# Quantum-Inspired Potential Mapping for Multi-Parametric MRI Radiomics–Based Post-Resection Glioblastoma Survival Prediction

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## ABSTRACT

**Purpose:** To develop a multi-parametric MRI (mp-MRI) radiomics framework for predicting post-resection glioblastoma (GBM) survival by integrating conventional MR modalities with a quantum mechanics–inspired imaging representation.

**Methods:** A public dataset (n=236) with pre-operative T1, T1ce, T2, and FLAIR images was studied. A potential field (V), modeling the distribution of voxel-wise multi-modality intensity vectors within the tumor ROI, was computed for every patient. V was designed to capture common versus rare mp-MRI patterns and provide an additional image contrast. Radiomic features (first-order intensity, texture, and shape) were extracted from mp-MRI and V. Non-imaging clinical variables (age, resection method, and volumes of tumor subregions) were incorporated via positional encoding to improve fusion with radiomic features. Feature selection was performed using LASSO, with hyperparameters tuned via nested cross-validation. Selected features were used to train a support vector machine (SVM) classifier for survival prediction (short-term vs long-term). Two feature sets were compared: (a) Clinical + mpMRI and (b) Clinical + mpMRI + V.

**Results**: Across outer validation folds, adding V improved AUC from 0.656±0.097 to 0.673±0.087. On the held-out test set, the potential-augmented model achieved higher ROCAUC (0.72 vs 0.68) and accuracy (0.71 vs 0.63), with consistent improvements in precision, recall, specificity, and F1 score.

**Conclusions**: Quantum-inspired potential fields provide complementary prognostic information beyond conventional radiomics and clinical variables for post-resection GBM survival prediction.

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## INTRODUCTION

- **Glioblastoma (GBM)** is the most common and aggressive primary malignant brain tumor in adults, with highly heterogeneous outcomes that motivate accurate survival prediction and personalized treatment planning.
- We developed a multi-parametric MRI (mp-MRI) radiomics method for post-resection GBM outcome prediction, featuring a novel **quantum mechanics-inspired image potential** field. We also adopted a **positional encoding (PE)** strategy from our prior work to quantitatively integrate non-imaging clinical variables into the radiomics pipeline.

## METHODS AND MATERIALS

- **Dataset:** This study used the public BraTS 2020[1] dataset comprising 236 GBM patients. The mp-MRI protocol includes T1, T1ce, T2, and FLAIR images. Patients were divided into two survival groups using a 1-year threshold. The dataset was split into training and test sets with an 8:2 ratio.
- **Potential Field:** For each patient, we derived a potential field $V$ as a new image contrast (**Fig. 1**). This is motivated by the time-independent Schrödinger equation and was originally used to develop an unsupervised data clustering method[2]. Specifically, given the distribution of MR signals $\boldsymbol{x_i} = [I_{T1}(i), I_{T1ce}(i), I_{T2}(i), I_{FLAIR}(i)] \in \mathbb{R}^4$ for each voxel $i$, we estimated $\psi(\boldsymbol{x})$ —which reflects the likelihood of occurrence for any multi-modality intensity pattern—using a Parzen-window kernel density estimator (KDE) and computed $V(\boldsymbol{x})$ :

$$\psi(\boldsymbol{x}) = \sum_{i=1}^{N} e^{-(x-x_i)^2/2\sigma^2}$$

$$V(\boldsymbol{x}) = E + \frac{\sigma^2}{2}\frac{\nabla^2\psi(\boldsymbol{x})}{\psi(\boldsymbol{x})} = const + \frac{1}{2\sigma^2}\frac{\sum_i (x-x_i)^2 e^{-(x-x_i)^2/2\sigma^2}}{\sum_i e^{-(x-x_i)^2/2\sigma^2}}$$

- **Radiomic Feature Extraction**: We used the PyRadiomics[3] package to extract 3D shape (n=12), intensity (n=18), and texture (n=75) features from each segmentation or image. Voxel intensities were clipped to the [0.5%, 99.5%] range and discretized into 64 gray-level bins.
- **Positional Encoding (PE):** Given radiomic features $\boldsymbol{x} \in \mathbb{R}^{d_1}$ and clinical variables $\boldsymbol{y} \in \mathbb{R}^{d_2}$, often with $d_1 \gg d_2$, direct concatenation $[\boldsymbol{x}, \boldsymbol{y}]$ may cause underrepresentation of clinical information. So we projected $\boldsymbol{y}$ into a higher-dimensional embedding[4] $\boldsymbol{y}^* \in \mathbb{R}^{d_2^*}$ via multi-scale sinusoidal transformations and used $[\boldsymbol{x}, \boldsymbol{y}^*]$ for downstream prediction:

$$PE(y, 2k|d_2^*) = \sin\left(\frac{y}{10000^{\frac{2k}{d_2^*}}}\right), PE(y, 2k+1|d_2^*) = \cos\left(\frac{y}{10000^{\frac{2k}{d_2^*}}}\right)$$

- **Survival Prediction**: Two feature sets were compared: (a) mp-MRI radiomic features with enhanced clinical features (n=579) and (b) the same features plus radiomic features from the potential field (n=717). Feature selection was performed using LASSO. Hyperparameters (regularization strength and maximum retained features) were optimized by nested cross-validation (5×5 outer, 3-fold inner) on the training set. Correlation filtering (Pearson $|r|>0.95$) and z-score standardization were applied within each training split. The optimized LASSO features were used to train an SVM classifier, which was finally evaluated on an independent held-out test set.

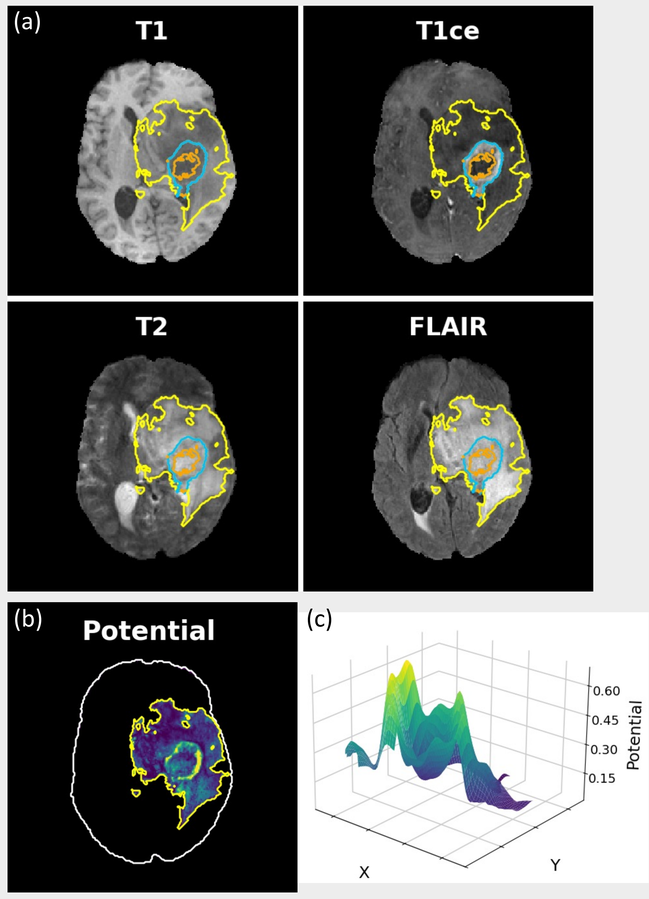


**Figure 1.** Representative case of mpMRI images and the derived potential field. (a) Axial views of T1, T1ce, T2, and FLAIR with contours of the necrotic core (orange), enhancing tumor (blue), and peritumoral edema (yellow). (b) Derived potential field on the same axial slice within the ROI. (c) 3D surface rendering of the same potential field.

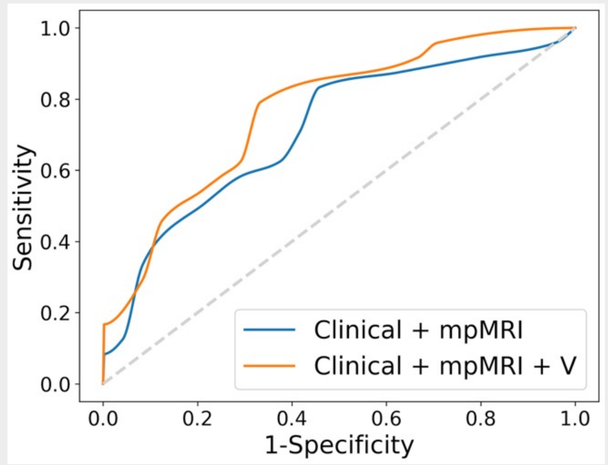


**Figure 2.** ROC curves on the held-out test set.

| Model | $ROC_{AUC}$ | Accuracy | Precision | Recall | Specificity | F1 |
|---|---|---|---|---|---|---|
| Clinical + mpMRI | 0.656 ± 0.097 | 0.627 ± 0.074 | 0.635 ± 0.076 | 0.628 ± 0.082 | 0.629 ± 0.115 | 0.625 ± 0.113 |
| Clinical + mpMRI + **V** | 0.673 ± 0.087 | 0.630 ± 0.073 | 0.641 ± 0.078 | 0.626 ± 0.075 | 0.617 ± 0.091 | 0.642 ± 0.106 |

**Table 1.** Outer cross-validation performance.

| Model | $ROC_{AUC}$ | Accuracy | Precision | Recall | Specificity | F1 |
|---|---|---|---|---|---|---|
| Clinical + mpMRI | 0.68 | 0.63 | 0.63 | 0.71 | 0.58 | 0.67 |
| Clinical + mpMRI + **V** | 0.72 | 0.71 | 0.69 | 0.75 | 0.67 | 0.72 |

**Table 2.** Final held-out test performance.

## RESULTS

- **Table 1** summarizes model performance on the outer validation folds. Class labels correspond to survival groups (label 0: <1 year; label 1: ≥1 year). Compared with the baseline feature set (Clinical + mpMRI), incorporating potential-derived radiomic features (Clinical + mpMRI + V) resulted in a consistent trend toward improved discrimination, with the $ROC_{AUC}$ increasing from 0.656 ± 0.097 to 0.673 ± 0.087.
- **Table 2** summarizes final model performance on the held-out test set. Consistent with the cross-validation results, the potential-augmented model achieved higher test-set AUC (0.72 vs 0.68) and accuracy (0.71 vs 0.63), along with improvements in precision, recall, specificity, and F1 score.
- **Fig. 2** illustrates the ROC curves for both feature sets. At a given false-positive rate, particularly in the low-to-moderate range, the potential-augmented model showed higher sensitivity, suggesting improved identification of long-term survivors without increasing the misclassification of short-term survivors as long-term.

## DISCUSSION

- The potential field $V$ is computed in the multi-modality feature space without explicitly incorporating spatial coordinates. However, since it is evaluated voxel-wise at each feature vector and mapped back to the original voxel, the resulting map remains spatially aligned with the anatomy.
- In positional encoding, a scaling factor $\gamma = d_2^*/d_1$ defines the dimension after vector growing. It was set to 0.5 based on comparison studies (omitted due to length).
- Future work will focus on validating and optimizing the proposed framework, as well as extending this approach to other imaging-based outcome prediction tasks.

## CONCLUSIONS

- In this study, we incorporated a quantum mechanics-inspired potential field into an mp-MRI radiomics framework for post-resection GBM survival prediction. The augmented model achieved higher $ROC_{AUC}$ and accuracy on the validation and test samples, suggesting that the potential field provides prognostic information beyond traditional radiomics and clinical features.

## REFERENCES

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