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Integrated PET/MRI in Pediatric CNS Tumors: Diagnostic Complexities

Adriana Blanda[1], Paolo Verderio[1], Sara Pizzamiglio[1], Paola Scifo[2], Federico Fallanca[2], Maurizio Barbera[3], Edoardo Masiello[3], Giovanna Gattuso[4], Maura Massimino[4], Cristina Baldoli[3], Filippo Spreafico[4]

(1) Unit of Bioinformatics and Biostatistics, Fondazione IRCCS Istituto Nazionale dei Tumori, Milan, Italy
(2) Nuclear Medicine Department, IRCCS San Raffaele Scientific Institute, Milan, Italy
(3) Neuroradiology Department, IRCCS San Raffaele Scientific Institute, Milan, Italy
(4) Pediatric Oncology Unit, Fondazione IRCCS Istituto Nazionale Dei Tumori, Milan, Italy

CORRESPONDING AUTHOR: *Blanda Adriana, adriana.blanda@istitutotumori.mi.it*

INTRODUCTION

Brain tumors are the most common solid tumors in children, with an annual incidence ranging from 1.12 to 5.14 cases per 100,000. Advances in treatment have led to a 70% five-year survival rate. Follow-up imaging—particularly in differentiating tumor recurrence from therapy-related toxicity—remains a critical clinical need. Advanced quantitative imaging techniques, such as Perfusion-Weighted Magnetic Resonance Imaging (PW-MRI) and Positron Emission Tomography (PET) with 11C-Methionine [1], may play a crucial role in therapy-related decision making in these patients. The use of simultaneous hybrid PET/MRI is highly beneficial in children as it allows for a one-stop-shop examination that limits the scanning procedures. Since both techniques generate a large number of imaging features, identifying and integrating those with the greatest impact on clinical outcomes could represent an effective strategy to improve and accelerate diagnostic accuracy. Machine Learning algorithms have significantly enhanced the analysis of multi data. In the specific context of PET imaging, missing data are often categorized as missing not at random [2] (MNAR), where the absence of data is systematically related to unobserved variables or the underlying condition being studied. This introduces potential biases and challenges for integrating and extracting meaningful features from the data.

AIM

The present study is aimed to achieve main objectives in the managing patients of care:

i) to investigate how features extracted from PW-MRI and PET can be integrated to develop a combined diagnostic score

ii) to manage missing data in the context of PET imaging

METHOD

PET/MRI features associated with tumor progression were analyzed both individually and in combination with the reference, introducing new variables into the model. Given the presence of missing not at random (MNAR) data in the PET set, missing values were imputed using a Bayesian approach [3] with the "stan" function using Monte Carlo sampling (MCMC), based on a truncated normal distribution. The algorithm DIABLO [4] has proven effective in integrating datasets from different sources and in identifying features across data from PET and from MRI. The DIABLO was used to integrate PET data (18 features, 42 patients) and MRI data (52 features, 40 patients). More specifically a sparse multiblock partial least square-discriminant analysis (sPLS-DA) was employed to integrate them, implemented via the block.plsda() function from the mixOmics R package [5]. sPLS-DA integrates an intrinsic variable selection procedure into the model fitting by applying a LASSO penalization to the loading vectors of the X data, thereby identifying the most discriminative features through latent components (ncomp=2) that maximize the shared covariance between data blocks. Model performance was evaluated by calculating the area under the receiver operating characteristic curve (AUC) as a measure of classification accuracy. 95% Confidence Interval [CI] was computed by resorting to a bootstrap method.

RESULTS

A total of 42 patients were enrolled in the study, including

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18 females. The median age at enrolment was 9 years, with an interquartile range (IQR) of 5 to 14 years. Tumor histologies were classified into the following categories: embryonal tumors (n=16), high-grade gliomas (n=14), germ cell tumors (n=5), ependymal tumors (n=5), and low-grade gliomas (n=2). For the following analysis, 40 out of the 42 patients were included, since two patients did not undergo the MRI. The overall correlation between the MRI and PET datasets, calculated using Pearson's method on the first latent component of each block, was 0.41(95% CI: 0.12-0.60). Regarding diagnostic performance, assessed via AUC, the second components of both MRI and PET data showed stronger discriminative ability. For MRI, the first component yielded an AUC of 0.722 (95% CI: 0.453–0.932), while the second component achieved 0.795 (95% CI: 0.515–0.951). Similarly, for PET, the first component demonstrated an AUC of 0.725 (95% CI: 0.517–0.906), and the second component obtained 0.753 (95% CI: 0.547–0.923).

CONCLUSIONS

Our findings reveal a moderate overall Pearson correlation of 0.41 between the MRI and PET datasets. This correlation is a positive indicator for a multi-modal approach; it suggests the modalities capture complementary, rather than entirely redundant, information. To enhance the generalizability and robustness of these findings, further validation of these results is essential.

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