Probabilistic Segmentation of Small Metastatic Brain Tumors using Liquid State Machine Ensemble

Andrew Elliott[a], Cole Morgan[b], Carlo Torres [c], Ayman Roslend[d] and Caroline Chung[a]

[a] U.T. M.D. Anderson Cancer Center 1515 Holcombe Blvd, Houston TX, 77030

[b] Rice University 6100 Main St, Houston TX, 77005

[c] Baylor Genetics Lab 2450 Holcombe Blvd, Houston, TX, 77021

[d] University of Illinois at Urbana Champaign, Urbana Illinois 61801

THE UNIVERSITY OF TEXAS MD Anderson Cancer Center

Making Cancer History®

Introduction

Accurate segmenting small brain tumors (diameter ≤ 0.5 cm) on contrast enhanced MRI images presents a particular problem when done by hand[1] or with conventional CNNs[2], as enhancing blood vessels of similar size can be detected as false positives. Fig. 1 shows the similarity of a normal vein and a metastatic tumor of almost the same size. The capabilities of Liquid State Machines (LSM) ensembles to separate high dimensional data are used in this project to overcome this problem. Combined output of an ensemble of LSMs was used as input into a random forest to classify the final result as tumor vs. non-tumor. In comparison with deep learning CNN our results show excellent small tumor recognition and generate probability maps that cover the tumors but ignore blood vessels and other contrast-enhancing objects.

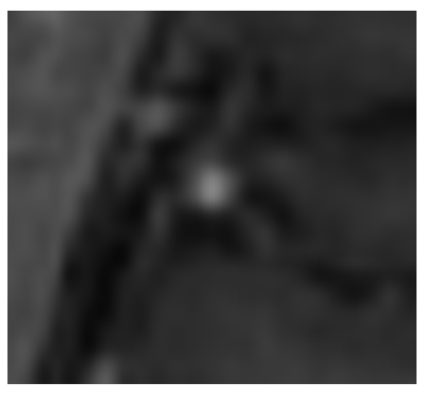

Figure 1a. Normal vein

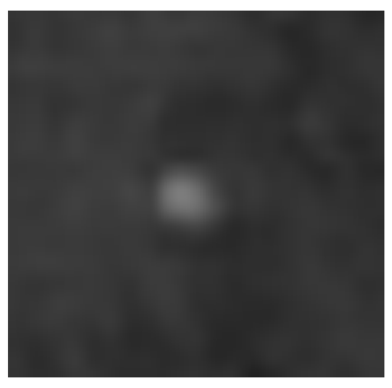

Figure 1b. Brain metastasis

Conventional Neurons:

1. **Add incoming signals (with/without bias)**
2. **Activation function determines output response**

Spiking Neurons:

1. **Complex response to input signal**
2. **Output can excite or suppress other neurons**

The LSM is made up of a grid of spiking neurons that represent the 3rd generation of neural networks and employ neuron models inspired by neurobiology[3]. Spiking neurons take a time series as input and their output response can enhance or suppress other neurons they are connected to, making them more complex than the neurons in conventional neural networks. The advantage of LSM it does not need to be trained but acts like high dimensional filter to separate data. Well separated data leads to faster training of ML algorithm that reads output of LSM.

Methods

3D MRI images were divided into multiple 17x17x17 voxel cubes which were converted into time series. An ensemble of two LSMs (fig. 2) took two versions of the time series (one rotated 90 degrees) as input. Output time series of LSMs produce district patterns for tumor/non-tumor (fig. 3), these train a Random Forest to recognize tumor vs non-tumor.

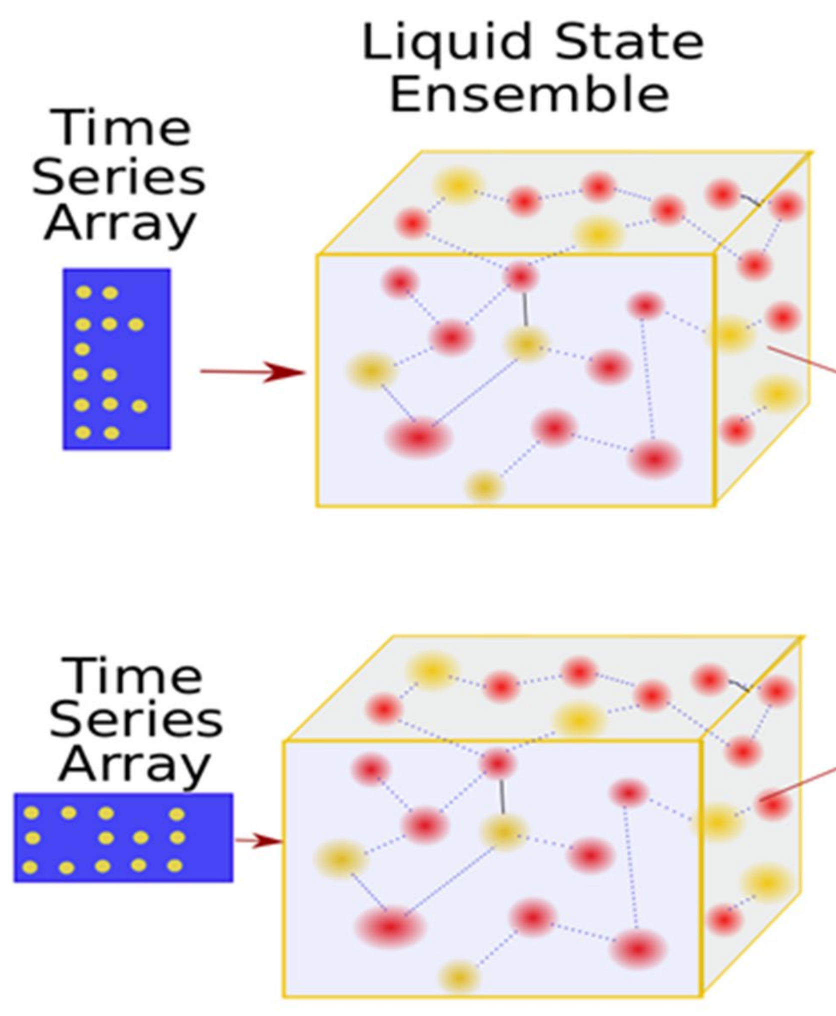

Fig 2. Liquid State Machine Ensemble

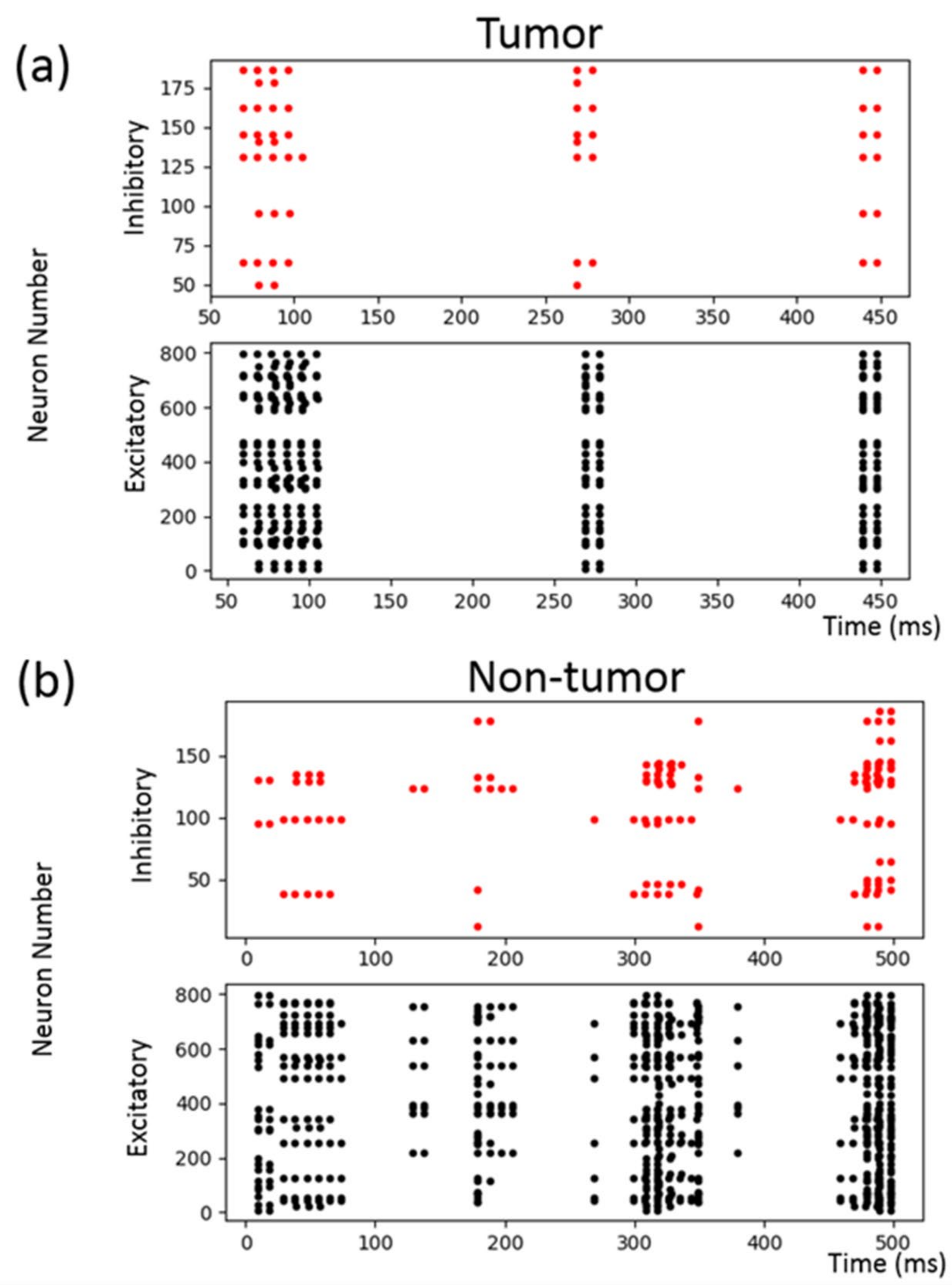

Fig 3. Spiking pattern for Tumor and non-Tumor

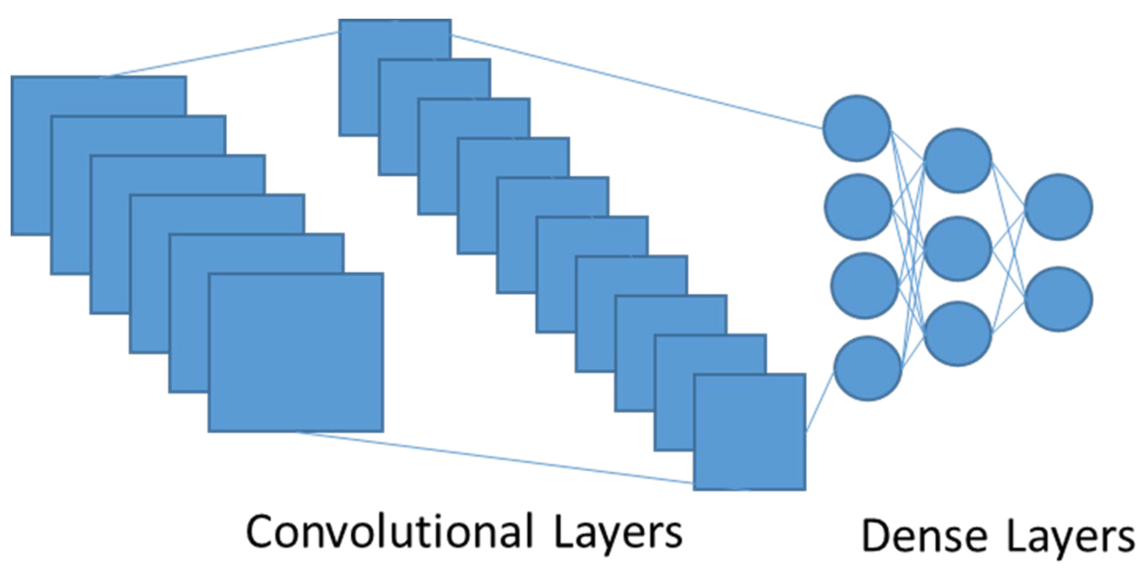

Fig4. Diagram of CNN that was compared to LSM

Results

LSM/Random Forest was tested against a conventional CNN (fig.4) written in Tensorflow 2.1 with two 3D convolutional layers and three dense layers using a Relu activation like those used in tumor segmentation. A sigmoid function was applied at the final output to generate the probability.

Conventional CNN detects both veins and tumor (fig 5(a)). LSM/Random Forest detects only tumor (fig5(b)). Fig 6 shows six cases of probability maps generated by LSM/Random Forest superimposed on the MRI images.

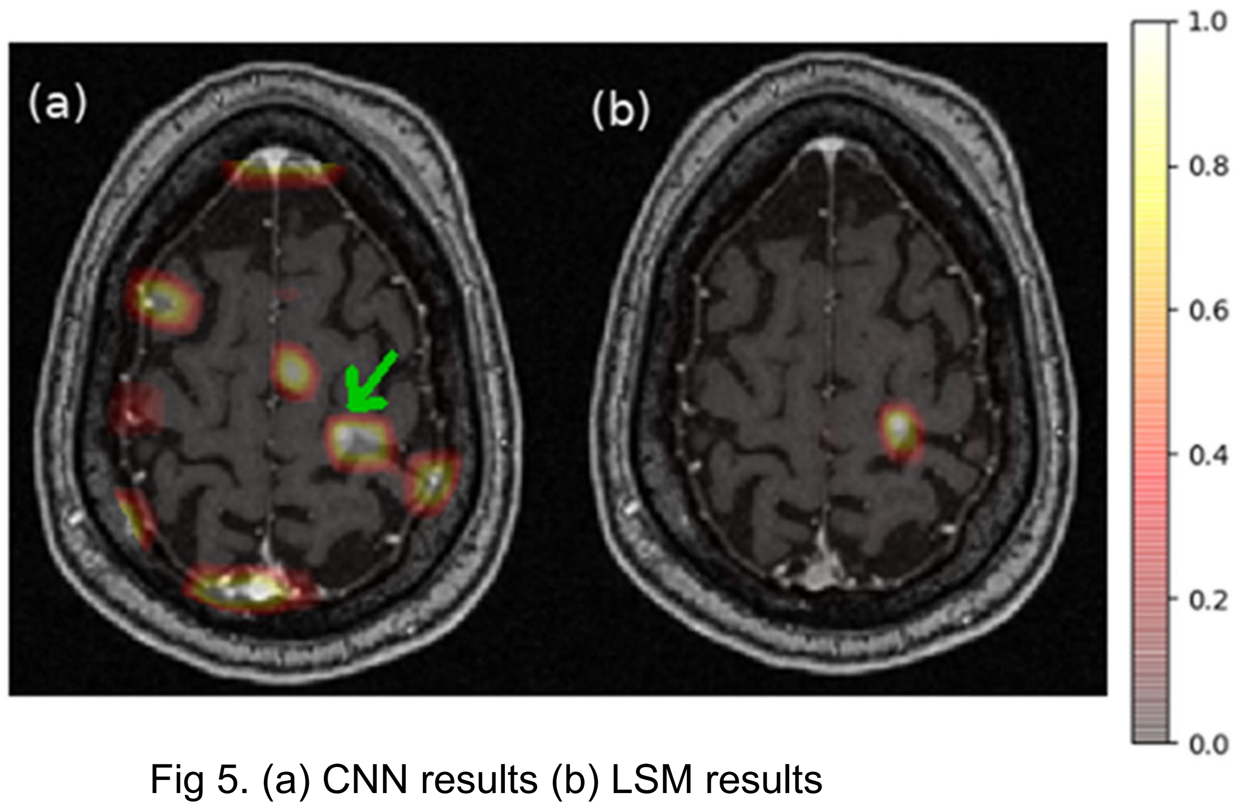

Fig 5. (a) CNN results (b) LSM results

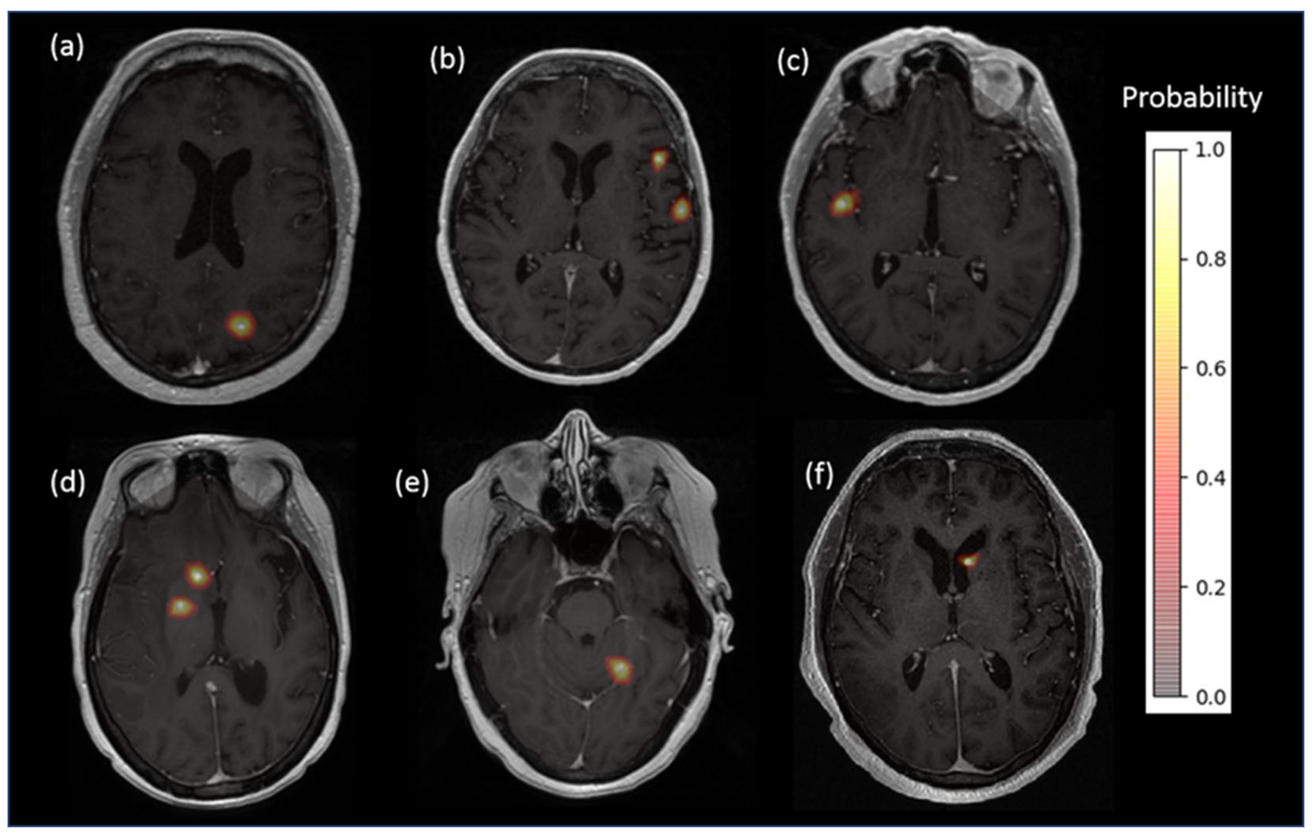

Fig 6. Probability maps superimposed on MRI results

Conclusions

1. **Automation tools to improve the consistency and efficiency of segmenting small brain tumors.**
2. **LSM combined with machine learning techniques leads to fewer false positives and negatives.**

Automation tools improve the consistency and efficiency of detecting and segmenting small brain tumors for radiosurgery. The current study provides very promising results for detecting and tracking tumors that is free of the inconsistencies associated with manually segmented brain tumors. The combination of a liquid state ensemble and a random forest classifier has yielded excellent calculating probability maps of small (≤0.5cm) within the brain while suppressing false positives better than conventional CNN.

References

1.Sandstrom *et al.*, *Anticancer Research.* 2021;41:279-288

2. Ashraf TH *et al.*, *Thesis Ahsanullah University of Science and Technology;* 2019

3. Maass *et al.*, *Neural Comput.* 2002:2531-2560

The author has no conflicts of interest to report.