Lời tựa đầu

Trong báo cáo này em xin trình bày lại sơ lược về chủ đề nghiên cứu **Brain Tumor MRI classification**, trong đó bao gồm việc lý do chọn đề tài, phát biểu lại bài toán, các cơ sở (insight) cho các phương pháp được đề xuất, quy trình thực hiện các phương pháp và cuối cùng là thống kê kết quả nghiên cứu thực nghiệm cho các phương pháp.

File báo cáo này cũng đã phần nào ghi lại toàn bộ quá trình thực hiện dự án nghiên cứu, từ việc quan sát (observation), thực hiện các survey - paper literature review; tìm và hiểu các insight, domain knowledge; cũng như make questions, make and refine ideas; code - experiment design and implementation; sau cùng em phân tích các kết quả nghiên cứu để tìm hướng đi cải tiến và đề ra các hướng nghiên cứu tiềm năng (new insight, new direction).

Cuối cùng, em xin chân thành cảm ơn thầy **Phd. Mai Tiến Dũng** đã hỗ trợ em trong việc chọn đề tài và cho em những lời khuyên quý giá để hoàn thiện hướng nghiên cứu cho dự án. Mình cũng xin cảm ơn các bạn trong lớp **CS231.O21.KHTN** nói chung và các bạn lớp **KHTN 2022** nói riêng đã luôn đồng hành cùng mình trong suốt môn học và một chặng đường dài đại học, các bạn đã tiếp thêm cho mình cảm hứng, niềm tin và ý tưởng những lúc mình bế tắc và tuyệt vọng trong quá trình tìm kiếm ý tưởng nghiên cứu, góp ý để mình hoàn thiện hơn bài báo cáo. Mình xin chân thành cảm ơn thầy và các bạn rất nhiều! Bên cạnh đó, em cũng xin cảm ơn một số người anh (bác sĩ) trong ngành đã cung cấp thêm cho em một vài kiến thức miền để em có thể hoàn thành tốt dự án. Sau cùng không có gì hơn, em xin chân thành cảm ơn vì tất cả.

Trân trọng,
Hoàng Ngọc Quân

Brain Tumor MRI Classification

In the study conducted by

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Phd. Dung Mai Tien

5/2024

This file is not final report

Problem Statement

1. Introduction

Brain tumor classification: is a crucial task in medical imaging for accurate diagnosis and treatment planning. Accurate classification of brain tumors helps in determining the type, grade, and prognosis of the tumor, as well as selecting appropriate treatment strategies. Early detection and classification of brain tumors is an important research domain in the field of medical imaging and accordingly helps in selecting the most convenient treatment method to save patients life therefore.

Literature Review: The tumor histological classification has been introduced by the World Health Organization and is based on the *predominant cell type*; the grade is based on the levels of necrosis, mitotic activity, nuclear atypia, and endothelial cell proliferation. Many molecular markers have also been identified in brain cancers, which provide valuable information for classification and prognosis. **However**, *these markers* require analysis of samples from the tumor tissues, which does not allow for a *rapid diagnosis* in a clinical trial. **Therefore**, there is a need for non-invasive diagnostic methods that can accurately classify brain tumors using imaging techniques such as MRI, CT, and nuclear medicine imaging.

Methods and Approaches: With the rapid development of AI in recent times, especially in the field of Computer Vision, we propose some brain tumor classification methods based on MRI images using machine learning algorithms, feature extraction techniques, and image processing methods. They showed high accuracy and predictive value in distinguishing between different types of brain tumors, as well as determining tumor grades in supporting doctors in early detection and diagnosis of brain tumor diseases.

2. Problem Modeling

The problem can be formulated as follows: Given a brain tumor MRI image, the aim of this project/research is to develop methods that can accurately classify the type of tumor to ensure generalizability and discrimination.

Input:

- The input is a brain MRI image, which can be a 2D slice.

- We can denote this as $I \in R^{(H \times W)}$, where: I represent the image. R signifies the data type (usually real numbers). H is the image height. W is the image width.

- Training:
  - The training dataset consists of labeled images with the corresponding class for each image. The label should indicate the type of tumor in the brain MRI image and each image can only be assigned a unique label.
  - **C** = {meningioma (M), glioma (G), pituitary (P) tumor and no tumor (N)}

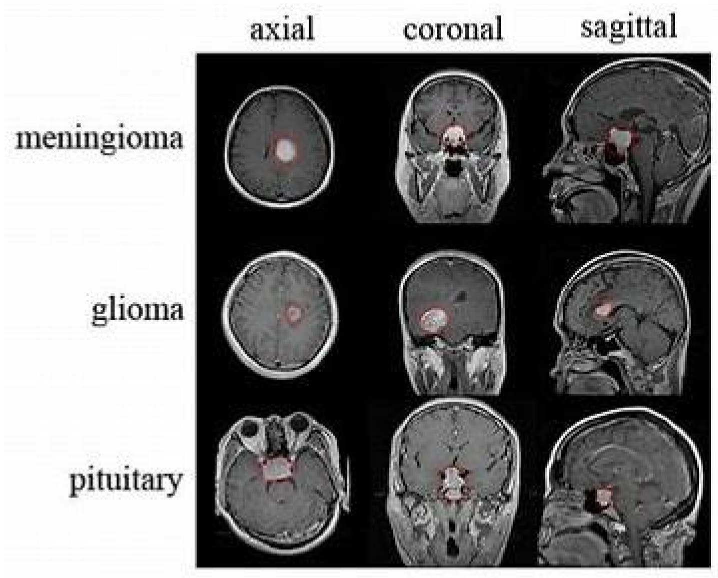
Output:

- The output of the model is a classification label, which can be probability scores indicating the likelihood of belonging to a specific tumor class.
  - The classes include meningioma (M), glioma (G), pituitary (P) tumor and no tumor (N).

Constraints:

- The brain MRI image only contains a unique type of tumor in the classes.
- The planes of the brain MRI image should be axial (also sometimes called a transverse MRI), which is a type of magnetic resonance imaging (MRI) scan that captures horizontal slices of the head. Because:
  - It provides a detailed view of the brain's structures layered on top of each other, including the cerebral cortex (outer layer), white matter (inner layer), ventricles (fluid-filled cavities), and cerebellum.
  - Doctors can examine the brain tissue consistency, look for abnormalities like tumors, bleeding, or swelling, and assess blood flow within the brain.
- The brain MRI image should be high in-plane resolution.

Examples: The examples of different types of tumors, as well as different planes, are shown in **Figure 1**. The tumors are marked with a red outline.



Additional Concepts:

- A brain tumor is a collection, or mass, of abnormal cells in your brain. Your skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems.
- Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside your skull to increase. This can cause brain damage, and it can be life-threatening.
- Type of tumor are different about position of tumor:
    - (M) meningioma tumor:
    - (G) glioma tumor
    - (P) pituitary tumor
    - (N) no tumor

Category	Origin	Type	Symptoms	MRI Appearance
Meningioma	Meninges	Usually benign	Headaches, vision problems, weakness	Well-defined mass, outer surface of brain

Glioma	Glial cells	Benign (low-grade) or malignant (high-grade)	Headaches, seizures, cognitive decline, weakness	Varies by grade, may be ill-defined or show enhancement
Pituitary Tumor	Pituitary gland	Benign or malignant	Headaches, vision problems, hormonal imbalances	Mass in sella turcica, may show enhancement
No Tumor	N/A	N/A	N/A	Normal brain anatomy and tissue signal intensities

- A brain tumor is defined as an abnormal mass of cells that grows in the brain. These cells can be cancerous (malignant) or non-cancerous (benign). Brain tumors can arise from different locations and cell types within the brain, leading to various classifications.

Key Distinguishing Factors:

The type and location of the abnormal cell growth determine the specific classification of a brain tumor. Here are some key factors that help distinguish between the categories you mentioned:

- **Origin:** Meningiomas arise from the meninges, gliomas from glial cells, pituitary tumors from the pituitary gland, and "no tumor" indicates a healthy brain.
- **Growth Rate:** Meningiomas are usually slow-growing, while gliomas can vary from slow-growing (low-grade) to fast-growing (high-grade). Pituitary tumors can be slow-growing or fast-growing as well.
- **Symptoms:** The specific symptoms depend on the location and size of the tumor, but some general patterns exist (e.g., headaches are common across many types).
- **MRI Appearance:** The appearance on MRI scans can vary depending on the tumor type and grade. Look for features like well-defined vs. ill-defined masses, location within the brain, and enhancement with contrast dye.

Evaluation Method

1. Mertrics

To meet the aim of this project/research is to develop methods that can accurately classify the type of tumor to ensure generalizability and discrimination, we use some common metrics for medical classification problem such as:

- *Accuracy*: The proportion of correctly classified instances to the total number of instances.
- *F1-score*: The harmonic mean of precision and recall, providing a balance between the two metrics.
  - Precision: The proportion of true positive instances to the total number of instances predicted as positive.
  - Recall: The proportion of true positive instances to the total number of actual positive instances.
- *Confusion matrix*: A matrix that shows the number of true positive, true negative, false positive, and false negative predictions made by the classifier.

References:

- On evaluation metrics for medical applications of artificial intelligence | Scientific Reports (nature.com) - 2022 - 163 citations
- Applied Sciences | Free Full-Text | Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network (mdpi.com) - 2020 - 302 citations
- TOWARDS A GUIDELINE FOR EVALUATION METRICS IN MEDICAL IMAGE SEGMENTATION - 2022 - 96 citations

2. Dataset for training and testing

Because of the specificity of the medical field, we use previously collected and processed datasets including: figshare, SARTAJ dataset, Br35H

Statistic about datasets:

Figshare Brain Tumor Image Dataset (kaggle.com)

The dataset provided as a set of slices, used in this paper contains 3064 T1-weighted contrast-enhanced MRI images acquired from Nanfang Hospital and General Hospital, Tianjin Medical University, China from 2005 to 2010. It was first published online in 2015, and the last modified version was realized in 2017 [**22**]. There are three types of tumors: meningioma (708 images), glioma (1426 images), and pituitary tumor (930 images). All images were acquired from 233 patients in three planes: sagittal (1025 images), axial (994 images), and coronal (1045 images) plane. The number of images is different for each patient.

In this research, we used a publicly available CE-MRI dataset (Cheng, 2017) available at (https://figshare.com/articles/brain_tumor_dataset/1512427). The proposed brain tumor classification is based on two-dimensional images (2D slices), not 3-D volume, because in most clinical practice, the acquired and available CE-MRI images are 2-D slices with a large slice gap. Therefore, our classification system based on 2-D MR images for clinical application is practical.

meningioma	glioma	pituitary	
708	1426	930	3064

SARTAJ

This brain tumor dataset contains MRI data. These images are already split into Training and Testing with 4 types of brain tumor.

Testing				
glioma	meningioma	no_tumor	pituitary	
100	115	105	74	394
Training (Error)				
glioma	meningioma	no_tumor	pituitary	
826	822	395	827	2870

Br35H

The dataset contains 3000 Brain MRI Image with binary class of brain tumor: yes or no.

Yes	No
1500	1500

About dataset that we use for this project/research:

Brain tumor MRI dataset Cheng [2017], Amin et al. [2022]

This dataset is a combination of the following three datasets. This dataset contains 7023 images of human brain MRI images which are classified into 4 classes: glioma - meningioma - no tumor and pituitary.

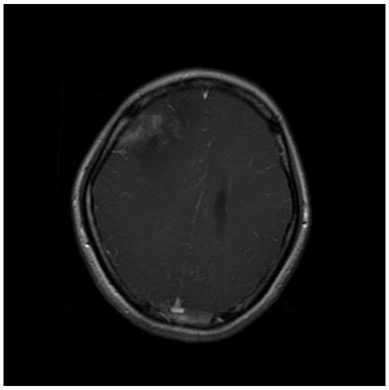
We used the dataset from [https://www.kaggle.com/datasets/masoudnickparvar/ brain-tumor-mri-dataset](https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset) that combines Br35H: Brain tumor Detection 2020 dataset used in "Retrieval of Brain tumors by Adaptive Spatial Pooling and Fisher Vector Representation" and Brain tumor classification curated by Navoneel Chakrabarty and Swati Kanchan.

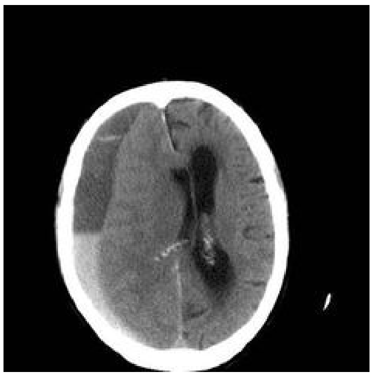
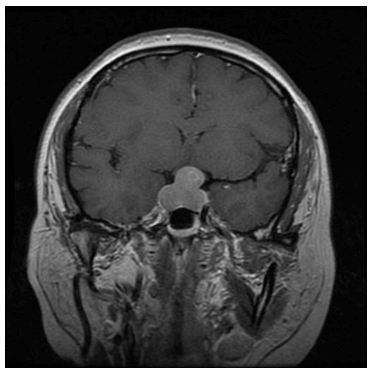
Out of these, the dataset curator created the training and testing splits. We followed their splits, 5,712 images for training and 1,311 for testing. Since this was a combination of multiple datasets, the size of images varied throughout the dataset from 512×512 to 219×234. The pretext of the task is multi-class classification, and we used the accuracy, F1 score as the metric.

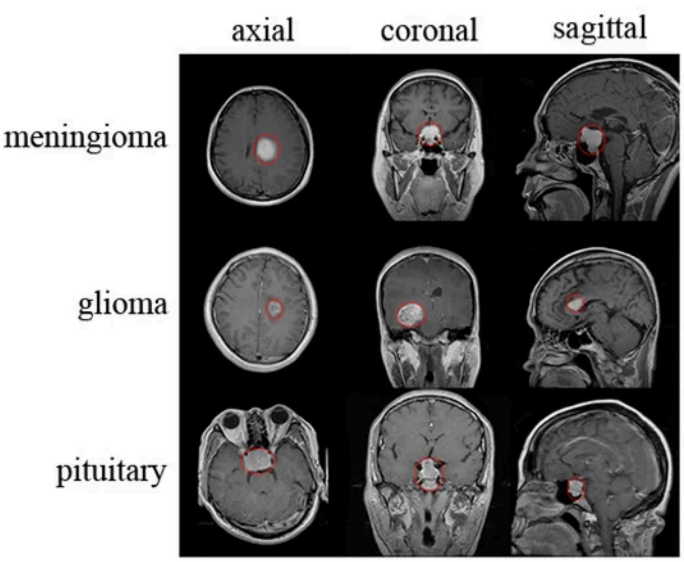
Additional Information:

- 'no tumor' class images were taken from the Br35H dataset.
- The author of this dataset thinks the SARTAJ dataset has a problem that the glioma class images are not categorized correctly, which is why they deleted the images in this folder and used the images on the figshare site instead.
- Pay attention that the size of the images in this dataset is different. We can resize the image to the desired size after pre-processing and removing the extra margins. This work will improve the accuracy of the model pre-processing code.

Testing				
G?	**M?**	**N?**	**P?**	
300	306	405	300	1311
Training				
G?	**M?**	**N?**	**P?**	
1321	1339	1595	1457	5712



References:

- Brain Tumor MRI Dataset (kaggle.com) - 2022
- Brain Tumor MRI Dataset Benchmark (Classification) | Papers With Code - 2022 - SoTA - CASS - DINO

3. Testing Method

- To test the generalization capability of methods in medical diagnostics, we use a K-fold cross-validation method for training and testing methods' performance.
- In this project, we use K = len(train) // len(test) = 4, with random_state set up 42 of sk-learn library.
- Besides, to ensure the objectivity of the evaluation, we keep the testing set of the dataset, and also evaluate the final results on this testing set.

References:

- Applied Sciences | Free Full-Text | Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network (mdpi.com) - 2020 - 302 citations - Figshare
- Brain tumor MRI images identification and classification based on the recurrent convolutional neural network - ScienceDirect - 2022 - 62 citations - Sartaj
- BRAIN TUMOR MRI IMAGE CLASSIFICATION WITH FEATURE SELECTION AND EXTRACTION USING LINEAR DISCRIMINANT ANALYSIS - 2012 - 79 citations
- Brain tumor detection and classification using machine learning: a comprehensive survey | Complex & Intelligent Systems (springer.com) - 2021 - 118 citations
- Brain tumor classification for MR images using transfer learning and fine-tuning - ScienceDirect - 2019 - 491 citations - lock [not free] - Figshare
- Medical images classification using deep learning: a survey | Multimedia Tools and Applications (springer.com) - 2023 - 1 cite - lock [not free]
- Brain MRI Detection | Segmentation | ResUNet (kaggle.com) - ResUnet

Related Work

Related Work in Brain Tumor MRI Classification:
Brain tumor classification using magnetic resonance imaging (MRI) is a crucial step in clinical diagnosis and treatment planning. Machine learning techniques, particularly deep learning, have achieved significant advancements in this field.

Early Machine Learning Approaches:

- BRAIN TUMOR MRI IMAGE CLASSIFICATION WITH FEATURE SELECTION AND EXTRACTION USING LINEAR DISCRIMINANT ANALYSIS (2012, 79 citations): This work explores traditional machine learning methods like feature extraction and Linear Discriminant Analysis (LDA) for brain tumor classification. While effective for its time, it might not compete with the accuracy of deep learning approaches.

Deep Learning Techniques:

- Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network (MDPI, 2020, 302 citations): This paper utilizes Convolutional Neural Networks (CNNs), a popular deep learning architecture, for brain tumor classification. CNNs excel at extracting features directly from images, achieving promising results.

- Brain tumor MRI images identification and classification based on the recurrent convolutional neural network (ScienceDirect, 2022, 62 citations): This study investigates Recurrent Neural Networks (RNNs) for brain tumor classification. RNNs can capture sequential information, potentially beneficial for analyzing MRI slices. - Segmentation

- Brain tumor classification for MR images using transfer learning and fine-tuning (ScienceDirect, 2019, 491 citations): This work explores transfer learning, a powerful deep learning technique where a pre-trained model is adapted for a new task (brain tumor classification). This approach leverages knowledge from a vast image dataset, potentially improving accuracy.

Recent Advancements:

- Brain tumor detection and classification using machine learning: a comprehensive survey (Springer, 2021, 118 citations): This comprehensive survey provides a detailed overview of various machine learning techniques used for brain tumor classification, including deep learning models. It offers valuable insights into the current state-of-the-art.

- Medical images classification using deep learning: a survey (Springer, 2023, 1 citation): While this survey is not freely available, it highlights the broader application of deep learning for medical image classification, including brain tumor MRIs.

Additional Resources:

- Brain MRI Detection | Segmentation | ResUNet (Kaggle): This Kaggle project demonstrates brain tumor segmentation using ResUnet, a deep learning architecture specifically designed for medical image segmentation. While not directly related to classification, segmentation is a crucial step in brain tumor analysis.
- Brain Tumor Classification from MRI Using Image Enhancement and Convolutional Neural Network Techniques - PMC (nih.gov) - 2023 - Same Dataset

These studies showcase the ongoing research and progress in brain tumor MRI classification using machine learning, particularly deep learning techniques. As research continues, we can expect even more accurate and efficient methods for diagnosing and treating brain tumors.

Proposal and Experiment Analysis

1. Enh + HOG - (Kaggle)

*****1. Purpose of Blur Gaussian Image?**

- The purpose of applying a blur Gaussian filter to an image is to reduce noise and smooth out the image, making it appear more visually appealing. This can be particularly useful in image processing applications where a clean and clear image is required for further analysis or presentation. The blur Gaussian filter works by convolving the image with a Gaussian distribution, which effectively blurs the edges and reduces the high-frequency components in the image.

Unsharp masking

- Unsharp masking is a technique used in image processing to sharpen images by creating a mask that enhances the edges and details in the image. The process involves creating a blurred version of the original image, subtracting this blurred version from the original to create a mask, and then adding this mask back to the original image to enhance the edges and details.

- The term "unsharp masking" may seem counterintuitive, as the process actually sharpens the image rather than making it blurry. The name comes from the traditional darkroom technique of using a blurred or unsharp negative to create a mask for sharpening a photographic print.
- Unsharp masking is commonly used in digital image editing software to improve the overall sharpness and clarity of an image. It can be particularly effective in enhancing fine details and textures in photographs.

Purpose of CLAHE:

- CLAHE stands for Contrast Limited Adaptive Histogram Equalization. It's an image processing technique specifically designed to address limitations of traditional Histogram Equalization (HE) when applied to local image regions.
- Enhance local contrast in images, particularly those with uneven illumination or low contrast in specific regions.
- Improve the visibility of details obscured by variations in lighting or shading within an image.
- Often used in medical imaging applications like brain tumor segmentation in MRI scans, where highlighting subtle differences in tissue contrast is crucial for accurate diagnosis.

*****References:**

Who:

Brain Tumor Classification from MRI Using Image Enhancement and Convolutional Neural Network Techniques - PMC (nih.gov) - 2023 - Same Dataset

***Purpose of HOG feature extraction**:

- HOG, which stands for **Histogram of Oriented Gradients**, is a feature descriptor technique commonly used in computer vision and image processing. Its primary purpose is to extract features from images that are informative for object detection and recognition tasks.

What HOG Captures:

- **Local Edge Information:** HOG focuses on capturing the distribution of oriented gradients (changes in intensity) within localized portions of an image. These gradients often correspond to edges and contours in the image, which are essential for shape and object recognition.
- **Gradient Orientation and Magnitude:** HOG calculates both the magnitude (strength) and orientation (direction) of the gradients at each pixel. This information provides a richer description of the local structure within an image compared to just using raw intensity values.

Steps Involved in HOG Feature Extraction:

1. **Gradients:** The image is first processed to compute the gradient in both horizontal and vertical directions for each pixel. This essentially captures how the intensity values change between neighboring pixels.
2. **Cells and Blocks:** The image is divided into overlapping or non-overlapping rectangular regions called "cells." These cells are then grouped into larger regions called "blocks."
3. **Histogram of Oriented Gradients:** Within each cell, a histogram is created to count the occurrences of gradients falling into predefined orientation bins. This histogram essentially captures the distribution of edge orientations within that specific cell.
4. **Normalization (Optional):** To account for variations in illumination and local contrast, the histograms can be normalized within each block. This helps make HOG features more robust to lighting changes.
5. **Feature Vector:** Finally, the histograms from all the cells within a block are concatenated to form a feature vector that represents the local structure of that image block.

Benefits of HOG Features:

- **Robust to Illumination Changes:** HOG features are relatively insensitive to variations in lighting conditions because of the optional normalization step.
- **Effective for Shape Representation:** By capturing the distribution of edge orientations, HOG features provide a good representation of the local object shape, which is crucial for object detection and recognition.
- **Computationally Efficient:** HOG can be calculated relatively efficiently compared to some other feature extraction techniques.
- **Successful in Various Applications:** HOG features have been successfully used in a wide range of applications, including:
  - **Pedestrian detection**
  - **Face detection**
  - **Object recognition**
  - **Image classification**

In essence, HOG provides a way to extract informative features from images that can be used to identify and classify objects within those images. Its ability to capture local edge information and its robustness to lighting variations make it a valuable tool for various computer vision tasks.

*****2. Config:**

<table>
<tr><th colspan="2">Image Enhancement + HOG feature extraction</th></tr>
<tr><td>Unsharp Masking</td><td>Gaussian Blur, 1.5 * original - 0.5 * blur</td></tr>
<tr><td>CLAHE</td><td>Sigma = 2
Clip_limit_value = 2.0
Tile_grid_size_value = (8, 8)</td></tr>
<tr><td>HOG feature extraction</td><td>pixels_per_cell=(8, 8),
cells_per_block=(2, 2),
orientations=9,
block_norm='L2-Hys',
visualize=True
# Compute HOG features: Set Default of Lib Example
# pixels_per_cell: Size (in pixels) of a cell.
# cells_per_block: Number of cells in each block.
# orientations: Number of orientation bins.
# block_norm: Block normalization method.
# visualize: If True, also returns an image of the HOG.</td></tr>
<tr><td>Tools</td><td>Skimage library
Kaggle GPU T4 computer</td></tr>
</table>

*****Pipeline Record:**

<table>
<tr><th colspan="4">Training Testing Dataset</th></tr>
<tr><td colspan="2">Dataframe [‘Path’, ‘Class’]</td><td colspan="2">(5712,)</td></tr>
<tr><td colspan="2">Dataframe_test [‘Path’, ‘Class’]</td><td colspan="2">(1311,)</td></tr>
<tr><td colspan="2">Input Image</td><td colspan="2">256x256, grayscale, [0-1]</td></tr>
<tr><td colspan="2">DType of label</td><td colspan="2">{0, 1, 2, 3}</td></tr>
<tr><th colspan="4">Enh → HOG</th></tr>
<tr><td>x_train</td><td>y_train</td><td>x_test</td><td>y_test</td></tr>
</table>

(5712, 34.596)	(5712,)	(1311, 34.596)	(1311,)
Std + PCA(0.95)			
(5712, 3.279)			
[(-86.3427096104763, 112.44228410419144), (-9.742167847638872e-19, 10.023317775686433, '5.04 %')]	[(0, 3), (1.55812324929972, 1.2193107635210942, '40.64 %')]	[(-86.3427096104763, 111.20106599655529), (0.0020891656969380663, 8.139932299007492, '4.12 %')]	[(0, 3), (1.5377574370709381, 1.1639061837261542, '38.8 %')]

*****A Comprehensive Evaluation Results:**

	KNN-10	**KNN-5**	**KNN-2**	**KNN-1**	**SVM-ln**	**SVM-rbf**	**RF**
CV acc	0.8783	0.8977	0.9060	0.9161	0.8213	0.8934	0.8507
CV acc	0.8633	0.8934	0.9340	0.9401	0.9084	0.9119	0.8598
acc	0.8367	0.8748	0.9549	0.9602	0.8535	0.9008	0.8848
acc	0.8291	0.8810	0.9603	0.9733	0.9252	0.9039	0.8940
F1-score	0.8192 0.8255	0.8654 0.8698	0.9528 0.9549	0.9586 0.9601	0.8445 0.8552	0.8932 0.8996	0.8749 0.8835
F1-score	0.8103 0.8167	0.8700 0.8734	0.9580 0.9604	0.9715 0.9731	0.9193 0.9248	0.8975 0.9025	0.8852 0.8924

	Top 3	**Unique Top 3**	**The best**
CV acc	0.9052	0.8867	0.9161

CV acc	0.9287	0.9039	0.9401
acc	0.9386	0.9153	0.9602
acc	0.9529	0.9308	0.9733
F1-score	0.9349 0.9382	0.9089 0.9144	0.9586 0.9601
F1-score	0.9496 0.9528	0.9253 0.9301	0.9715 0.9731

*****3. Limitation:**

- **Sensitivity to Local Deformations:** HOG focuses on capturing local gradients and orientations, which can be affected by deformations of the object in the image. For example, if an object is stretched or compressed, the distribution of gradients might change, leading to less accurate feature representation.
- **Grid-Based Discretization:** HOG divides the image into a grid of cells and blocks. This grid-based approach can be sensitive to the specific chosen grid size and orientation. If the grid is too coarse, it might miss important details, while a very fine grid can lead to increased computational costs and potentially overfitting.
- **Limited Rotation Invariance:** While HOG captures gradient orientations, it doesn't achieve perfect rotation invariance. If an object is rotated in the image, the distribution of gradients will change, potentially affecting feature representation and reducing recognition accuracy for rotated objects.
- **Difficulty with Fine-Grained Classification:** HOG features are primarily effective for capturing larger-scale object shapes and textures. They might not be as efficient for distinguishing between fine-grained object categories that have subtle differences or complex shapes.
- **Computational Cost:** Although computationally efficient compared to some other feature extraction techniques, HOG can still be computationally expensive, especially for high-resolution images. This can be a limitation for real-time applications or processing large datasets.

Alternatives and Addressing Limitations:

- **Combine with Other Features:** HOG can be combined with other feature extraction techniques like shape descriptors or local binary patterns (LBP) to capture complementary information and improve classification performance.
- **Spatial Pyramid Matching (SPM):** This technique incorporates spatial information into HOG features by dividing the image into a pyramid of regions and extracting HOG features at each level. This can improve robustness to deformations and rotations.
- **Deep Learning-based Feature Extraction:** Deep convolutional neural networks (CNNs) have shown remarkable success in learning powerful and discriminative features directly from images.

While HOG might still be a valuable pre-processing step in some cases, CNNs can potentially learn more robust features for various object recognition tasks.

Conclusion:

HOG feature extraction is a powerful and widely used technique, but it's not without limitations. Understanding these limitations and potentially using it in conjunction with other features or exploring alternative approaches like deep learning can help improve the overall performance of your computer vision tasks.

Curse of tumor is: There can be many shapes in a single type of tumor. Why:

- **Cancerous cells lose growth control:** Tumors arise from abnormal cell growth. These cancerous cells often lose the normal regulatory mechanisms that control cell shape and size. This can lead to a variety of irregular shapes within the tumor mass.
- **Internal tumor structure:** Tumors aren't uniform structures. They can have areas of necrosis (cell death), fluid-filled cysts, and regions with different growth patterns. These variations contribute to the overall shape of the tumor.
- **Surrounding tissue influence:** Tumors can grow by pushing against and invading surrounding healthy tissues. The shape of these surrounding structures can influence the final form of the tumor.

While some tumors might have a more stereotypical round or oval shape, the presence of many shapes within a single tumor type is a common occurrence.

2. **Enh + Statistics - (Kaggle)**

*****1. Local Statistics Intensity Based feature extraction**: as the name suggests, focuses on extracting features from images based on the statistical analysis of intensity values within localized regions. This technique is particularly useful in applications where <u>image texture, contrast</u>, and <u>spatial relationships</u> between <u>intensity values</u> play a significant role in differentiating objects or structures.

Purpose:

- To capture characteristics of an image beyond just the raw pixel intensities.
- To provide features that describe the <u>spatial distribution</u> and <u>variation of intensity values</u> within <u>localized image regions</u>.
- To be informative for tasks like image segmentation, texture classification, and object recognition.

Types of Local Statistics:

- **Mean:** Represents the average intensity value within a local region.

- **Standard Deviation:** Captures the variation of intensity values around the mean. A high standard deviation indicates high contrast or a textured region, while a low standard deviation indicates a more uniform region.
- **Variance:** Similar to standard deviation, but squared.
- **Skewness:** Measures the asymmetry of the distribution of intensity values within a region.
- **Kurtosis:** Captures the "peakedness" of the intensity value distribution. A high kurtosis indicates a more peaked distribution with sharp intensity changes, whereas a low kurtosis indicates a flatter distribution.

Local Region Definition:

- The image is typically divided into small, non-overlapping or overlapping regions (e.g., squares, rectangles) for local statistics calculation. These regions are often referred to as "windows" or "neighborhoods."
- The size and shape of these local regions can be chosen based on the specific image characteristics and the desired features to be captured.

Benefits:

- **Effective for Texture Analysis:** Local statistics features are particularly effective for <u>capturing texture information</u> in images, as textures often involve <u>variations in intensity values</u> within a local area.
- **Useful for Segmentation:** By analyzing intensity variations, these features can help differentiate between objects or regions with <u>different intensity distributions</u> in an image. This can be beneficial for tasks like image segmentation where you want to separate objects from the background or identify different regions of interest.
- **Complementary to Raw Intensity Values:** Local statistics features provide additional information beyond just the raw pixel intensities. This can be advantageous when dealing with images that have similar average intensity values but differ in texture or spatial variations.

Applications:

- **Medical image analysis:** Extracting features from tissues in MRI scans for tumor segmentation or tissue classification.
- **Remote sensing image analysis:** Characterizing land cover types based on texture and spatial variations in satellite imagery.
- **Content-based image retrieval:** Matching images based on their texture and intensity patterns.
- **Object recognition:** Extracting features from image patches that are informative for identifying specific objects.

In summary, Local Statistics Intensity Based feature extraction is a powerful technique for <u>capturing texture, contrast, and spatial relationships between intensity values in images</u>. This information can be crucial for various image analysis tasks, especially those that involve texture analysis, image segmentation, and object recognition.

***2. **Config:**

Image Enhancement + Local Statistics Intensity Based feature extraction	
Unsharp Masking	Gaussian Blur, 1.5 * original - 0.5 * blur
CLAHE	Sigma = 2 Clip_limit_value = 2.0 Tile_grid_size_value = (8, 8)

Local Statistics Intensity Based feature extraction	*footprint* = np.one(3, 3)
	local_mean = filters.rank.mean(resize_image, np.ones((3, 3))).flatten()
	local_entropy = filters.rank.entropy(resize_image, np.ones((3, 3))).flatten()
	local_max = filters.rank.maximum(resize_image, np.ones((3, 3))).flatten()
	# local_min = filters.rank.minimum(resize_image, np.ones((3, 3))).flatten()
	fd = np.concatenate((local_max, local_mean, local_entropy), *axis*=0)
	# Compute Local Statistics: Set Default of Lib Example

Tools	*Skimage library* *Kaggle GPU T4 computer*

***Pipeline Record:

Training Testing Dataset			
Dataframe [‘Path’, ‘Class’]		(5712,)	
Dataframe_test [‘Path’, ‘Class’]		(1311,)	
Input Image		256x256, grayscale, [0-1]	
DType of label		{0, 1, 2, 3}	
Enh → Resize(84x84) → Local-Statistics-Rank(Mean, Max, Entropy)			
x_train	**y_train**	**x_test**	**y_test**
(5712, 21.675)	(5712,)	(1311, 21675)	(1311,)
Std + PCA(0.95)			
(5712, 2.355)			
[(-129.14776664412489, 405.4116365985052), (1.1943743472705063e-17,	[(0, 3), (1.582282913165266, 1.2642379255623815, '42.14 %')]	[(-114.49866057186871, 305.9299831803864), (-0.0011667612107056288,	[(0, 3), (1.6178489702517163, 1.3116264943524867, '43.72 %')]

8.743789605838797, '1.64 %')]		8.30087569683906, '1.97 %')]	

*****A Comprehensive Evaluation Results:**

	KNN-10	KNN-5	KNN-2	KNN-1	SVM-ln	SVM-rbf	RF
CV acc	0.8633	0.8934	<u>0.9340</u>	<u>0.9401</u>	0.9084	<u>0.9119</u>	<u>0.8598</u>
acc	0.8291	0.8810	<u>0.9603</u>	<u>0.9733</u>	<u>0.9252</u>	0.9039	<u>0.8940</u>
F1-score	0.8103 0.8167	0.8700 0.8734	<u>0.9580</u> <u>0.9604</u>	<u>0.9715</u> <u>0.9731</u>	<u>0.9193</u> <u>0.9248</u>	0.8975 0.9025	<u>0.8852</u> <u>0.8924</u>

	Top 3	Unique Top 3	The best
CV acc	0.9287	0.9039	0.9401
acc	0.9529	0.9308	0.9733
F1-score	0.9496 0.9528	0.9253 0.9301	0.9715 0.9731

*****3. Limitation:**

- **Sensitivity to Noise:** Statistical features like mean and standard deviation can be <u>sensitive to noise</u> in the image. Noise can introduce <u>random variations in intensity values</u>, potentially affecting the calculated statistics and leading to unreliable features. Techniques like image <u>denoising or filtering</u> might be necessary as a <u>preprocessing step</u>.
- **Limited Spatial Information:** While local statistics capture some spatial characteristics by analyzing intensity values within localized regions, they may not capture the <u>broader spatial relationships between different parts of the image</u>. For tasks requiring analysis of larger structures or object shapes, additional feature extraction techniques like shape features or spatial filtering might be needed.
- **Dependence on Region Size and Shape:** The choice of <u>local region size and shape</u> can significantly impact the extracted features. For example, a very small region size might not capture sufficient texture information, while a very large region might lose details due to averaging over a large area. Experimentation with different region sizes and shapes might be necessary to find the optimal configuration for your specific task.
- **Limited Feature Richness:** Local statistics features may not be sufficient for complex image classification tasks or situations where <u>objects have high variability in shape and appearance</u>. In such cases, combining local statistics with other feature extraction techniques like HOG

(Histogram of Oriented Gradients) or Gabor filters might be beneficial to capture a richer set of features.

- **Computational Cost:** Depending on the number of local regions and the complexity of the statistics calculated, this feature extraction method can be computationally expensive for large images. If processing speed is a concern, consider using a smaller number of regions or exploring more efficient ways to calculate the statistics.

In conclusion, while Local Statistics Intensity Based feature extraction is a valuable technique, it's essential to be aware of its limitations. Consider these limitations when designing your image analysis pipeline and potentially combine it with other feature extraction methods for more robust and informative feature sets.

3. Segmentation - (Kaggle)

*****1. Why segmentation for classification?**

In brain tumor MRI classification, segmentation plays a critical role in isolating the tumor region from the rest of the brain tissue. This isolation allows for more accurate analysis and classification of the tumor.

Purpose of Segmentation:

- **Isolate the Tumor Region**: Segmentation aims to create a binary mask or label map that distinguishes the tumor pixels from healthy brain tissue pixels in the MRI scan.
- **Focus Analysis on Tumor**: By isolating the tumor region, subsequent analysis and classification algorithms can focus specifically on the area of interest. This helps to improve the accuracy and reliability of tumor classification, particularly when dealing with small tumors or tumors with subtle intensity variations.

Benefits of Segmentation:

- **Improved Feature Extraction**: Segmentation allows for the extraction of features specifically from the tumor region. These features, such as *size, shape*, texture, and intensity distribution, are crucial for accurate tumor classification. Analyzing features from the entire brain (including healthy tissue) might introduce noise and make classification more challenging.
- **Accurate Tumor Volume Measurement**: Once the tumor area is segmented, the number of tumor pixels can be used to calculate the tumor volume in cubic millimeters. This information is valuable for treatment planning and monitoring tumor progression over time.
- **Visualization and Localization**: Segmentation provides a visual representation of the tumor location and extent within the brain. This can be helpful for surgeons to plan biopsies or resections, and for radiologists to interpret other imaging studies.
- **Improved Classification Performance**: By focusing analysis on the tumor region and extracting relevant features, segmentation can significantly improve the performance of machine learning and deep learning algorithms for brain tumor classification.

Overall, segmentation is an essential pre-processing step that lays the foundation for accurate tumor classification in brain MRI scans. It helps isolate the tumor region, allowing subsequent analysis and classification algorithms to focus on the area of interest and extract relevant features for better performance.

*****References:**
Who:
Computer Science & Engineering at Osmania University Hyderabad, India
Department of Computer Science & Engineering University College of Engineering (A). Osmania University Hyderabad, India
Brain tumor MRI images identification and classification based on the recurrent convolutional neural network - ScienceDirect - 2022 - 62 citations - Sartaj

***2. **Config:**

Segmentation	
K Means	K = 5
Input image size	Input_image_size = (128, 128)
Feature Vector for each pixel	*concatenate(hog, local_mean, local_entropy, loacal_max)*
Tools	*Skimage library* *Kaggle GPU T4 computer*

*****Pipeline Record:**

Training Testing Dataset			
Dataframe ['Path', 'Class']		(5712,)	
Dataframe_test ['Path', 'Class']		(1311,)	
Input Image		256x256, grayscale, [0-1]	
DType of label		{0, 1, 2, 3}	
Resize(128x128) → Kmeans			
x_train	**y_train**	**x_test**	**y_test**
(5712, 65.536)	(5712,)	(1311, 65.536)	(1311,)
Std + PCA(0.95)			

(5712, 2.323)			
[(-279.43585694533226, 729.0427480432056), (4.283934107711704e-19, 27.647614904611217, '2.74 %')]	[(0, 3), (1.4446778711484594, 1.2742503864290815, '42.48 %')]	[(-233.23755592428734, 511.58852011214896), (0.009141302195373794, 27.91532146592999, '3.75 %')]	[(0, 3), (1.3867276887871853, 1.321837575732187, '44.06 %')]

*****A Comprehensive Evaluation Results:**

	KNN-10	KNN-5	KNN-2	KNN-1	SVM-ln	SVM-rbf	RF
CV acc	0.8633	0.8934	0.9340	0.9401	0.9084	0.9119	0.8598
acc	0.8291	0.8810	0.9603	0.9733	0.9252	0.9039	0.8940
F1-score	0.8103 0.8167	0.8700 0.8734	0.9580 0.9604	0.9715 0.9731	0.9193 0.9248	0.8975 0.9025	0.8852 0.8924
CV acc	0.8403	0.8725	0.8965	0.9326	0.8920	0.9035	0.8181
acc	0.8032	0.8604	0.9207	0.9756	0.9237	0.9092	0.8703
F1-score	0.7820 0.7887	0.8484 0.8532	0.9122 0.9156	0.9735 0.9755	0.9181 0.9233	0.9033 0.9083	0.8588 0.8684

	Top 3	Unique Top 3	The best
CV acc	0.9287	0.9039	0.9401
acc	0.9529	0.9308	0.9733
F1-score	0.9496 0.9528	0.9253 0.9301	0.9715 0.9731
CV acc	0.9109	0.8847	0.9326
acc	0.9400	0.9232	0.9756
F1-score	0.9346 0.9381	0.9168 0.9224	0.9735 0.9755

*****3. Limitation:**

A. **Segmentation**, while a crucial step in brain tumor classification using MRI scans, has limitations that can impact the overall classification accuracy. Here are some key limitations to consider:

- **Inaccurate Segmentation:** Segmentation errors can directly affect classification performance. If the segmentation mask inaccurately captures the tumor region, including healthy tissue or excluding parts of the tumor, the features extracted for classification might not be representative of the true tumor characteristics. This can lead to misclassification.
- **Incomplete Information:** Segmentation only provides a binary mask (tumor vs. non-tumor). It doesn't capture the rich information within the tumor region, such as internal variations in intensity, texture, or shape. This information might be crucial for accurate classification, especially when differentiating between different tumor types.
- **Dependence on Feature Extraction:** The success of classification also depends on the effectiveness of the feature extraction techniques applied after segmentation. Features extracted from the segmented tumor region need to be informative and discriminative enough to distinguish between different tumor types or healthy tissue.
- **Limited Generalizability:** Segmentation algorithms might be trained and optimized on a specific dataset. If the new unseen MRI scans have different acquisition protocols, noise characteristics, or tumor presentations not present in the training data, the segmentation might perform poorly, leading to classification errors.
- **Computational Cost:** Depending on the segmentation technique, the process can be very very computationally expensive, especially for high-resolution MRI scans. This can be a limitation for real-time applications or large datasets.

Mitigating these Limitations:

Here are some strategies to address these limitations and improve the overall classification performance:

- **Refine Segmentation Techniques:** Explore advanced segmentation methods like deep learning-based approaches that can handle tumor heterogeneity and achieve higher segmentation accuracy.
- **Feature Engineering:** In addition to basic features extracted from the segmented region, consider incorporating additional features that capture the internal variations within the tumor. Texture analysis or shape descriptors might be beneficial.
- **Data Augmentation:** Artificially expand your training dataset with variations of existing MRI scans to improve the generalizability of both segmentation and classification models.
- **Ensemble Methods:** Combine the predictions from multiple segmentation and classification models to potentially achieve more robust and accurate results.

Conclusion:

Segmentation is a valuable tool for brain tumor classification, but it's important to acknowledge its limitations. By employing advanced segmentation techniques, robust feature extraction methods, and addressing generalizability issues, you can improve the overall accuracy and reliability of brain tumor classification in MRI scans.

B. Limitations to consider when using **Local Statistics Intensity Based feature extraction for segmentation**, particularly in brain tumor MRI classification:

- **Intensity Variations within Tumors:** Brain tumors can exhibit heterogeneity, meaning they have varying intensities within the tumor itself. Local statistics features might not capture this internal variation effectively. This can lead to inaccurate segmentation boundaries, especially if the tumor has regions with similar intensity to surrounding healthy tissue.
- **Similar Intensity Between Tumor and Healthy Tissue:** In some cases, the intensity of the tumor may be very similar to surrounding healthy brain tissue. Local statistics features rely on analyzing intensity variations, and if the variations are minimal, segmentation might struggle to differentiate between the two regions.
- **Sensitivity to Noise:** As mentioned previously, local statistics features are sensitive to noise in the image. Noise can introduce random variations in intensity values, potentially leading to inaccurate segmentation boundaries. Techniques like image denoising or filtering might be necessary as a preprocessing step.
- **Difficulty with Ill-defined Tumor Borders:** Tumors with indistinct or blurry borders can be challenging to segment using local statistics features alone. These features rely on clear intensity differences between regions, and with ill-defined borders, the transition between tumor and healthy tissue might be gradual, making segmentation inaccurate.
- **Limited Spatial Information:** Local statistics capture intensity variations within small regions, but they might not capture the broader spatial context of the image. This can be problematic for tumors with complex shapes or those that infiltrate surrounding brain tissue. Additional techniques like spatial filtering or incorporating shape features might be needed.

Alternative Approaches:

Here are some alternative approaches to consider for brain tumor segmentation that might address these limitations:

- **Deep Learning Segmentation:** Deep learning models like convolutional neural networks (CNNs) can learn complex relationships between pixels and effectively segment tumors even with intensity variations or similar intensity between tumor and healthy tissue.
- **Active Contour Models (Snakes):** These models can deform a curve based on image features to fit the tumor boundary. They can be helpful for segmenting tumors with ill-defined borders.
- **Atlas-based Segmentation:** This approach compares the MRI scan to a database of labeled brain anatomy images to identify the tumor region. While effective, it might require a large and diverse atlas database.

Conclusion:

While Local Statistics Intensity Based feature extraction can be a starting point for brain tumor segmentation, its limitations, particularly with tumor heterogeneity and similar intensity between tissues, are important to consider. Explore alternative approaches or combine it with other segmentation techniques like deep learning or active contour models for more robust and accurate tumor segmentation in brain MRI scans.

4. Why these classifiers?

In brain tumor classification using MRI scans, several machine learning and deep learning approaches have emerged as promising classifiers

1. Support Vector Machines (SVM):

- SVMs are a powerful machine learning algorithm for classification tasks. They work by finding a hyperplane in the feature space that maximizes the margin between different classes (e.g., tumor vs. non-tumor, different tumor types).
- **Advantages:**
  - Effective for high-dimensional data like features extracted from MRI scans.
  - Good performance with limited training data (important when large labeled datasets might not be readily available).
  - Can provide interpretability of the model to understand which features are most important for classification.
- **Disadvantages:**
  - Performance can be sensitive to the choice of kernel function (which defines how data points are mapped in the feature space).
  - Might not be as efficient as deep learning models for very large datasets.

2. Random Forests:

- Random forests are ensemble methods that combine the predictions of multiple decision trees. Each tree is trained on a random subset of features and a random subset of the training data.
- **Advantages:**
  - Robust to overfitting, which can be a problem with complex feature spaces.
  - Can handle high-dimensional data effectively.
  - Provide some level of interpretability through feature importance analysis.
- **Disadvantages:**
  - Can be computationally expensive to train compared to some other models.
  - Might not achieve the same level of accuracy as deep learning models for complex classification tasks.

Table 4 | Brain tumor detection and classification using machine learning: a comprehensive survey | Complex & Intelligent Systems (springer.com)

5. Why use PCA?

In brain tumor MRI classification using machine learning and deep learning models, PCA (Principal Component Analysis) serves a valuable purpose as a dimensionality reduction technique.

The Challenge of High-Dimensional Data:

- MRI scans and the features extracted from them can be high-dimensional, meaning they contain a large number of features. This high dimensionality can pose challenges for machine learning classifiers:
  - **Increased Computational Cost:** Training classifiers on high-dimensional data can be computationally expensive and time-consuming.
  - **Curse of Dimensionality:** With many features, the classifier might struggle to learn effective decision boundaries, potentially leading to overfitting and poor performance on unseen data.

How PCA Helps:

- PCA addresses these challenges by reducing the dimensionality of the data while aiming to preserve the most important information for classification. It achieves this by:
  - Identifying the directions of greatest variance in the data (these directions capture the most informative variations in the features).
  - Projecting the data onto a lower-dimensional subspace spanned by these principal components (PCs) that capture the majority of the variance.

Benefits of Using PCA before Classification:

- **Reduced Computational Cost:** Training classifiers on the lower-dimensional data obtained from PCA is faster and less computationally expensive.
- **Improved Classification Performance:** By reducing irrelevant or redundant information, PCA can help the classifier focus on the most discriminative features for accurate tumor classification. This can potentially lead to better generalization on unseen data and avoid overfitting.
- **Visualization:** In some cases, PCA can help visualize the data in a lower-dimensional space, allowing for easier exploration of relationships between features and potentially aiding in understanding the classification task.

Important Considerations:

- PCA assumes a linear relationship between features. If the relationships between features are non-linear, PCA might not be the most effective dimensionality reduction technique.
- The choice of how many principal components to retain involves a trade-off between preserving information and reducing dimensionality. Too few components might discard crucial information, while too many might not provide significant dimensionality reduction benefits.

Overall, PCA is a valuable pre-processing step for brain tumor MRI classification using machine learning and deep learning models. It helps reduce computational costs, potentially improves classification performance, and can aid in data visualization in some cases. However, it's important to consider the underlying assumptions of PCA and choose the number of components to retain carefully for optimal results.

6. Comparison with related work

Method	Dataset	CV accuracy	Accuracy	F1-score
Enh + HOG (the best)	**BRMRI 2022**	0.9161	0.9602	0.9586 0.9601
Enh + Statistics (the best)	**BRMRI 2022**	0.9401	0.9733	0.9715 0.9731
Segmentation (the best)	**BRMRI 2022**	0.9326	0.9756	0.9735 0.9755
Enh + CNN - 2023 paper	**BRMRI 2022**	None	0.9784	0.9790
I&C + RCNN - 2022 paper	**SARTAJ**	None	0.9517	0.9363 (89.28-98.42)
Xception FineTuning	**BRMRI**	0.9739	0.9764	0.9750 0.9765

I&C + RCNN - 2022 paper:

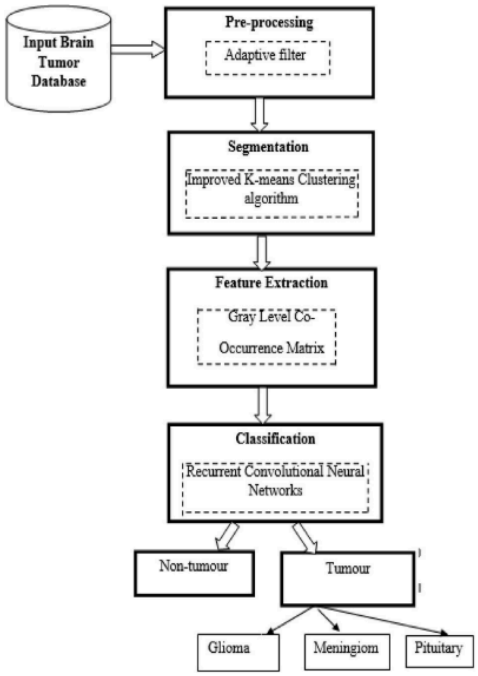


Fig. 2. Proposed methodology overview.

Steps for Improved K-means clustering Algorithm:

Step1: Take MRI scan of brain as an image

Step2: Convert it into the greyscale image if it is not

Step3: Then we apply noise removal on a greyscale image

Step4: Sharp the image

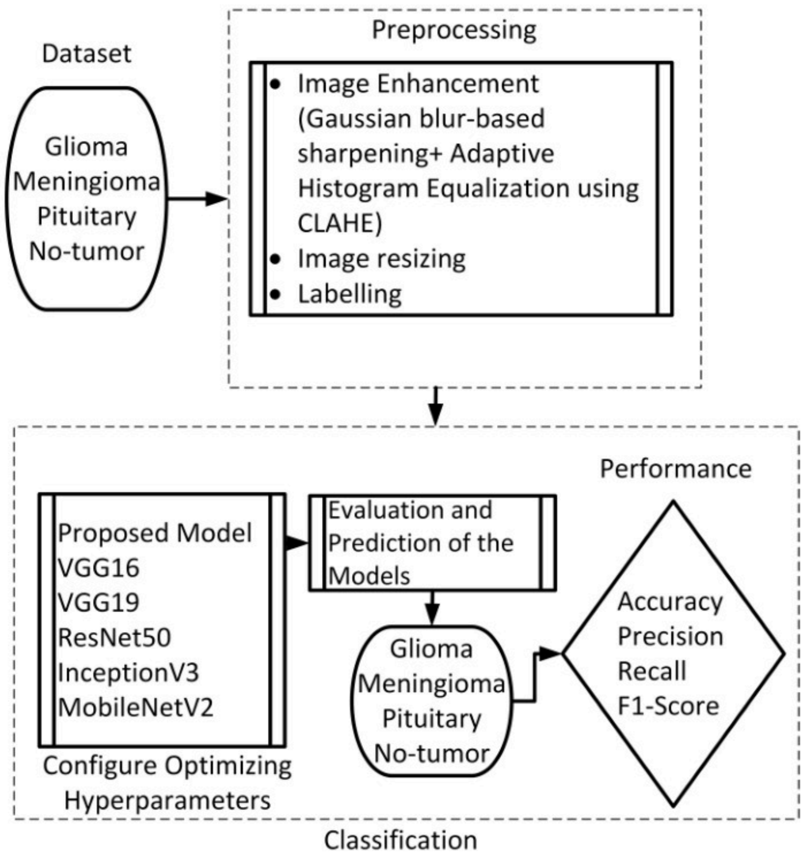
Step5: Pass the resulting image through Adaptive filter to enhance the quality of an image

Step6: Compute K − means segmentation

Step7: Compute thresholding segmentation

Step8: Finally output will be a tumor region

Enh + CNN - 2023 paper:



Xception FineTuning:

- Input Image size = (256, 265, 3)
- Batch size = 32
- Epoch = 5

Layer (type)	Output Shape	Param #
xception (Functional)	?	20,861,480
flatten_1 (Flatten)	?	0 (unbuilt)
dropout_2 (Dropout)	?	0
dense_2 (Dense)	?	0 (unbuilt)
dropout_3 (Dropout)	?	0
dense_3 (Dense)	?	0 (unbuilt)

Total params: 20,861,480 (79.58 MB)

Trainable params: 20,806,952 (79.37 MB)

Non-trainable params: 54,528 (213.00 KB)

Build a MVP for prediction and evidences (segmentation - featuremap image)

- .NET c# winform framework: for View - Controller - DA
- Flask Client Server: for server development
- Keras Kaggle: for model training
- Communicate: through internet networking environment