Additional information

Machine learning to improve interpretability of clinical, radiological and panel-based genomic data of glioma grade 4 patients undergoing surgical resection.

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Additional Methods

Clinical characterization of the patient cohort

The 102 GG4 patients were enrolled in the case cohort according to the following inclusion criteria: age ≥ 18 years; no previous surgery; no preoperative chemo- or radiotherapy; objective evaluation of preoperative tumor volume on MRI images in DICOM format based on post-contrast T1-weighted MRI sequences and T2-weighted MRI sequences; objective estimation of EOR on post-contrast T1 weighted MRI sequences. Cases were excluded from the case cohort if one or more of the following criteria were present: incomplete imaging data, follow-up interval, and multicentric tumors. Clinical, histopathological and molecular data were collected at the time of diagnosis from medical records. Histological examination, immunohistochemistry for Ki67, analysis of the genetic status of MGMT promoter and IDH1/2 genes were performed as previously described [1-5]. Regarding volumetric analysis, all pre and postoperative tumor segmentations were performed manually across all MRI slices using the OsiriX software tool [2, 6].

The achieved EOR in each case was objectively evaluated using preoperative and postoperative MRI images (DICOM format), based on the contrast area of post-contrast T1 MRI sequences, using the below formula: (Pre-operative tumor volume – Post-operative tumor volume)/Pre-operative tumor volume [2, 6].

Regarding post-operative treatment, after surgery, all patients were treated with combinations of concomitant adjuvant radiotherapy and chemotherapy, followed by adjuvant chemotherapy, as recommended by Stupp [7, 8].

Protein–protein interaction (PPI) Network analysis of genes with somatic mutations

The genes name used to create the matrix were mapped by Search Tool for the Retrieval of Interacting Genes (STRING) database (version 10.5) [9], by using Cytoscape (3.8.2) [10]. The PPI network was generated based on the medium confidence score of 0.40. The pathway were selected for importance and for the biological meaning in the context of GG4.

Machine Learning Modeling

EXtreme Gradient Boosting for survival (XGBoost-Surv) XGBoost modeling t was performed in Python (V3.8) using the xgboost and sklearn surv library partially evaluated using the scikit-learn library [11]. In each of the datasets, string-based categorical variables were converted to numerical values, and each continuous variable was standardized. To perform survival prediction in XGBoost, the survival time in the original dataset, *ti*, was transformed into Ti for each patient (i) according to the censoring information, where $Ci =1$ if patient i was not censored and $Ci =-1$ otherwise.

Ti=Ci× ti

All XGBoost models were trained using the survival Cox objective function. Additionally, for each data set, hyperparameter tuning was performed using the HyperOpt package [12], with 100 evaluation rounds in accordance with parameter ranges that have been previously used in the literature with the exception of capping the min child weight (minimum sum of instance weight), reg_alpha (L1 regularization term on weights), and reg_lambda (L2 regularization term on weights) at 10 rather 100 [13]. As the objective function for hyperparameter tuning, we computed the mean Harrell's concordance index (c-index) using the five-fold cross-validation (CV) approach [14-16]. We optimized

the parameter using HyperOpt and C-index was used as metric. Once the hyperparameters have been identified, the model was subsequently evaluated on the same total data set using five-fold CV as explained above, but with the randomly selected folds being distinct from those used in the hyperparameter tuning process to accurately assess the generalizability of the model [15].

Statistical analyses

All statistical analyses were performed in R environment (v4.2). The primary endpoints was overall survival (OS). OS data were defined as time from surgery and event (death) or end of follow up (censored observation). OS data were available for all the GG4 cases entering the study. For OS analysis, all events were considered as GG4-related, i.e. all deaths were considered as events whatever the cause. OS were estimated using the Kaplan-Meier plots and comparisons between groups were made by means of log-rank test.

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Additional figure legends

Figure S1. Distribution and classification of the gene alterations found in the 102 sequenced GG4 cases. A) Distribution of the type of alterations (e.g. missense mutations, nonsense mutations, deletions, amplifications, multihits, complex events) and frequencies for the 20 genes most frequently found altered are shown. The number of sequenced cases found altered for each gene is also shown.

Figure S2. ML model obtained by considering somatic mutations involving genes belonging to the PI3K-AKT-mTOR signaling pathway (WP3844). A) Feature importance ranked by the "mean absolute magnitude" of the SHAP values of the model obtained for the 71 GG4 cases with available TMB values using a dataset (dataset 4) that included 27 features constituted by 16 genes, 10 clinical and surgical variables and the biomarker TMB. This selection was chosen in order to circumscribe the ML approach to the genes belonging to the PI3K-AKT-mTOR signaling pathway (WP3844). Upper panel: mean absolute values corresponding to the magnitude of feature importance. Lower panel: summary plots for SHAP values; for each considered feature, a single patient is represented by one point. Along the x axis the position of a point corresponds to the logarithm of the mortality risk associated with that feature for a specific patients. This value corresponds to the impact that the feature had on the model output for that specific patient. Along the y axis, the different features are disposed according to their importance corresponding to the mean of their absolute SHAP values. Features with the higher importance are disposed on the upper part of the summary plots. Data clusters with SHAP values around zero indicate low impact on the model. SHAP, Shapley Additive exPlanation. B) Circulating barplot recapitulating the contribution in predicting OS of clinical/surgical parameters, TMB values and somatic gene mutations included in the model.

Figure S3. Impact of TMB on survival in the TCGA high grade glioma series. Kaplan-Meier curves comparing the OS intervals of cases with high TMB (TMB \geq 1.7, red line) and cases with low TMB (TMB <1.7, blu line). The p-value reported refers to the log-rank test.

Table S1. Clinical characterization of the GG4 cohort (102 cases).

Abbreviations: IQR, interquartile range; CW, carmustine wafer; EOR, extent of resection.

Table S2. Categorization of variables in datasets.

Table S3.

Dataset name and composition of the datasets used with the relative reported metrics from xgboost analysis.

Abbreviations: CI, confidence interval; TMB, tumor mutational burden.

Table S4. Detailed lists of clinical/surgical variables and gene alterations composing datasests employed for the xgboost analysis.

 FBXW7 FGF1 FGF10 FGF23 FGF3

Abbreviations: CW, carmustine wafer; EOR, extent of resection; TMB, tumor mutational burden.

Altered in 99 (97.06%) of 102 cases

FIGURE S1

Survival Xgboost Feature Importance

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FIGURE S2

FIGURE S3