



Empowering Glioma Prognosis With Transparent Machine Learning and Interpretative Insights Using Explainable AI

In Fulfillment of Semester Project

Machine Learning

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Project Report

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1. Background and Importance of the Project

The advancement of artificial intelligence AI has been phenomenal and the application of AI has been done in many sensitive areas like medical, defence, finance and auto-mobile industries. But, it is when the AI is applied more frequently, that issues of interpretability, trust, and transparency arise. Explaining such ambiguities and oddities is done in the Explainable AI (XAI) systems that make users appreciate the work of the AI systems. Due to the nature of decisions taken within this sector which has a direct bearing on people's lives, interpretability should be more desirable in this sector. When it comes to information processing, AI tools are considered as black boxes that make medical professionals hesitant to trust AI tools even when they can serve as tools to enhance diagnostic speed and accuracy.

To address this issue, this project's purpose is to create an approachable tool that gives understandable explanations of the AI-made decisions in practical, such as healthcare occupations, contexts. Making this tool interpretable harvests the ethical use of AI in such sensitive issues as glioma classification among others, establishes trust and boosts its adoption.

2. Problem Statement

Despite its advancements, artificial intelligence has proven challenging to use in delicate industries like healthcare due to its uninterpretable nature. Nowadays, a lot of AI systems function as opaque black boxes that provide little to no justification for their recommendations or predictions. This lack of transparency undermines user trust and raises ethical concerns when the AI's decisions affect human lives. Furthermore, understanding the risk levels of gliomas (low-grade glioma, or LGG) in the context of glioma classification is crucial for an accurate diagnosis and timely treatment. The existing solutions are either difficult for clinicians to understand or are not incorporated into their workflows. There is thus an urgent need for a user-friendly, efficient, and useful glioma classification-specific XAI tool.

3. Literature Review

Explainable AI has been the subject of several studies, which have emphasized its significance in the domains of critical decision-making and healthcare. According to Doshi-Velez and Kim (2017), interpretability is crucial for AI tools to ensure accountability and ethical deployment. Interpretable

models, they argued, are essential, particularly in high-stakes situations like the medical field where poor decisions can have disastrous consequences.

According to Miller (2019), human-centered approaches to explainable AI are recommended, and explanations should be consistent with human cognition. The significance of keeping explanations simple was emphasized by this study for non-technical stakeholders. The lack of practical, domain-specific applications was also highlighted by Guidotti et al. (2018), who analyzed existing XAI approaches and contrasted their benefits and drawbacks.

Lundberg and Lee (2017) introduced SHAP (SHapley Additive exPlanations), a powerful framework for trustworthy and intelligible feature attribution. SHAP’s increasing popularity can be attributed to its capacity to provide clear, quantitative insights into model predictions. Abu Sayeed et al. (2020) state that two of the challenges to XAI adoption in healthcare are the technical complexity of existing methods and their lack of integration with clinical workflows. In their additional review of machine learning applications in healthcare, Ahmed et al. (2021) emphasised on the importance of the transparency issue and the difficulties of their real-life application.

Although these studies have a solid background, they fail to meet the characteristics related to glioma classification needs like giving clinicians useful and informative information and predicting the risk level of glioma (LGG or GBM).

4. Proposed Solution and Results

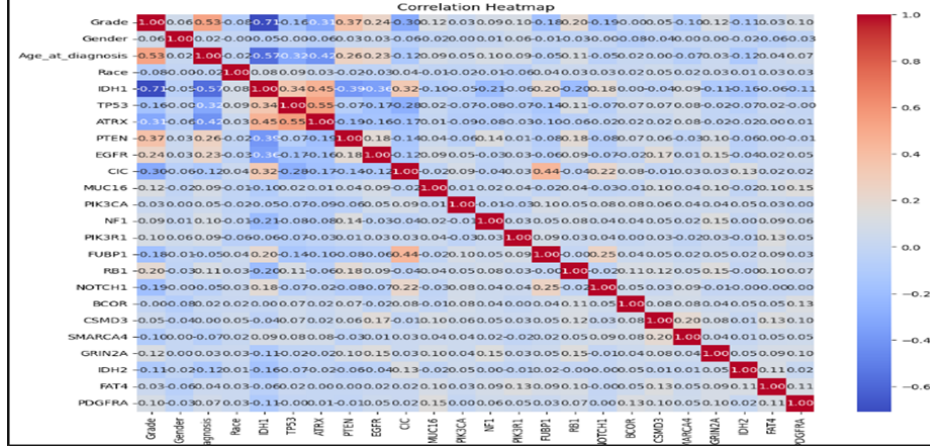
Ipynb Code:

Data uploading, preprocessing, and encoding are covered in the first few lines of the ipynb code. It refines the data set due to missing values and columns that aren’t needed for the analysis. The mutation statuses are encoded using binary encoding prior to being sent to machine learning algorithms, and LabelEncoder is used to transform the remaining categorical data, such as gender and race, into actual numeric encodings. Furthermore, because we define the target variable (GBM or LGG) in the analysis directly using the "Grade" column, the classification task’s nature is simplified.

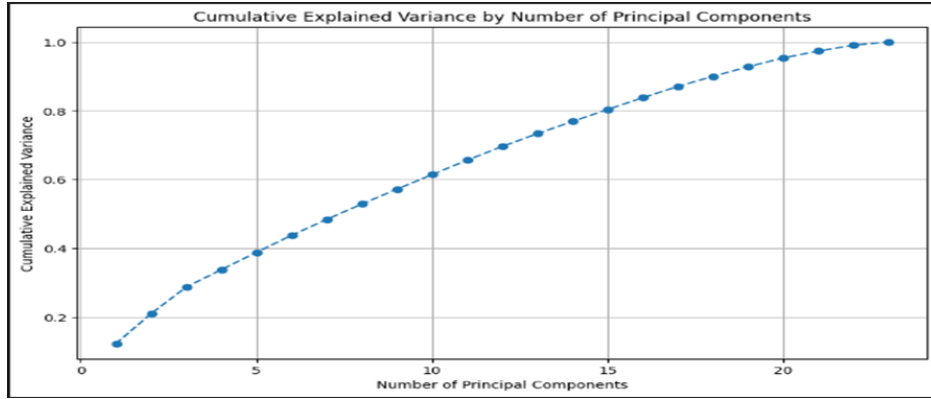
Grade	Gender	Age_at_diagnosis	Race	IDH1	TP53	ATRX	PTEN	EGFR	CIC	...	FUBP1	RB1	NOTCH1	BCOR	CSMD3	SMARCA4	GRIN2A
0	0	1	0.035447	3	1	0	0	0	0	0	1	0	0	0	0	0	0
1	0	1	-0.792423	3	1	0	0	0	0	1	0	0	0	0	0	0	0
2	0	1	-0.983470	3	1	1	1	0	0	0	0	0	0	0	0	0	0
3	0	0	-1.174517	3	1	1	1	0	0	0	0	0	0	0	0	0	0
4	0	1	-1.238199	3	1	1	1	0	0	0	0	0	0	0	0	0	0

There is also a class of techniques, which involves using Mutual Information scores and correlation matrices to assess feature relevance during

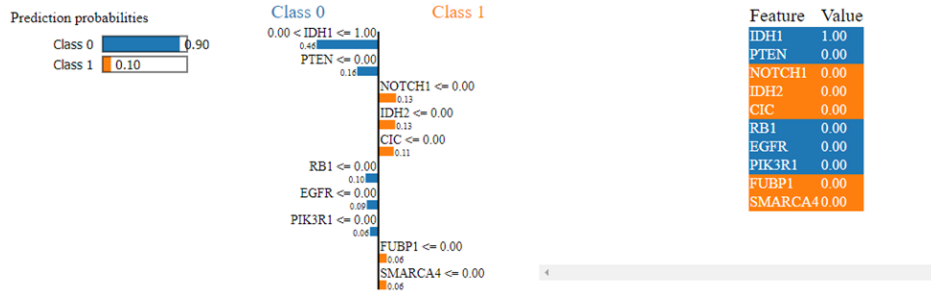
exploratory data analysis (EDA). It turns out that this step gives the clue for feature dependency and selection for subsequent dimensionality reduction and model construction.



To maintain equal stands of the system's computational cost and predictive capability, a balance is made using the Principal Component Analysis (PCA) to determine the number of components of the feature space.



The code involves a rich set of machine learning models and more complex ensemble methods XGBoost, LightGBM, CatBoost as well as more basic Random Forest KNN and Logistic Regression. The accuracy of these predictions is further improved when the models are integrated into a meta classifier. Moreover, using grid search, GridSearchCV also ensures the task-optimization of the created models during hyperparameter tuning. Based on the following metrics: classification reports, accuracy, SHAP, LIME, and permutation importance, the thorough model evaluation is developed.



Web App

The Flask web application is the alternative suggested remedy that uses xAI models to diagnose gliomas. The patient's data can be entered into a new CSV file, and the application will use XAI techniques to create an ML model. The AI model report includes quantitative justifications of the decision-making process that include glioma risk (LGG or GBM) and result prediction.

Features of Web Application:

1. User-Friendly Interface

Users can upload datasets in CSV format using the platform's user-friendly upload system. Additionally, by presenting SHAP explanations, predictions, and processed data directly on the interface, it offers dynamic visualizations that simplify results.

2. Data Preprocessing

Features such as Case-ID and Primary-Diagnosis are some of the supporting features that are not important to the end-users as they are shaved off automatically by the platform cleansing the data in a manner that important features such as age and gender remain seen by the users. Age strings such as '30 years 150 days' are also transformed into a comparable single numerical value; total days. If age data is missing or invalid, the column mean is used as sort of a 'last resort' to maintain data integrity. Nominal data types like gender, race, and mutation status are converted into numeric style which is the standard for machine learning algorithms. Furthermore, predictors such as Age-at-diagnosis and genomic variations are standardized to achieve conditioning with ongoing features.

3. Machine Learning Predictions

Glioma risk is predicted by the platform, which then classifies it as either LGG (low-grade glioma) or GBM (glioblastoma multiforme, a high-risk condition). For convenience, the uploaded dataset is then annotated with the predicted risk classification. If ground truth labels are available, the platform also shows the model’s accuracy score, which gives users a sense of confidence in the predictions and lets them evaluate the model’s performance.

Explainability with SHAP

In order to explain how each feature contributes to each prediction, the platform uses SHAP (SHapley Additive exPlanations), which integrates feature importance analysis. By highlighting the key elements in the risk prediction process, SHAP summary plots—which are shown as bar charts—provide visual insights. This increases the model’s credibility and interpretability by enabling users to comprehend the logic underlying each prediction.

5. Flexible Reporting

The platform provides interactive tables in an intuitive HTML table format that show the processed dataset along with predictions and risk levels. The processed dataset with predictions can also be downloaded by users, allowing offline analysis or sharing with colleagues for additional review and cooperation.

6. Robust Error Handling

To make sure uploaded files are in CSV format and have the necessary features, the platform has a feature called file validation. Additionally, it manages data format problems by identifying and fixing missing or invalid values in the dataset and by giving users useful error messages for unsupported formats to help them solve problems quickly.

7. Lightweight and Efficient

Flask, which is used in the platform’s construction, ensures backend efficiency by making the application quick and light. Because of its low resource requirements, it can function flawlessly on systems with common configurations without requiring a lot of processing power, making it effective and accessible in a variety of settings.

5. Use Case

The web application is intended for use in the following situations by researchers, educators, and healthcare professionals.:

- **Clinical Decision Support**

To ascertain a patient's glioma risk level, a neurologist uploads clinical data to the web application. In addition to predicting if the glioma is LGG or GBM, the application highlights important characteristics such as tumor size and mutation markers. This helps the neurologist make well-informed decisions about treatment.

- **Research on Glioma Prediction Models**

The application is used by researchers to assess how well various models perform on experimental glioma datasets. Their models become more robust as a result of their ability to detect biases or an excessive dependence on particular features thanks to the explainability insights.

- **Educational Training in Medical AI**

It is used by such medical educators as part of doctor and student training programs. By using AI models students get insights on how clinical factors are used in making a decision on gliomas classification.

Conclusion

These efforts collectively provide a suitable explainable AI tool for the classification of gliomas. By using Flask and making thoughtful design choices, a web application bridges the gap between the theoretical demonstration of AI systems and their use in clinical settings by offering usability and transparency. The application of the concept in healthcare is improved by the integration of SHAP into the AI since it makes the interpretation clear and people trust what they understand.
