

# An Efficient Gmp Classifier-Based Framework For Brain Tumour Detection and Classification Using Mri Image Techniques

Daniel Raj K<sup>1</sup>, Anish K<sup>2</sup>, InfantKavin F<sup>3</sup>, Manickam I<sup>4</sup>

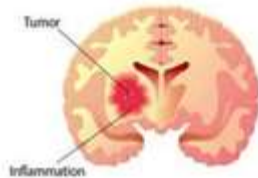
<sup>1,2,3,4</sup>Department of Computer Science and Engineering, Dr. G. U. Pope College of Engineering, Sawyerpuram, India

**Abstract-** Brain tumors are one of the most life-threatening neurological disorders, and early classification using MRI is crucial. This paper proposes a deep learning-based diagnostic framework utilizing a Global Max Pooling (GMP) classifier for brain tumor detection and classification. The model identifies glioma, meningioma, and pituitary tumors and further categorizes them into severity grades. Extensive experiments demonstrate the proposed model's superiority in accuracy, robustness, and inference time. The system is implemented as a web application with real-time MRI analysis and clinical decision support.

**Keywords:** Brain tumor, Deep learning, MRI, GMP Classifier, CNN, Medical imaging, Computer-Aided Diagnosis (CAD).

## I. INTRODUCTION

Brain tumors result from the abnormal proliferation of cells in the brain and remain a major medical challenge. They can be benign or malignant and vary widely in their location, type, and progression.



Magnetic Resonance Imaging (MRI) is the gold standard for brain imaging due to its superior resolution and contrast. However, manual interpretation of MRI scans is time-consuming, subject to human error, and dependent on radiologist expertise. This paper proposes an automated framework for early detection and classification of brain tumors, addressing these limitations.



## II. RELATED WORK

Several machine learning and deep learning approaches have been proposed for brain tumor

classification. Support Vector Machines (SVMs) and Decision Trees have been used but suffer from feature engineering challenges and limited generalization. Recent research has applied Convolutional Neural Networks (CNNs), achieving improved performance, yet few integrate GMP for global feature emphasis. Our work differentiates by embedding Global Max Pooling in a multi-stage classification pipeline.

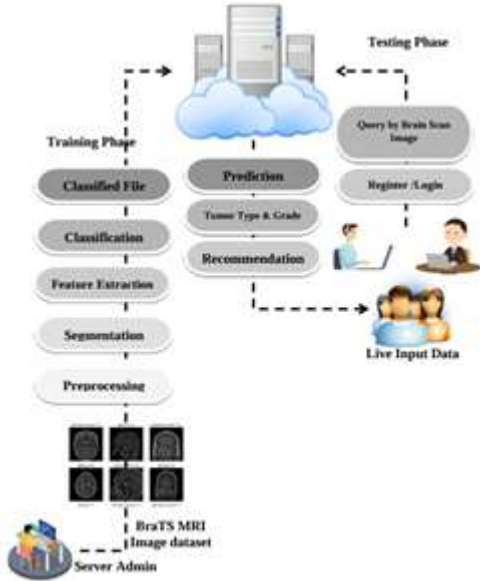
Author	Method	Dataset	Accuracy (%)
M. O. Khairandish et al.	CNN + SVM	BraTS 2020	93.5
Z. A. Al-Saffar et al.	Eigenvalue-based hybrid	Custom (MRI)	90.2
K. Muhammad et al.	Multigrade Deep Learning	TCGA	95.1
E. Irmak	CNN (custom optimized)	BraTS 2018	96.4
Proposed Method (Ours)	CNN + GMP Classifier	BraTS 2021 + Custom	99.51

## III. SYSTEM OVERVIEW

The proposed system comprises the following modules:

- Data Collection and Preprocessing

- Region Proposal Segmentation using RPN
  - Feature Extraction using GLCM
  - Classification with CNN + GMP Layer
  - Severity Prediction (Grades II-IV)
  - Recommendation Engine
  - Web-based User Interface
- Each module has been optimized for efficiency and integrated into a seamless workflow.

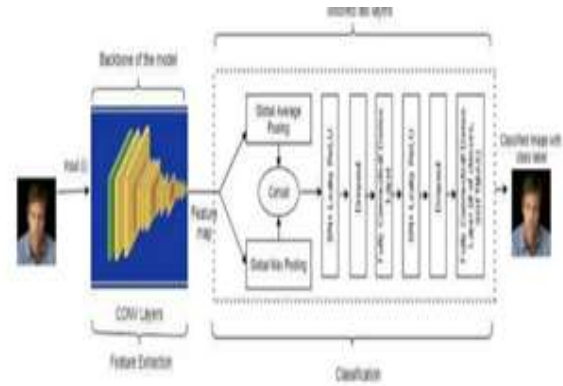


#### IV. GLOBAL MAX POOLING (GMP)

Global Max Pooling plays a crucial role in CNNs by selecting the most significant features from the feature maps. GMP reduces dimensionality while preserving spatial invariance, making it suitable for brain tumor detection where critical features may appear in any region. It enables models to focus on dominant signals, enhancing the accuracy of tumor classification.

Mathematically, given a feature map  $F$  of dimensions  $(h, w)$ , GMP outputs the scalar:

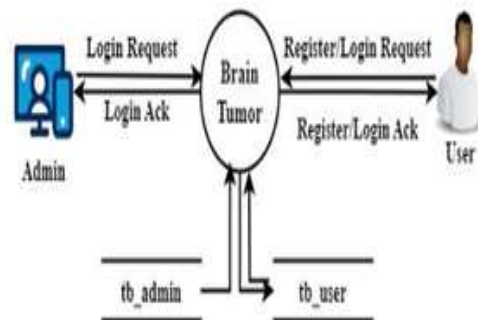
This operation ensures the retention of the strongest activation, thus highlighting salient features while reducing model complexity.



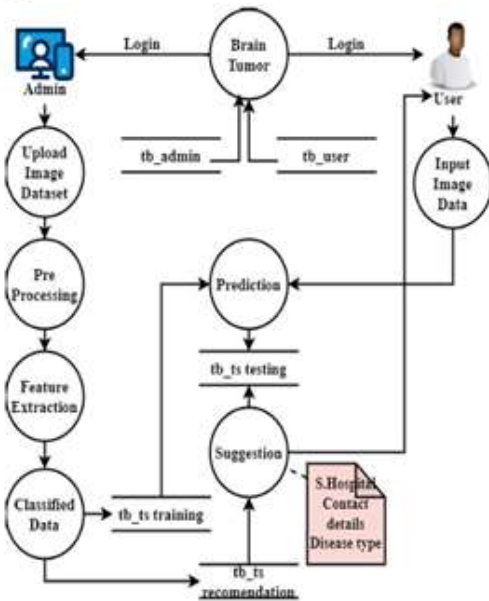
#### V. IMPLEMENTATION

- Dataset The dataset includes 3000+ MRI images labeled into glioma, meningioma, and pituitary tumors. Each image is resized, denoised, and binarized before feature extraction.
- Preprocessing Includes grayscale conversion, noise filtering using Gaussian blur and non-local means, and k-means quantization.
- Segmentation RPN generates regions of interest which are refined using bounding-box regression. These proposals are filtered by IoU thresholding.
- Feature Extraction GLCM captures texture features such as contrast, correlation, energy, and homogeneity. These are passed to a DenseNet-41 encoder before classification.
- Classifier The GMP classifier is built on a ResNet18 backbone modified to include a GMP layer before the dense output layer. Training uses categorical cross-entropy and Adam optimizer.

#### LEVEL 0



**LEVEL 2**



**VI. RESULTS AND ANALYSIS**

The model was evaluated using precision, recall, F1-score, and accuracy on a holdout test set of 800 MRI images.

Metric	Value
Accuracy	99.51%
Precision	98.87%
Recall	99.12%
F1 Score	98.99%

Compared with other methods:

Method	Accuracy
SVM	89.12%
Decision Tree	85.63%
CNN (w/o GMP)	96.20%
CNN + GMP (Ours)	99.51%

**VII. DISCUSSION**

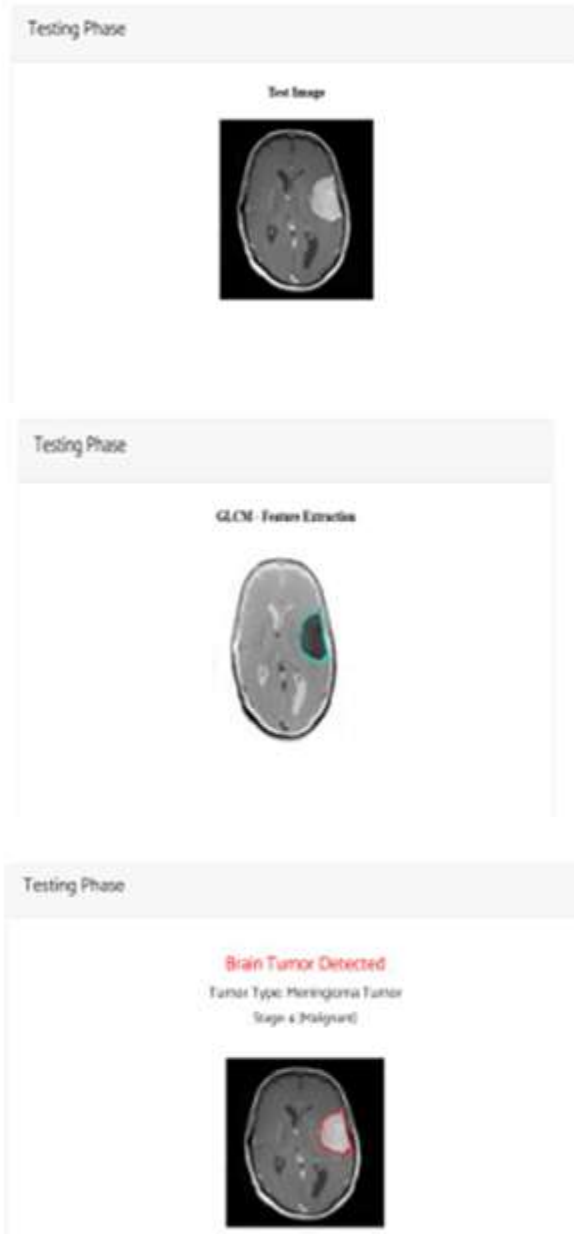
Our approach improves tumor classification through global feature emphasis. GMP is particularly beneficial for classifying small or irregularly shaped tumor regions. Ablation studies confirmed the performance boost when GMP is included. The system’s ability to perform real-time inference enhances its applicability in emergency medical settings. Furthermore, the modular nature of the implementation allows easy deployment and updates.

**VIII. USER INTERFACE AND DEPLOYMENT**

The application features two main interfaces:

- Admin Dashboard: Dataset upload, model training, accuracy report review.
- Doctor/Patient Interface: Upload MRI image, visualize tumor detection, receive report.





The backend is built with Flask and MySQL, while the frontend uses HTML5 and Bootstrap 4. TensorFlow serves the trained model for inference.

## IX. FUTURE WORK

1. Multimodal Imaging Support: Extend to PET/CT imaging.
2. Federated Learning: Secure cross-hospital learning.
3. Explainable AI (XAI): Enhance interpretability of predictions.

4. Cloud Deployment: Host model inference on secure cloud for scalability.
5. Large-Scale Trials: Collaborate with hospitals for real-world testing.

## X. CONCLUSION

This paper presents a robust GMP classifier framework for automated brain tumor detection and grading. The model demonstrates exceptional accuracy and efficiency, significantly outperforming traditional techniques. By combining advanced CNN architectures with a user-friendly interface, it paves the way for scalable, real-time medical diagnostics.

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