Multiparametric MRI analysis of Glioblastoma Multiforme tissues using Multi-Class Support Vector Machines

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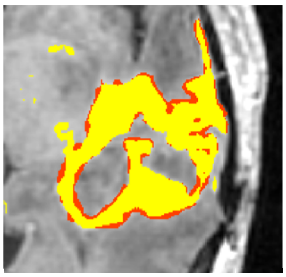
Target Audience: Neuroradiologist, MR Physicist

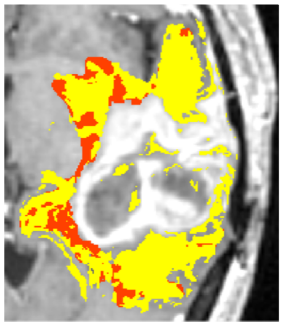
Purpose: To test the accuracy of Multi-class Support Vector Machines[1] (SVM) in the classification of tissue types in patients with glioblastoma multiforme (GBM) tumors.

Methods: Various MRI scans were collected from patients with recurrent GBM. Each scan session collected post-contrast T1(+C T1), T2, diffusion, perfusion, and multi-echo hypoxia images[2]. The hypoxia image is a subtraction image obtained from a normoxic condition multi-echo scan and carbogen breathing multi-echo scan. The perfusion images were corrected for leakage and represented as corrected rCBV maps. All of these scans were co-registered to each other, giving an input matrix to our support vector machine consisting of roughly 13,000 voxels, each with 5 feature values (+C T1, T2, ADC, rCBV_corrected, delta T2*). The SVM was then trained using radiologist confirmed labels for 'necrosis' , 'tumor', and 'edema'. These labels were obtained using longitudinal data as well as clinical scans, and tested on new data to determine the accuracy of the classifier. The basic two-class SVM classified voxels as either ‘tumor’ or ‘not tumor’. The multi-class SVM classified voxels as either ‘tumor’, ‘necrosis’, or ‘edema’.

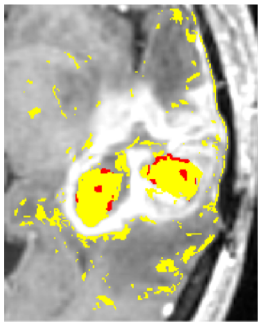
Results: The two-class SVM classified tumor voxels with a sensitivity of 88.8% and specificity of 96.1%. The multi-class SVM classified necrosis, edema, and tumor voxels with a sensitivity of 85.3% and specificity of 79.7%.



Two-class Tumor



Multi-class Edema



Multi-class Necrosis

Discussion: The figures show the SVM voxels in yellow overlaid on the red radiologist labels. Visual inspection agrees that the tumor model outperforms the multi-class model. The multi-class model shows that the SVM is under-predicting the edema voxels, while over-predicting the necrosis voxels. The two-class tumor model showed a high degree of accuracy, but when introduced into a multi-class model, it suffered substantial losses in specificity. Although this is to be expected in a more complex model, the losses could be exaggerated by the misclassification of the ‘edema’ or ‘necrosis’ voxels. The performance of both models improved with increasing features.

Conclusion: These results show that the SVM is capable of classifying tumor voxels in a single case study. Aside from optimizing the current tumor model, we will also seek to improve the multi-class model as this more complex model would offer increased clinical advantages over the simple tumor model alone. Future work will focus on the potential for the SVM to help in early detection of recurrence. In order to achieve this, we will need to test SVMs across patients. If we truly aim for early detection, then we need to prove that the algorithm can be trained on a pool of subjects with recurrent disease, and then test that model on a new patient before recurrence is obvious.

References: 1. *Cortes, C. and V. Vapnik, Support-Vector Networks. Machine Learning, 1995. 20(3): p. 273-297.*
2. *Dunn, J.F., et al., Changes in oxygenation of intracranial tumors with carbogen: a BOLD MRI and EPR oximetry study. J Magn Reson Imaging, 2002. 16(5): p. 511-21.*