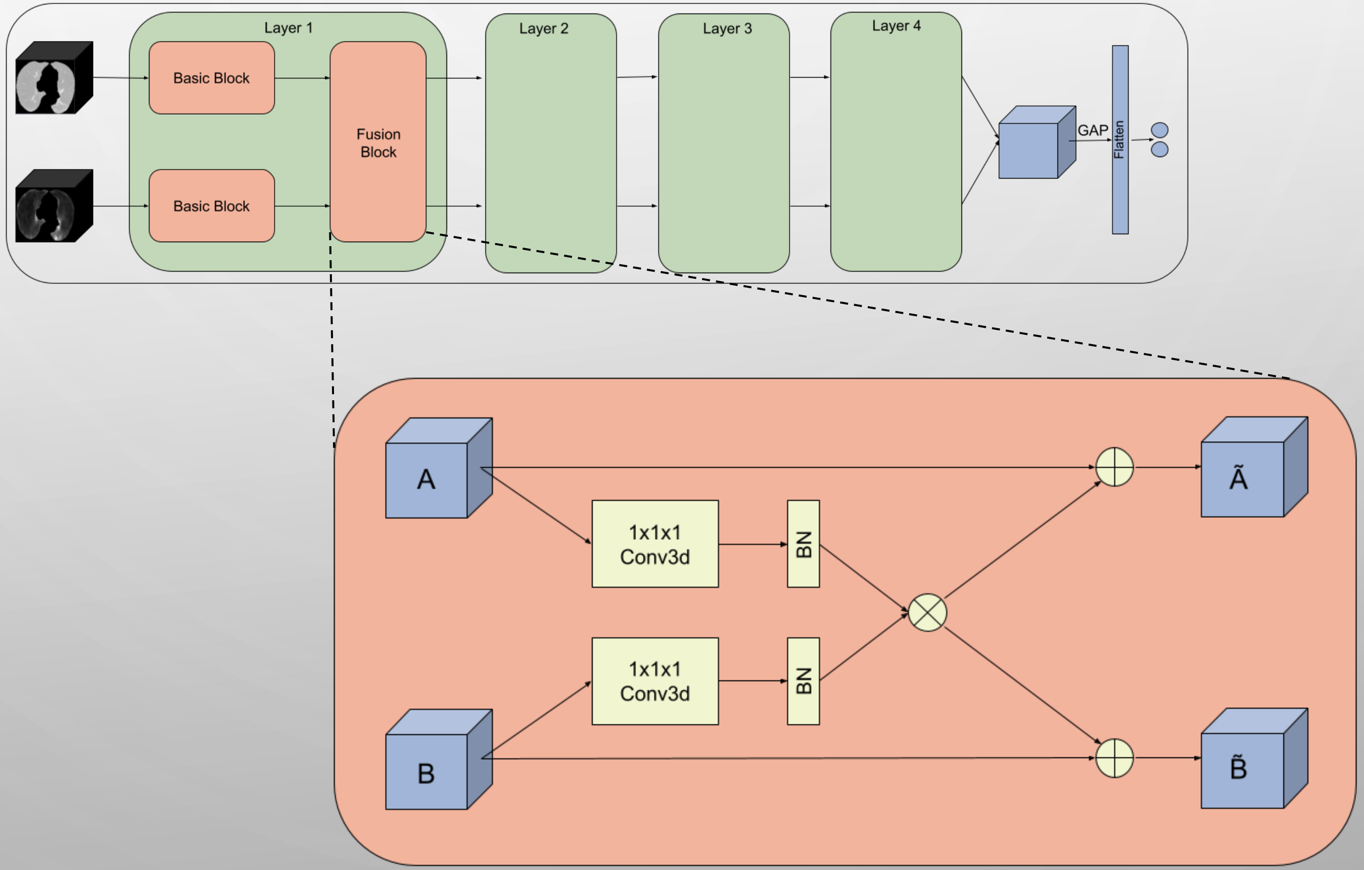


Basic Block



Layer 1
Basic Block
Fusion Block
Basic Block
Layer 2
Layer 3
Layer 4
GAP
Flatten
1x1x1 Conv3d
BN
3x3x3 Conv3d
BN
ReLU
3x3x3 Conv3d
BN
ReLU

Fusion Block



Results

Model	Accuracy	Sensitivity	Specificity	Gmean
Proposed Method	0.692	0.767	0.446	**0.580**
Unimodal (CT)	0.766	1.000	0.006	0.034
Unimodal (PET)	0.662	0.804	0.204	0.319
LUCY [3]	0.762	0.976	0.065	0.175
LUCY (Undersampled) [3]	0.775	0.976	0.119	0.295
DetectLC [4]	0.342	0.200	0.800	0.000

Conclusion

- We implemented a novel intermediate fusion approach
- Results show that our approach performs better than the unimodal approaches
- Using the complementary information from both PET and CT images improves the classification performance
- Eventually, it leads to a more personalized and effective treatment planning

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