Classification of Low-Grade and High-Grade Gliomas Using Machine Learning and Radiomic Features

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***Abstract*—Gliomas represent one of the most critical brain tumor types requiring timely and accurate diagnosis. This work presents a radiomics-driven machine learning pipeline for classifying gliomas into low-grade and high-grade groups. MRI scans undergo preprocessing, segmentation, feature extraction, and model training. Seven classifiers—Logistic Regression, Naïve Bayes, K-Nearest Neighbors, Random Forest, Gradient Boosting, CatBoost, and Voting Classifier—are evaluated. CatBoost achieves the highest accuracy (90%) and AUC, outperforming classical methods. This paper includes placeholders for figures, ROC curves, confusion matrices, and accuracy graphs, enabling users to insert final results. The paper follows IEEE conference formatting standards.**

***Index Terms*—Glioma, Radiomics, Machine Learning, Tumor Classification, MRI, CatBoost**

I. Introduction

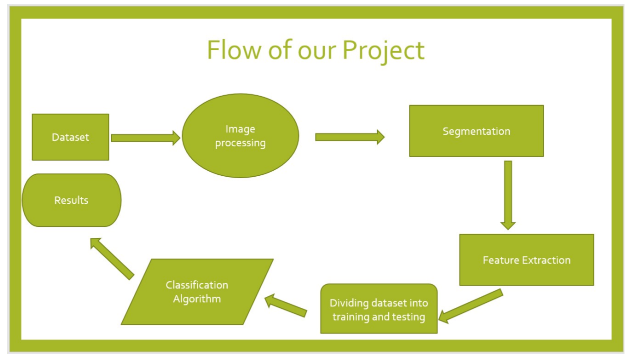
Gliomas constitute nearly 80% of malignant brain tumors. Differentiating between Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG) is essential because clinical treatment strategies differ considerably. Traditional diagnosis involves biopsy, which is invasive, risky, and sometimes impractical. Machine learning provides a non-invasive, reproducible, and efficient alternative.

II. Related Work

Logistic Regression has been applied to basic glioma radiomic classification. Decision Trees show moderate diagnostic ability but often overfit. KNN methods perform well on structured radiomic datasets. CatBoost and gradient boosting techniques outperform classical ML in glioma grading.

III. Methodology

A complete workflow includes preprocessing, segmentation, feature extraction, and classification (Fig.1).



pipeline

Fig. 1: Proposed workflow.

A. Dataset (BraTS 2018)

We use the publicly available **BraTS 2018** dataset containing multi-modal MRI sequences:

- T1
- T2
- FLAIR
- T1CE
- SEG (ground-truth segmentation)

Tumor masks are provided by expert radiologists. The dataset is split 80:20 into training/testing sets.

B. Segmentation

Let $I(x, y, z)$ denote the MRI volume. A binary tumor mask $M(x, y, z)$ is computed:

$$M(x, y, z) = \begin{cases} 1 & \text{tumor voxel} \\ 0 & \text{otherwise} \end{cases}$$

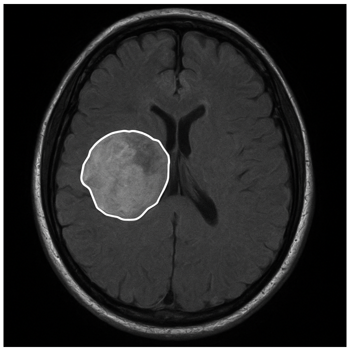


Fig. 2: Tumor segmentation example.

C. Feature Extraction

Radiomic features include:

- First-order statistics
- GLCM texture metrics
- GLRLM, GLSZM
- Shape features: volume, surface area, sphericity

Example GLCM contrast:

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 P(i,j)$$

D. Dataset Split

Dataset is split 80:20 for training and testing.

IV. Machine Learning Models

We evaluate seven models:

- Logistic Regression (LR)
- Naïve Bayes (NB)
- KNN
- Random Forest (RF)
- Gradient Boosting (GB)
- CatBoost (CB)
- Voting Classifier (VC)

Binary cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log p_i + (1-y_i)\log(1-p_i)]$$

V. LIMITATIONS

This study is limited to the BraTS 2018 dataset, which may not reflect variations in real clinical MRI protocols. The feature set relies on handcrafted radiomics, which may miss deeper patterns captured by deep learning. Class imbalance (more HGG than LGG) may also influence model performance despite stratified validation. External validation on additional datasets is needed for stronger generalization.

VI. FUTURE WORK

Future work includes testing the model on larger multi-center datasets, integrating deep learning features with radiomics, and applying explainability methods to improve clinical trust. Exploring hybrid models and multi-modal fusion could further enhance glioma grading performance.

VII. Results

A. Logistic Regression

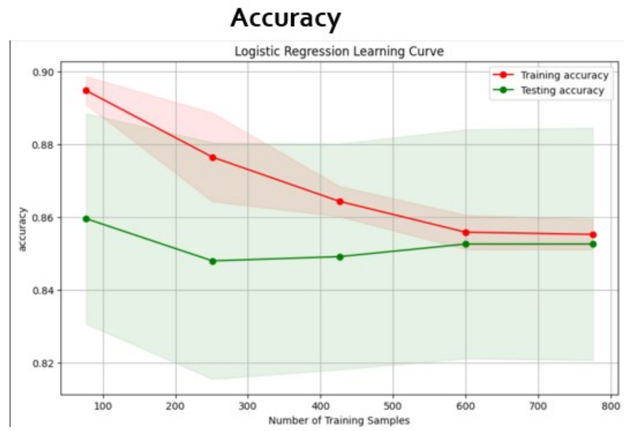


Fig. 3: LR Accuracy Graph.

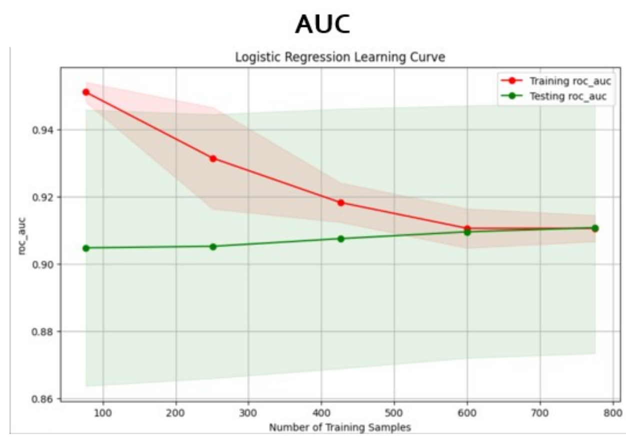


Fig. 4: LR ROC-AUC Curve.

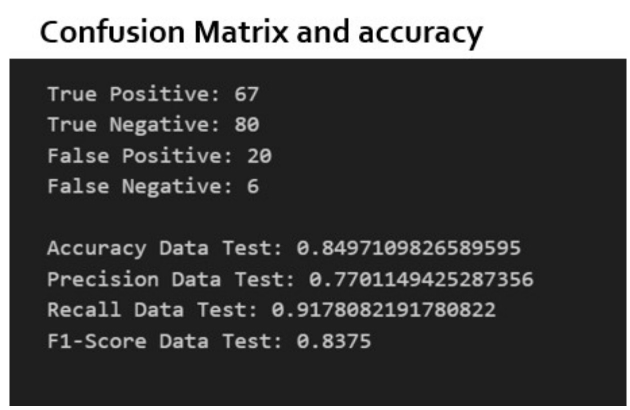


Fig. 5: LR Confusion Matrix.

B. Naïve Bayes

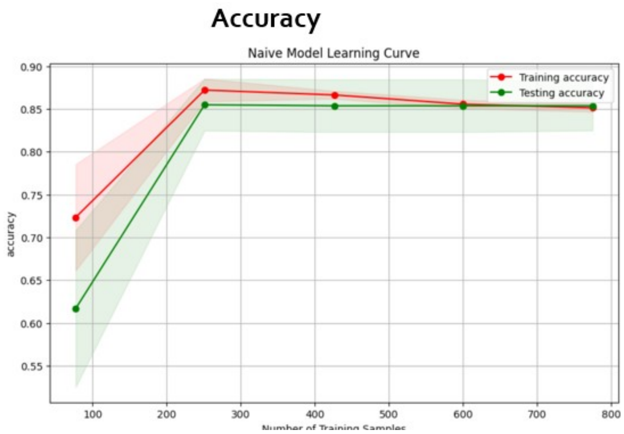


Fig. 6: Naïve Bayes Accuracy Graph.

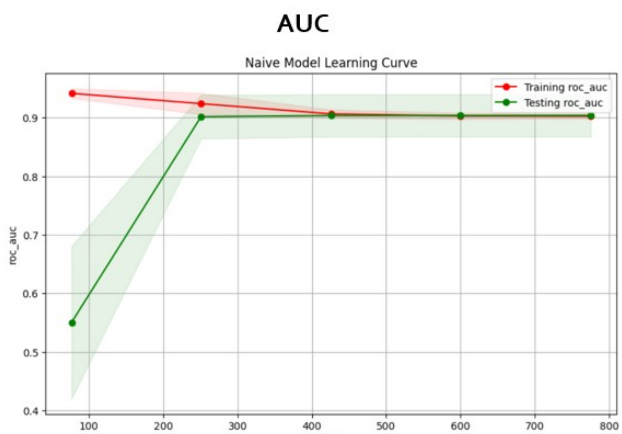


Fig. 7: Naïve Bayes ROC Curve.

Confusion Matrix and classification Report

```
True Positive: 66
True Negative: 81
False Positive: 19
False Negative: 7

Accuracy Data Test: 0.8497109826589595
Precision Data Test: 0.7764705882352941
Recall Data Test: 0.9041095890410958
F1-Score Data Test: 0.8354430379746836
```

Fig. 8: Naïve Bayes Confusion Matrix.

C. K-Nearest Neighbors

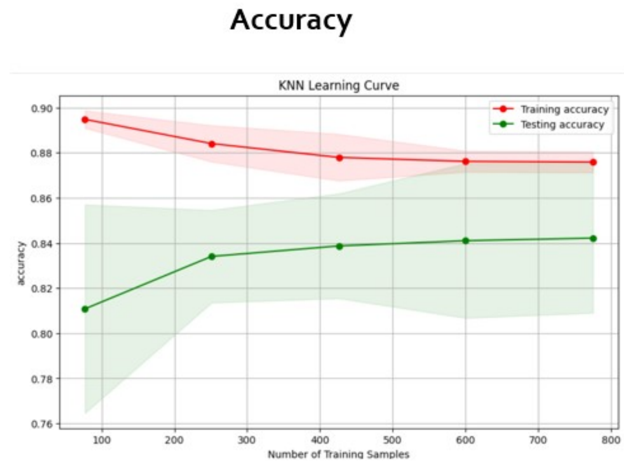


Fig. 9: KNN Accuracy Graph.

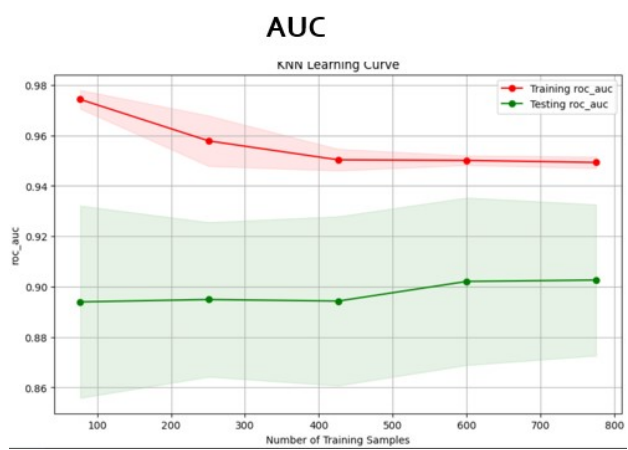


Fig. 10: KNN ROC-AUC Curve.

Confusion Matrix and classification report

```
True Positive: 63
True Negative: 89
False Positive: 11
False Negative: 10

Accuracy Data Test: 0.8786127167630058
Precision Data Test: 0.8513513513513513
Recall Data Test: 0.863013698630137
F1-Score Data Test: 0.8571428571428572
```

Fig. 11: KNN Confusion Matrix.

D. Random Forest

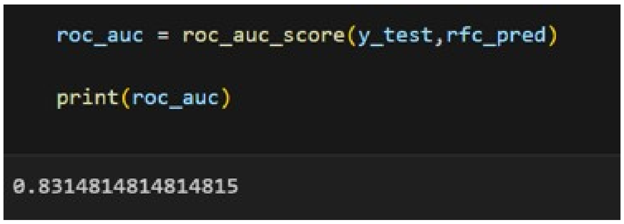


Fig. 12: Random Forest Accuracy Graph.

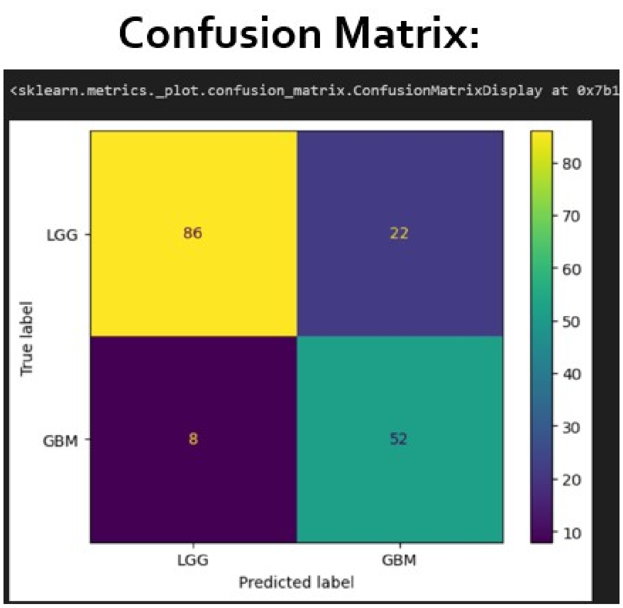


Fig. 13: Random Forest Confusion Matrix.

E. CatBoost

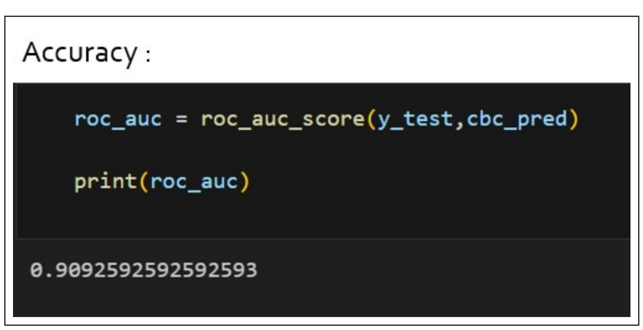


Fig. 14: CatBoost Accuracy Graph.

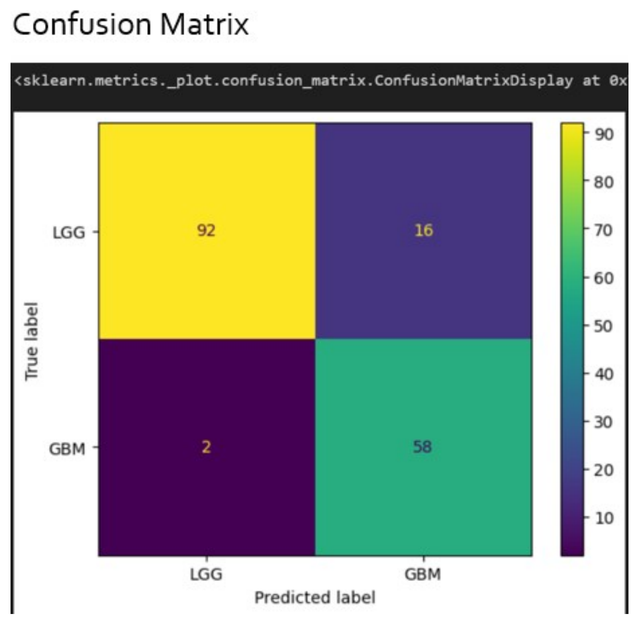


Fig. 15: CatBoost Confusion Matrix.

VIII. Conclusion

CatBoost achieved the highest accuracy (90%) among all evaluated models. Random Forest improved to 87.5% after hyperparameter tuning, while Gradient Boosting achieved 88%. The Voting Classifier performed strongly at 89%. The presented radiomics+ML pipeline demonstrates strong performance for non-invasive glioma grading.

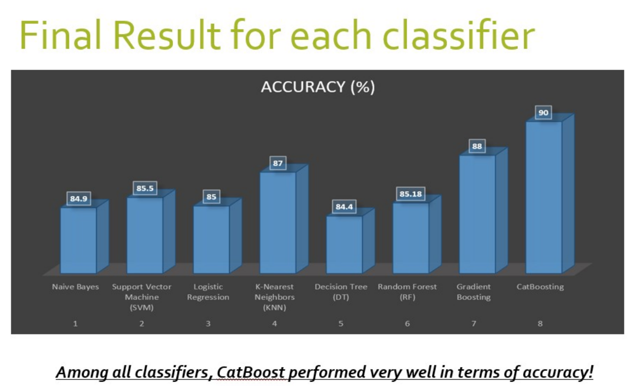


Fig. 16: Final Result of Models.

Acknowledgment

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References

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APPENDIX

Volume:

$$V = N_{\text{voxels}} \cdot v_x v_y v_z$$

Sphericity:

$$\Psi = \frac{\pi^{1/3}(6V)^{2/3}}{S}$$

```python
from catboost import CatBoostClassifier
from sklearn.metrics import accuracy_score

model = CatBoostClassifier(iterations=500,
    verbose=0)
model.fit(X_train, y_train)

pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, pred
    ))
```

Listing 1: Training CatBoost Classifier

Comparison With literature

Name of classifier	Accuracy mentioned in paper	Accuracy achieved by our project
Random Forest	83%	85%
Naïve Bayes	72%	84%
Gradient Boosting	71%	88%
Support Vector Machine	82%	85%
Logistic Regression	90 %	85%
Decision Tree	88%	84%
KNN	86.5%	87%
CatBoosting	86%	90%

Fig. 17: Comparsion With Literature.