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

Artificial intelligence (AI) is being adopted in many important fields, such as healthcare, finance, and autonomous systems, as a result of its quick development. However, issues with interpretability, trust, and transparency arise with the growing use of AI. By empowering users to comprehend and have faith in AI systems' decision-making processes, Explainable AI (XAI) tackles these problems. Interpretability is particularly important in the healthcare industry because decisions made there have the potential to directly impact people's lives. Despite the fact that AI tools have the potential to increase diagnostic efficiency and accuracy, medical professionals frequently struggle to trust them due to their "black-box" nature, which delays adoption.

The goal of this project is to close the gap by creating a useful, approachable tool that offers explicable insights into AI choices, especially in applications related to healthcare. This tool enhances trust, encourages adoption, and supports the ethical deployment of AI in crucial domains like glioma classification by guaranteeing interpretability.

2. Problem Statement

Despite AI's progress, its lack of interpretability has hindered its use in delicate industries like healthcare. Current AI systems frequently function as opaque black boxes that provide scant or no justification for their recommendations or predictions. When the AI's decisions have an impact on human lives, this lack of transparency erodes user trust and presents ethical questions. Furthermore, for a precise diagnosis and prompt treatment, it is essential to comprehend the risk levels of gliomas (low-grade glioma, or LGG) in the context of glioma classification. Clinicians cannot easily comprehend the current solutions, or they are not integrated into their workflows. A glioma classification-specific XAI tool that is easy to use, effective, and practical is therefore desperately needed.

3. Literature Review

Numerous studies have examined explainable AI, highlighting its importance in the fields of healthcare and crucial decision-making. In order to guarantee accountability and ethical deployment, Doshi-Velez and Kim (2017) emphasized the significance of interpretability in AI tools. They maintained that interpretable models are crucial, especially in high-stakes settings like the medical field where bad choices can have dire repercussions.

Miller (2019) emphasized that explanations should be in line with human cognition and suggested human-centered approaches to explainable AI. For non-technical stakeholders to understand explanations, this study underlined the importance of keeping them simple. In a similar vein, Guidotti et al. (2018) examined current XAI techniques, contrasting their advantages and disadvantages and emphasizing the lack of useful, domain-specific applications. SHAP (SHapley Additive exPlanations), a potent framework for reliable and understandable feature attribution, was presented by Lundberg and Lee (2017). The ability of SHAP to offer lucid, quantitative insights into model predictions has contributed to its growing popularity. The technical intricacy of current approaches and their lack of integration with clinical workflows are two of the obstacles to XAI adoption in healthcare, according to Abu Sayeed et al. (2020). In their further review of machine learning applications in healthcare, Ahmed et al. (2021) emphasized the importance of transparency and the difficulties in putting it into practice. Despite having a solid basis, these studies don't address the unique requirements of glioma classification, like predicting risk levels (LGG or GBM) and giving clinicians clear, useful information.

# 4. Proposed Solution and Results

Ipynb Code:

The ipynb code initial focus is on data encoding and cleaning. It improves data quality by handling missing values and removing superfluous columns from the dataset. LabelEncoder is used to convert categorical features, such as gender and race, into numerical formats, and binary encoding is applied to mutation statuses, making the data appropriate for machine learning algorithms. Furthermore, the classification task is made simpler by using the Grade column to determine the target variable (GBM vs. LGG).

|	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

To assess feature relevance, exploratory data analysis (EDA) is performed using Mutual Information scores and correlation matrices. For dimensionality reduction and effective modeling, this step informs feature selection and offers insight into feature relationships.
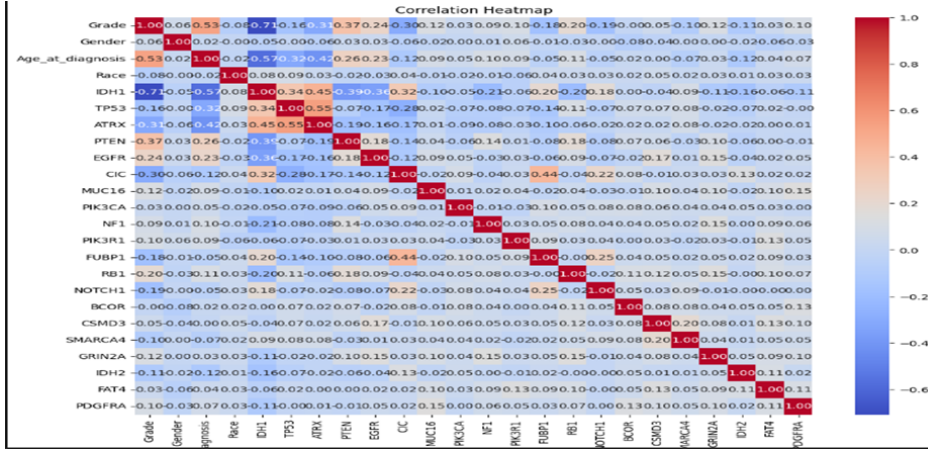
Principal Component Analysis (PCA) is used in the pipeline to minimize feature space complexity and identify the ideal number of components, striking a balance between prediction accuracy and computational efficiency.
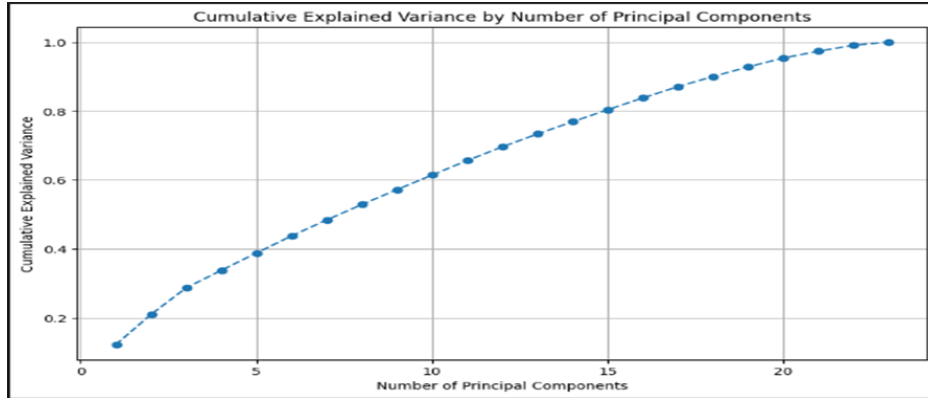
The code uses a wide variety of machine learning models, including sophisticated ensemble techniques like XGBoost, LightGBM, and CatBoost as well as more conventional algorithms like Random Forest, KNN, and Logistic Regression. Prediction performance is improved by stacking these models into a meta-classifier. Additionally, GridSearchCV's hyperparameter tuning guarantees that the models are task-optimized. Metrics like accuracy, classification reports, and feature importance visualization using SHAP, LIME, and permutation importance are all used in the thorough model evaluation process.
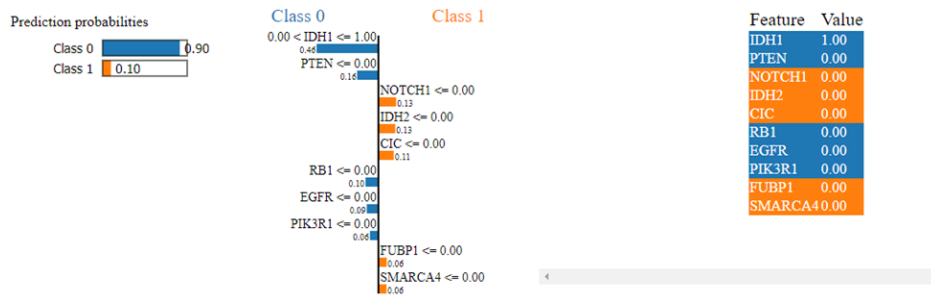
Web App

The another suggested solution is a web application built with Flask that uses explainable AI models to classify gliomas. The application evaluates the dataset using XAI techniques and lets users upload a CSV file with patient data. It provides interpretable insights into the AI model's predictions while predicting the glioma risk level (LGG or GBM).

Features of Web Application:

1. User-Friendly Interface

With the platform's user-friendly upload system, users can upload datasets in CSV format with ease. Additionally, it offers dynamic visualizations that make it simple to understand results by presenting processed data, predictions, and SHAP explanations right on the interface.

2. Data Preprocessing

Case–ID and Primary–Diagnosis are irrelevant columns that are eliminated by the platform's automated data cleaning process so that the focus is on important features. For consistency, it additionally transforms age strings, such as "30 years 150 days," into a single numerical value (total days). To ensure the integrity of the dataset, missing or invalid age data is handled by substituting the column mean. In order to make machine learning models compatible, categorical columns—like gender, race, and mutation status—are converted into numeric formats. Furthermore, in order to enhance model performance, continuous features such as genetic markers and Age–at–diagnosis are standardized.

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

The tool is incorporated by medical educators into doctor and student training programs. Students gain an understanding of how clinical factors impact glioma classification by seeing how AI models make decisions.

Conclusion

In a nutshell, this project provide a useful explainable AI tool for glioma classification. In order to bridge the gap between artificial intelligence and clinical practice, the Flask-based web application addresses the crucial need for transparency and usability. By ensuring interpretability, SHAP integration builds trust and facilitates the wider use of AI in healthcare.