3D Multi-Scale Convolutional Networks For Glioma Grading using MR Images

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Contents

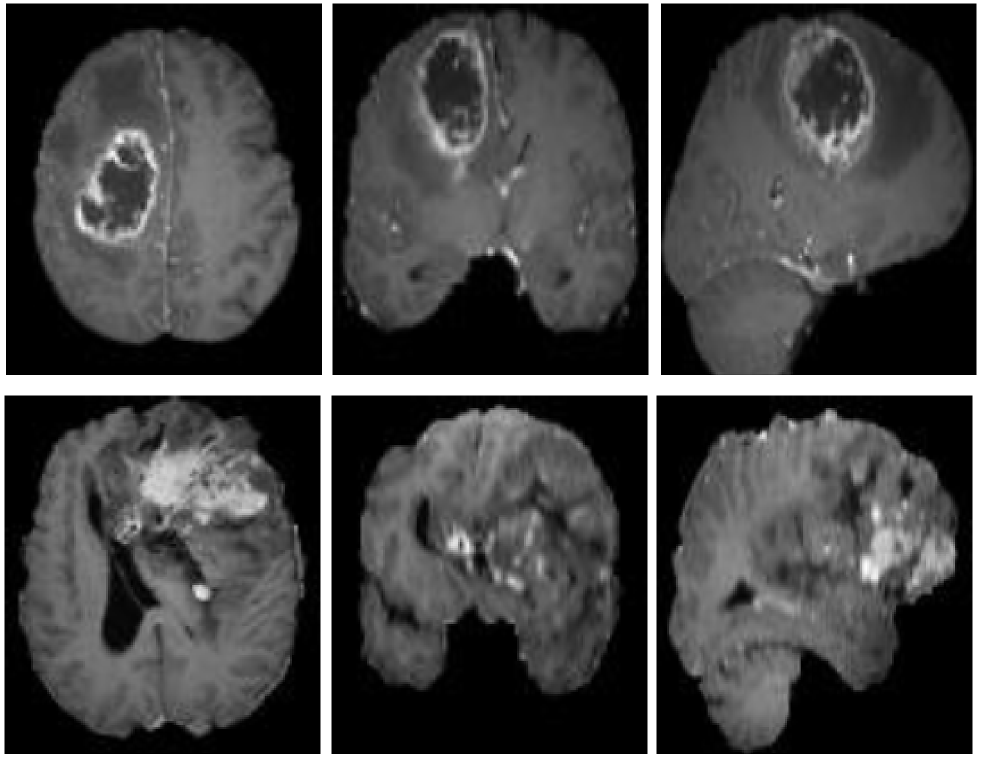
1. Introduction

Addressed issue

Deep learning for brain tumor classification
using MRIs (+ biomarkers)

High Grade Glioma, HGG (in axial, coronal, sagittal views)

Low Grade Glioma, LGG



Why glioma classification using MRIs ?

- Tumor grading is important to clinical planning
- Non-invasive method for diagnostics
- Determine tumor types without biomarker

Picture from:Website
in University of Utah

2. Related Work: Review

- **Using hand-crafted features [2,3]**

  e.g. size, shape, location, intensity, texture of tumors

- **Using deep learning for features [4]**

  3 layer 2D CNN structure and large size kernels

- **Combined models (traditional ML and DL) [5]**

  Fish vector (through clustering) to encode DL learned features

- **Using 2D CNN for learning features [Ge'18]**

  based on slice of MRIs and simple augmentation

3. Proposed Method：Motivation

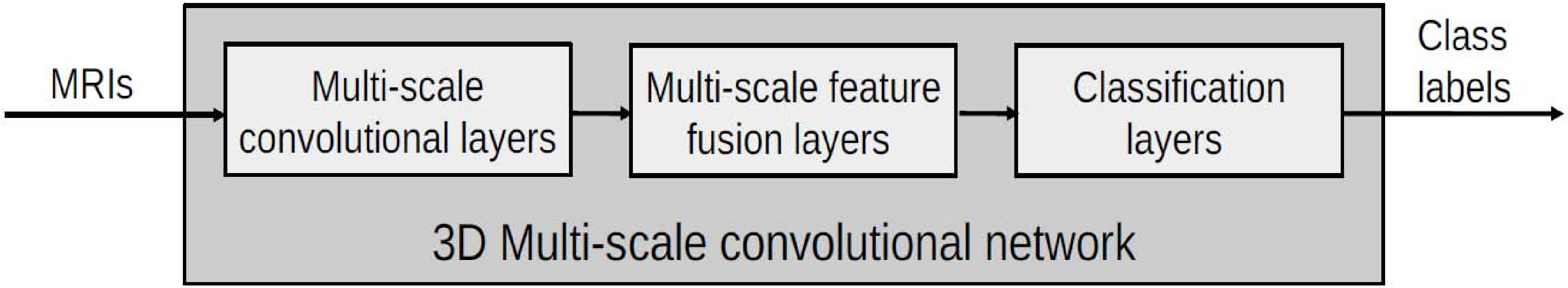
- Brain tumors may vary in shape, size and location

Tumor characterization: using multi-scale learning to capture both image-level and semantic-level features

- Tumor is relatively small in a 3D volume image

Require: saliency-awareness for highlighting the tumor area, where deep learning can be focused on.

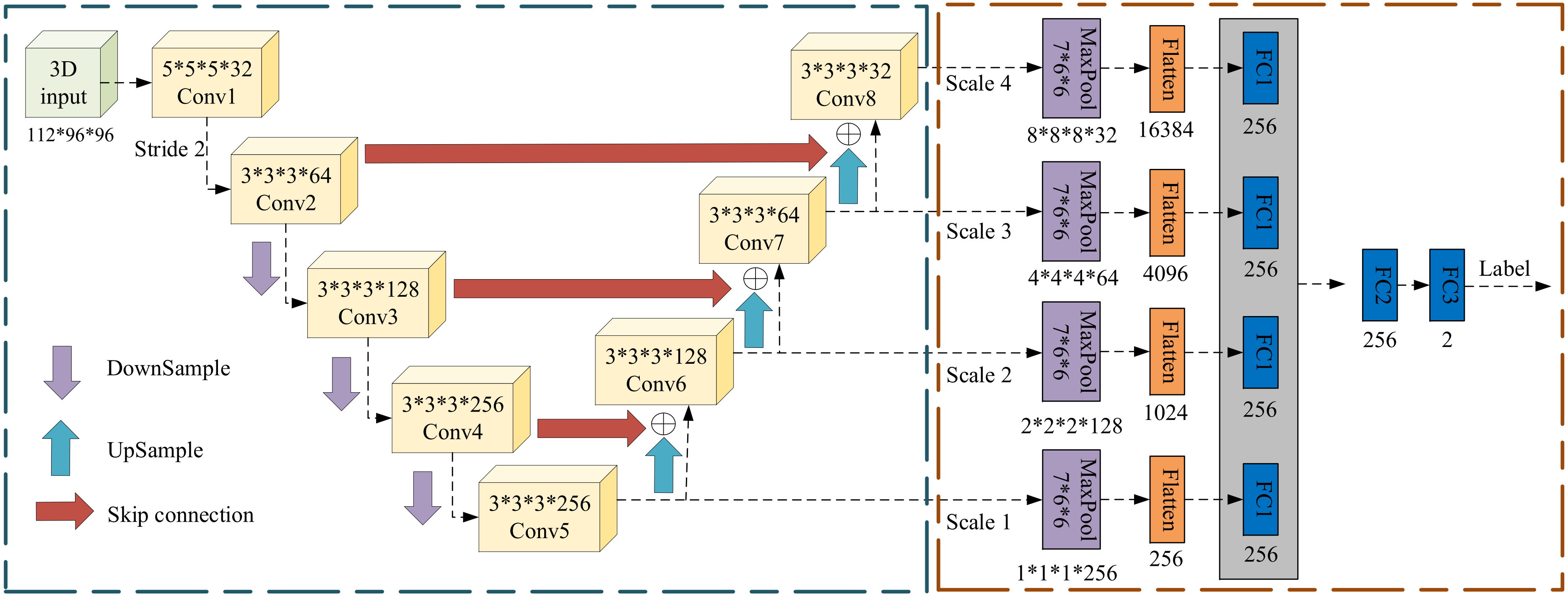
3. Proposed Method: Overview



Main Novelties

- Multi-scale 3D CNN architecture for feature learning.
- Fusion of multi-scale features
- Saliency-aware strategy to enhance tumor regions in MRIs.

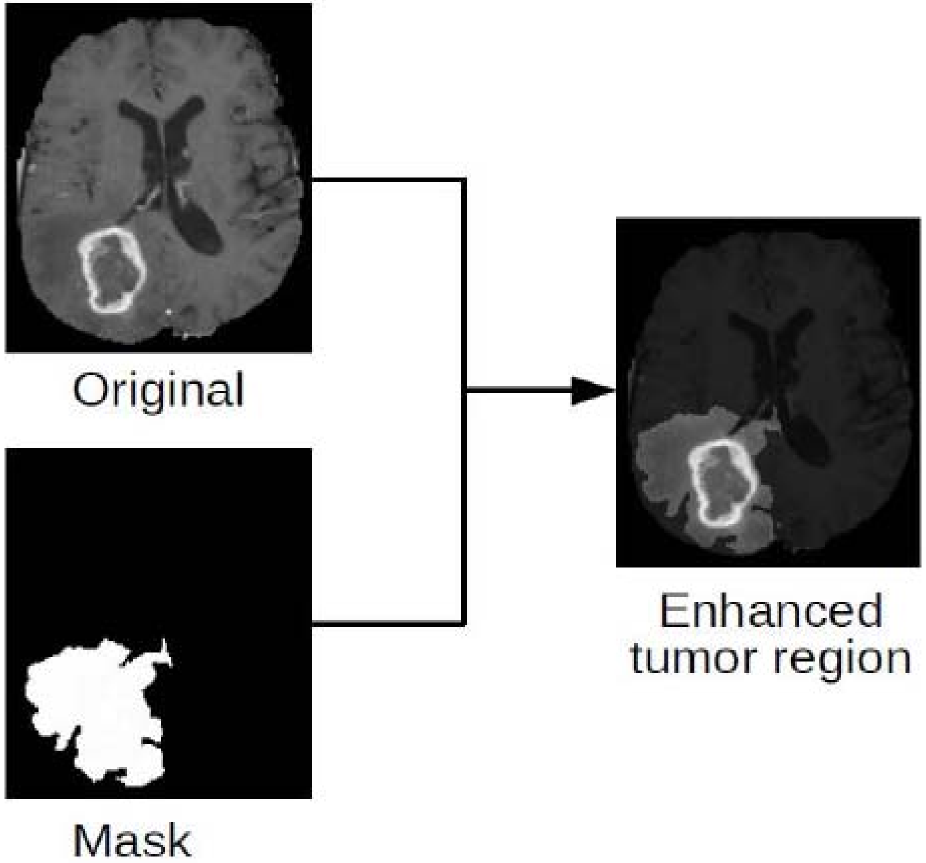
3. Proposed method: 3D multi-scale CNN scheme



Difference from [6] (using pyramid-structure CNNs):

- Different applications: MRIs (vs Visual images)
- 3D (vs 2D), different architecture (# layers, hyper-parameters etc.).
- End-to-end scheme

c) Saliency-aware tumor enhancement



Tumor enhancement with segmentation masks, reducing intensity values in non-tumor region (to 1/3)

4. Test Results and Evaluation

a) Dataset: BraTS 2017

class	# subjects	#scans in en-T1-MRI	#scans in tra. set	#scans in val. set	#scans in test set
	-				
HGG	210	210	126	42	42
LGG	75	75	45(90)	15	15

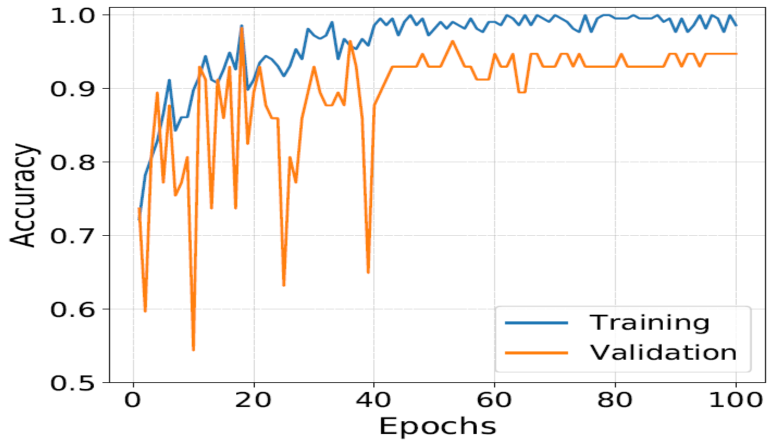
Flipping for data augmentation in LGG

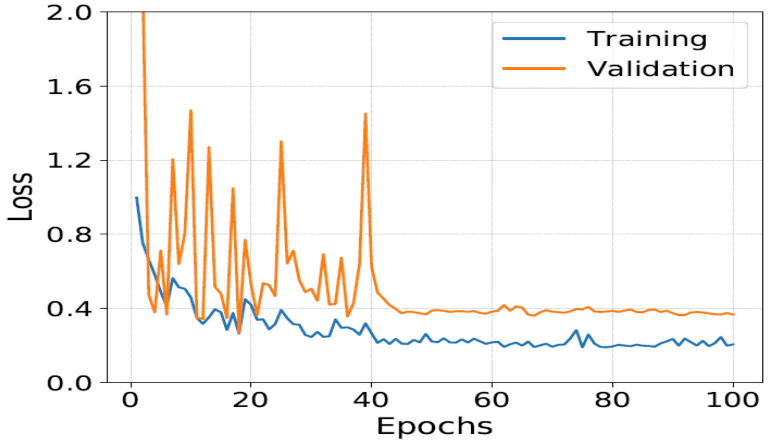
4. Test Results and Evaluation

b) Setup

- Use KERAS library with TensorFlow backend
- Use “Adam” optimizer for the back propagation
- Step-wise learning rate: *0.001 for epochs 1-40; 0.0001 for epochs 41-70; 0.00001 for epochs 71-100*
- Dataset partitioned randomly:
  training (60%), validation(20%),testing (20%)
- Use drop out, L2 regularization to mitigate the overfitting

c) Performance





Performance using the proposed scheme. Left: accuracy vs. epochs; right: loss vs. epochs.

Performance	training	validation	test
accuracy	98.61%	94.74%	89.47%

Overall performance

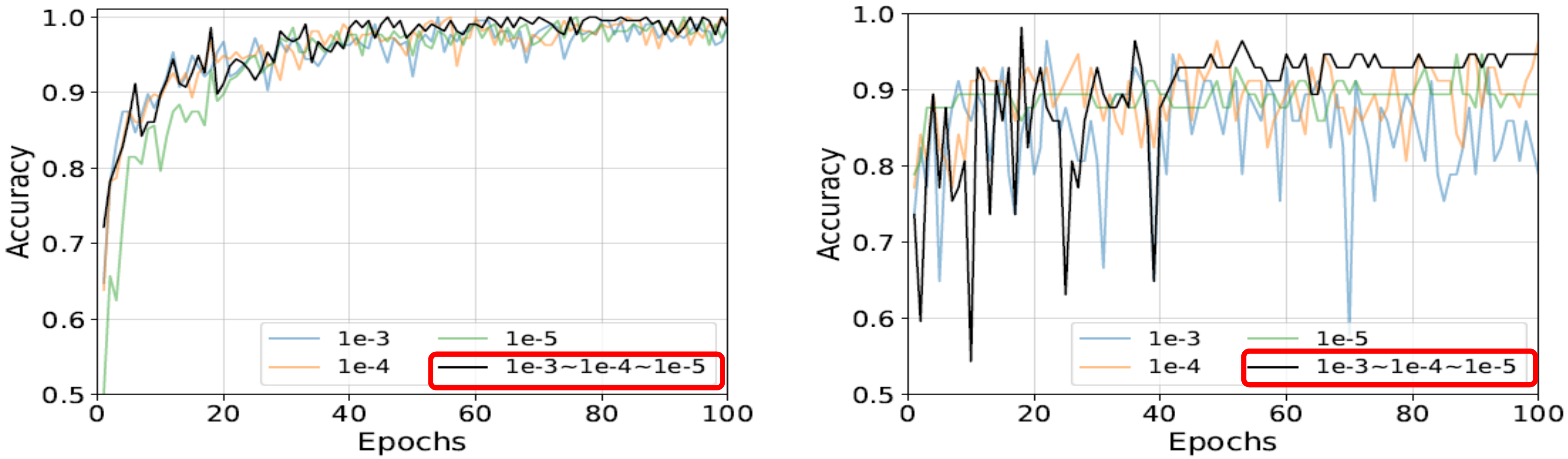
True/classified	HGG	LGG
HGG	90.48%	9.52%
LGG	13.33%	86.67%

Confusion matrix on the test set

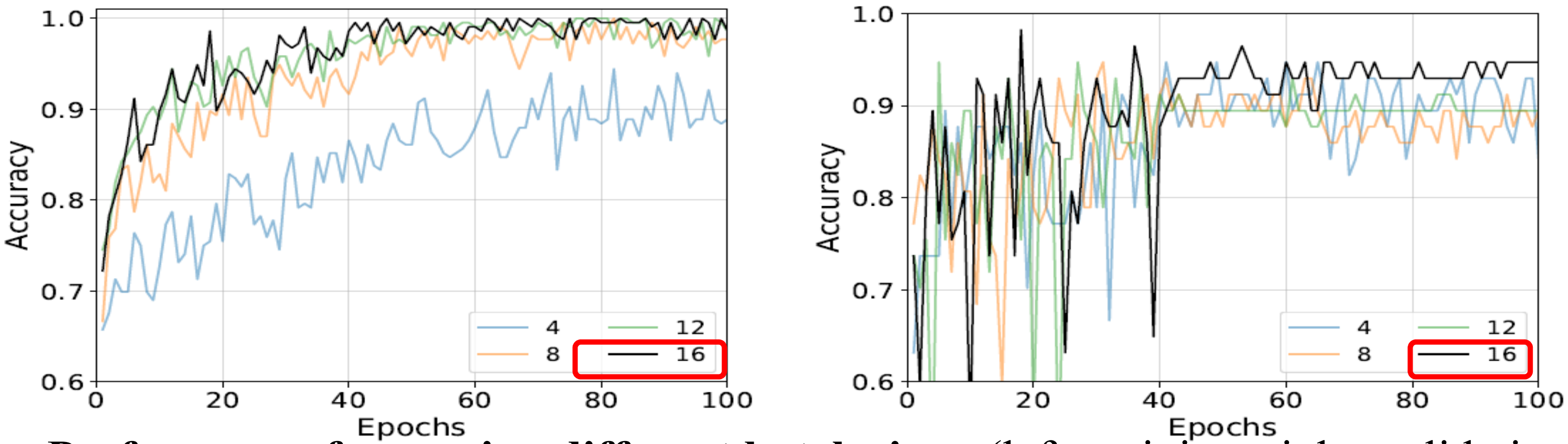
Run	1	2	3	4	5	Average
Acc.(%)	**89.47**	85.96	87.72	**89.47**	87.72	88.07

Performance of 5 runs on the test set (with datasets randomly re-partitioned)

d) Empirical analysis on hyper-parameters



Performance from using different learning rates. (left: training; right: validation).



Performance from using different batch sizes. (left: training; right: validation)

d) Comparison: with/without saliency enhancement

Method	Without enhancement	With enhancement
Training accuracy(%)	**99.01**	98.61
Validation accuracy(%)	85.96	**94.74**
Test accuracy (%)	84.21	**89.47**

Remarks:
Performance of glioma classification was heavily dependent on the tumor masks

e) Comparison and Discussion

	Method	Accuracy
Pan [4]	CNN	73.33%
Ge [*]	CNN	90.87%
Proposed scheme	CNN	89.47%

Comparison: with other glioma grading methods (HGG/LGG).

	Glioma classes	Method	Accuracy
Macyszyn [2]	Glioblastoma: 4 classes	SVM	75.56%
Yu [3]	IDH mutation: 2 classes	SVM	80.00%
Li [5]	IDH mutation: 2 classes	CNN	86.55%
Akkus [12]	1p19q prediction: 2 classes	CNN	87.70%
Ge [*]	1p19q prediction: 2 classes	CNN	89.39%

Related classifier: other glioma classification methods (using biomarkers)

[*] C Ge, I Gu, A Jakola, J Yang. Deep Learning and Multi-Sensor Fusion for Glioma Classification using Multistream 2D Convolutional Networks, in EMBC 2018.

5. Conclusion

Proposed a 3D multi-scale CNN architecture for glioma grading using MRIs

- Characterize tumors by image- and semantic-level features
- Saliency-awareness for enhancing tumor regions
- Multi-scale feature fusion

Results showed

- Proposed network architecture is effective for brain tumor classification
- Salient region enhancement improves the performance
- Performance comparable to the state-of-the-art

Future/ongoing work

- Tests on larger datasets
- Extend to clinically more important issues:

  classification of different types of gliomas

  (e.g., IDH mutation, 1p19q codeletion …)
- Apply saliency techniques to enhance the tumor regions without requiring masks.
- Robust data augmentation for enlarging training dataset

Thank you for your attention!

Questions ?