UCSB LIMPID Feb 3 - 5, 2020

Two-Level Ensemble Methods for Improving CNNs for MRI Brain Tumor Segmentation

S. Shailja[1], Po-Yu Kao[1], Jiaxiang Jiang[1], Angela Zhang[1], Amil Khan[1], Jefferson Chen[2], B.S. Manjunath[1]

[1]University of California, Santa Barbara, [2]University of California, Irvine

Introduction

Ensemble methods are

- meta-algorithms to leverage the uniqueness of each model for building one predictive model

We aim to use an ensemble model to

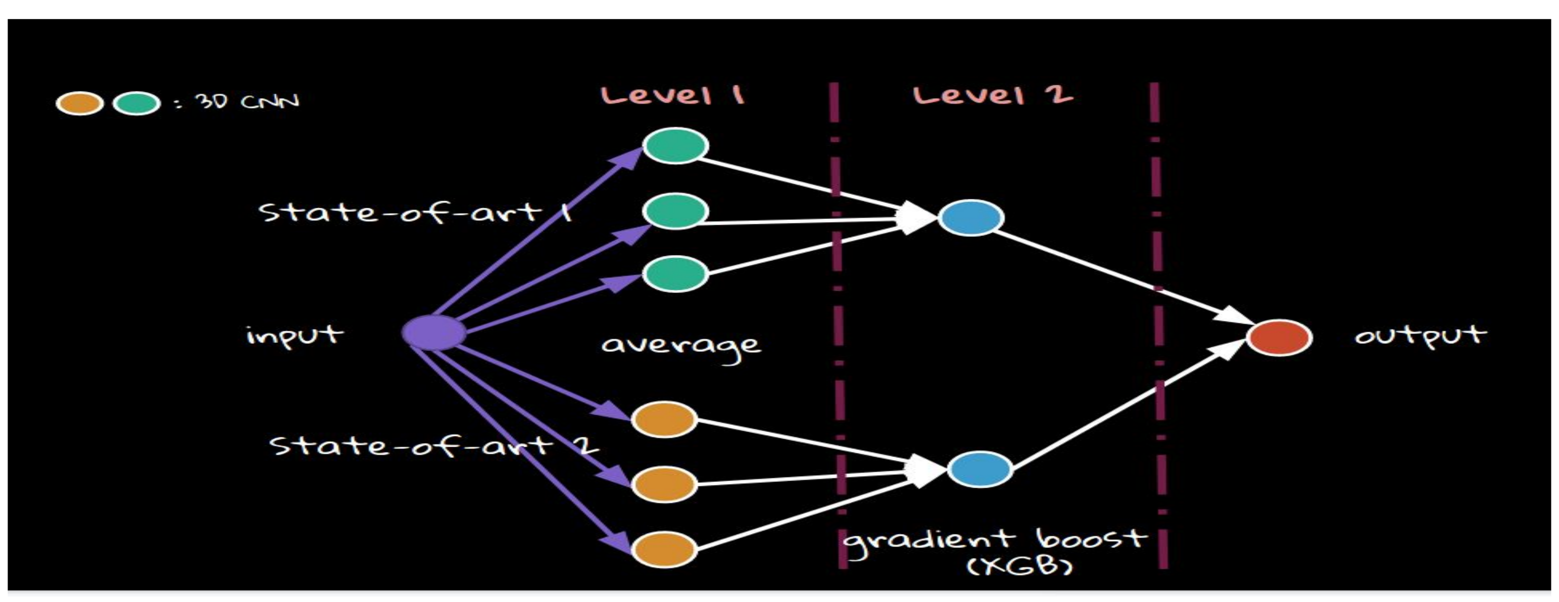
- achieve better segmentation performance compared to the state-of-the-art networks

Motivation

- Each model has different advantages and disadvantages and they tend to seize the data from different angles.
- Can build several estimators independently and ensemble their predictions.

Methodology

- Proposed a two-level ensemble approach:
  - first level: averages the probability maps from the same type of models
  - second level: boosts the averaged probability maps from different models by using the XGBoost algorithm in the second level.



Segmentation Task

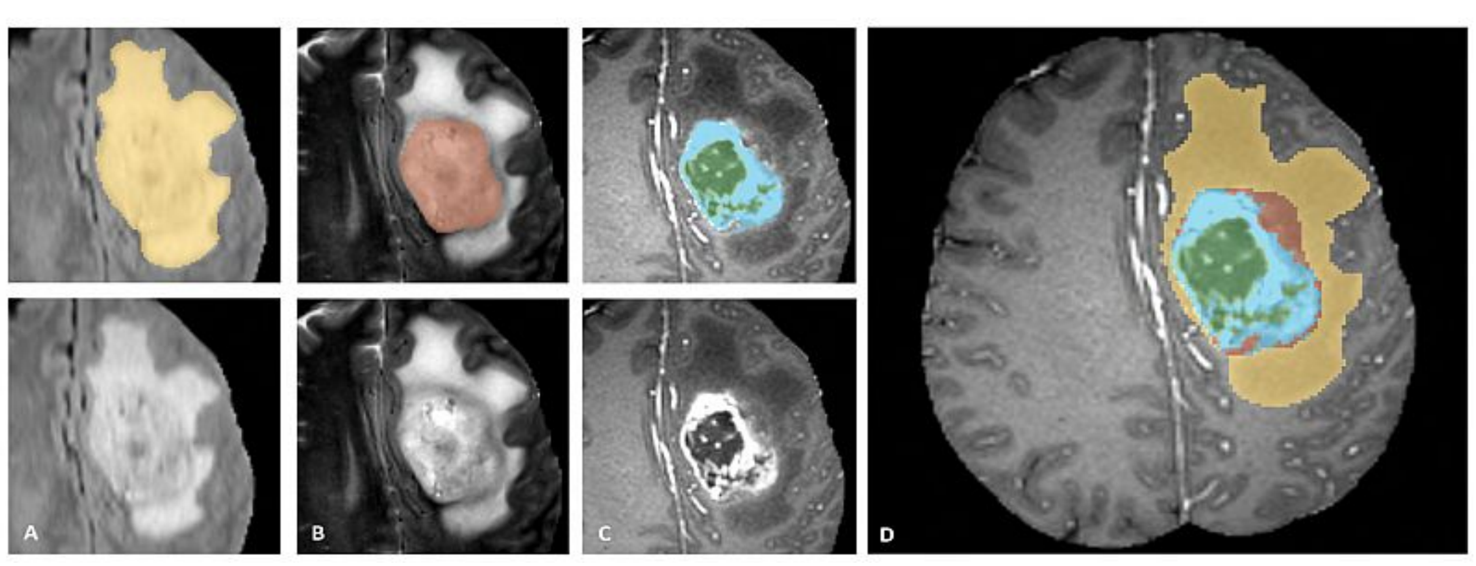


Fig.1: Glioma sub-regions, edema (yellow), non-enhancing solid core (red), necrotic core (green) and enhancing core(blue)

Models

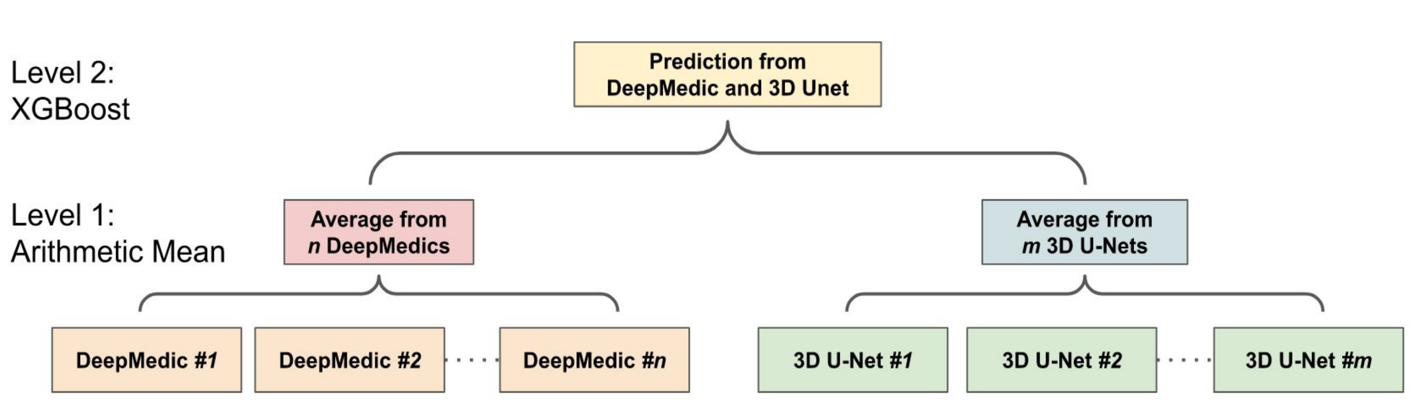


Fig.2:The workflow of two-level ensemble approach to improve state-of-art CNNs.

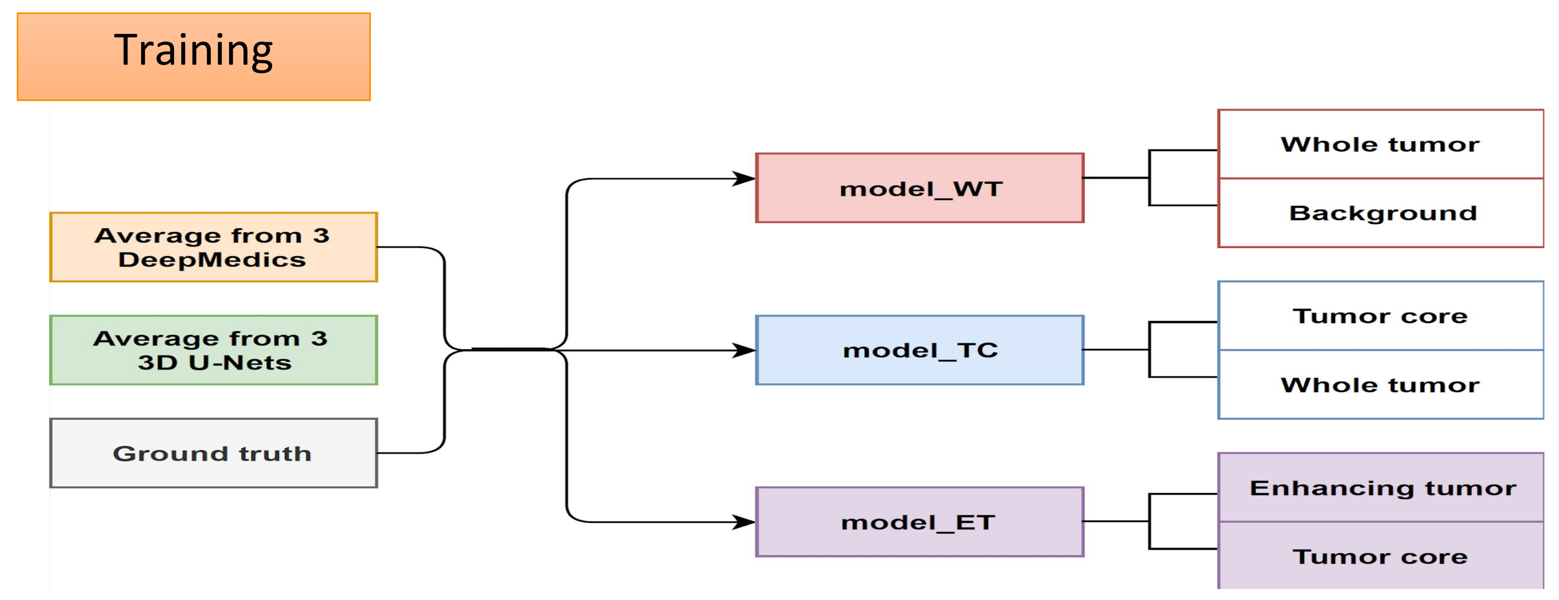


Fig.3:The training workflow of two-level binary classification approach.

Experimental Results

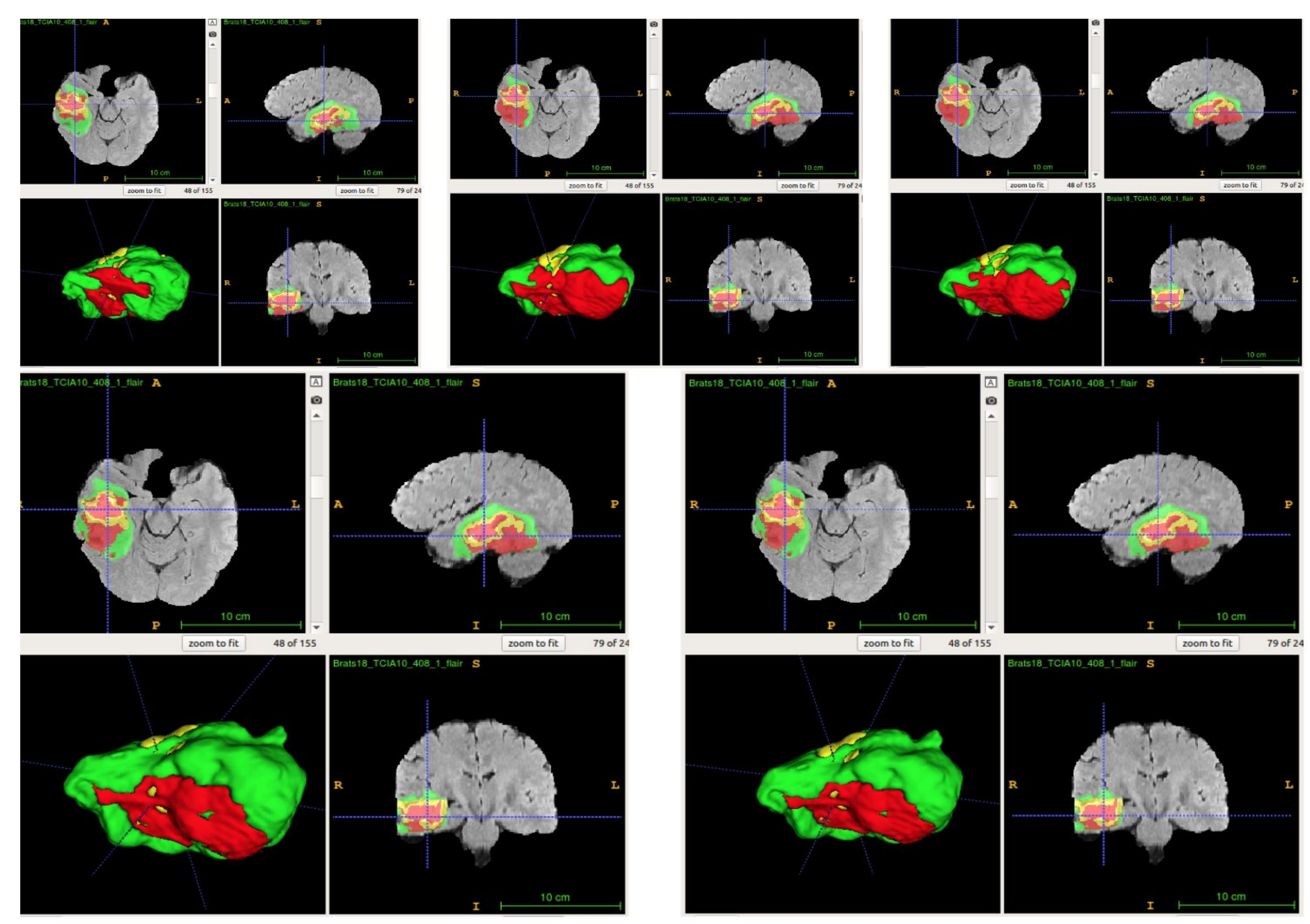


Fig.4: Examples of predictions from different ensemble methods. The top left image shows the ground-truth lesion mask, and the top middle image shows the predictions using the arithmetic mean. The top right image shows the prediction using a two-level multi-class classification (TLMC) method. The bottom left image shows the prediction using a two-level binary classification (TLBC) method, and the bottom right image shows the prediction using a two-level fusion classification (TLFC) method. Red: enhancing tumor, yellow: necrosis & non-enhancing tumor, and green: edema. ITK-SNAP (Fedorov et al., 2012) is used to visualize the MR images and lesion masks.

Methods	DSC_ET	DSC_WT	DSC_TC
DeepMedic	**79.0 (22.6)**	89.6(6.4)	81.3(21.8)
3D U-Net	76.4(25.4)	90.1(6.4)	76.9(24.4)
TLFC	78.2(25.6)	**90.8(6.1)**	**82.3(21.2)**

Table 1: Comparison of Dice Scores for various algorithms on BraTS 2018 validation set. The results are reported as mean (standard deviation). Bold numbers highlight the improved results.

Conclusion

Summary :

- Proposed a two-level fusion classification method.
- This method can also be easily integrated with more different types of neural networks.

Future Work :

- Explore and generalize multi-level fusion classification methods.
- Create an automated tool for ensembling the different models.

Contact

Shailja
Vision Research Lab,
University of California, Santa Barbara
Email: shailja@ucsb.edu

Acknowledgements

NIH award No. 5R01NS103774-03
NSF MCB Grant No. 1715544

References

1. Kao, Po-Yu, Shailja Shailja, Jiaxiang Jiang, Angela Zhang, Amil Khan, Jefferson W. Chen, B.S. Manjunath. Improving Patch-Based Convolutional Neural Networks for MRI Brain Tumor Segmentation by Leveraging Location Information. 2020, Frontiers in Neuroscience.