Brain Tumor MRI Classification

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Introduction to Computer Vision – CS231
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5/2024

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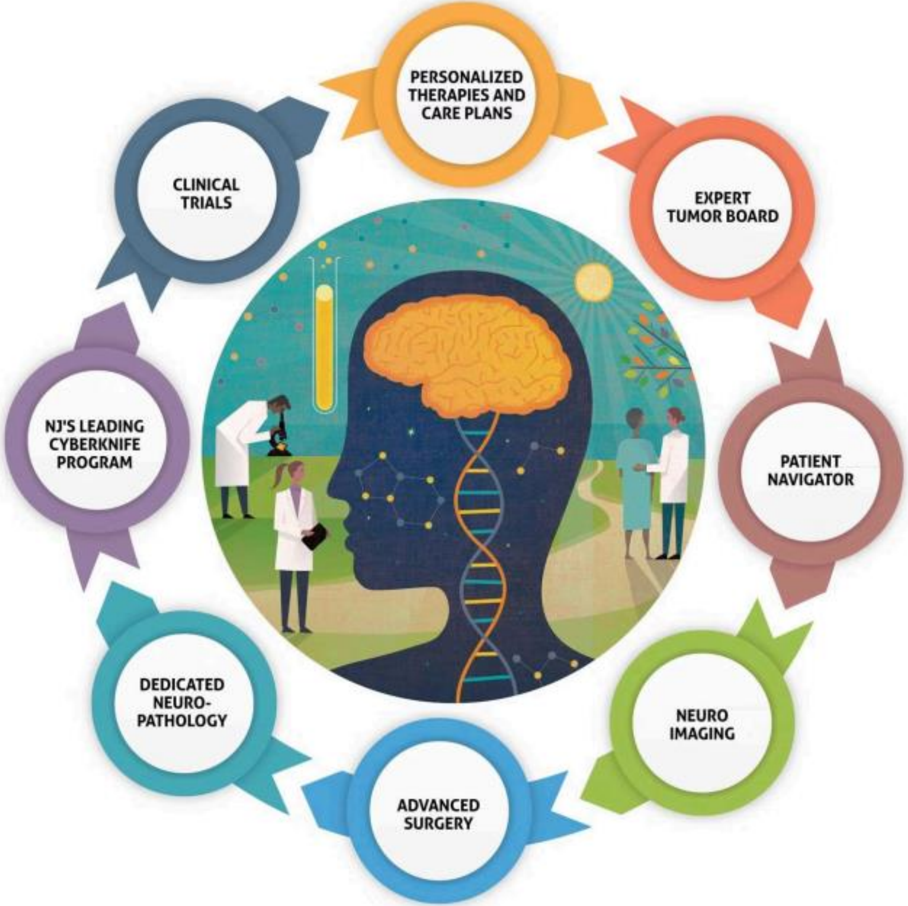
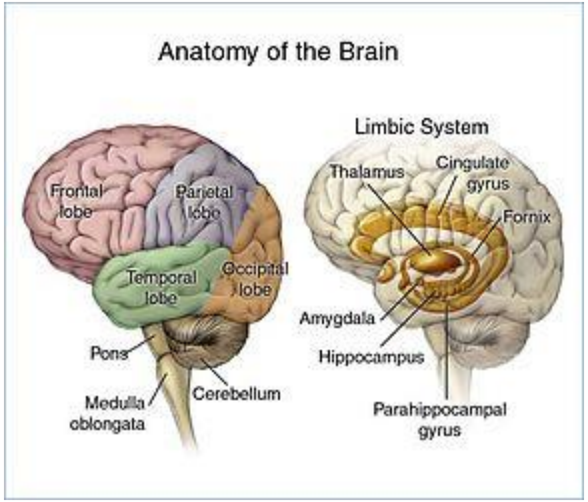


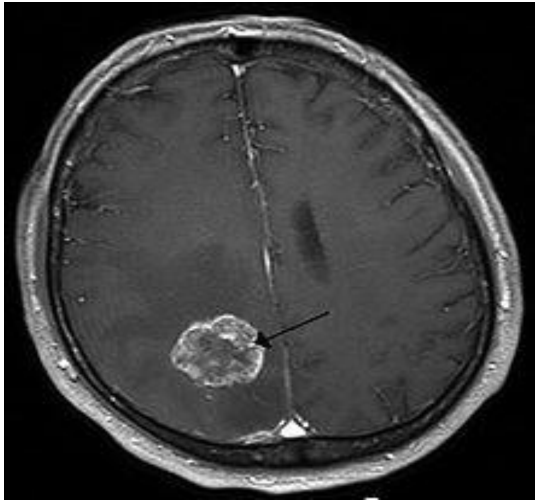
Introduction

Why it matters?

Brain tumor classification: is a crucial task in medical imaging for accurate diagnosis and treatment planning.



Invasive diagnostic methods of WHO: *not allow rapid diagnosis* in a clinical trial, *expensive cost*



Non-invasive diagnostic methods base on MRI, CT: help rapid diagnosis and accurately classify

Problem

Input:	**Output:**
• Inference: a brain MRI image, which can be a 2D slice. • Training: a **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).	• The output of the model is a classification label, which can be probability scores indicating the likelihood of belonging to a specific tumor class. • These classes include: meningioma (*M*), glioma (*G*), pituitary (*P*) tumor, and no tumor (*N*).

Problem

Input Output Formula

$x \in R^{(H \times W)}$,
$D = \{(x, y)\}$

x represent the image, **y** is label of image
R signifies the data type
H is the image height
W is the image width
D is training dataset

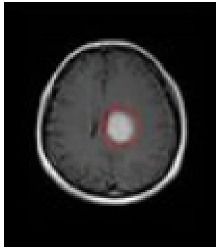
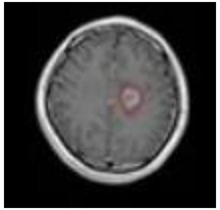
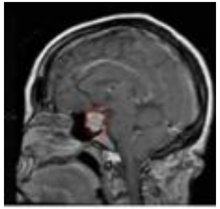
$y' \in C$

y' is prediction label of model
C = {meningioma, glioma, pituitary, no_tumor}

Constraint: The brain MRI image only contains **a unique type of tumor** in these classes.

Problem

Inference illustration

	Meningioma
	Glioma
	Pituitary

Contribution

The aim of research project

The aim of this research project is to develop methods that can accurately classify the type of tumor to ensure generalizability and discrimination.

Besides, we also perform a comprehensive comparison of various feature extraction methods and evaluate their effectiveness. Analyze experimental results and point out their advantages and disadvantages.

Finally, we find out the potential of model's decision resonation that use a ML method.

Methodology

Related work

Various approach for brain tumor MRI classification	
In the early time:	In recent years:
• Traditional ML used such as combine PCA and LDA (*V.P.Gladis-2012-79 cites*)	• With the development of Deep Learning, methods such as CNN, RCNN, transfer learning emerged and showed amazing results (*Zar-2019-491 cites, Milica-2020-302 cites, Ramdas-2022-62cites, Zahid-2023*)

Methodology (1)

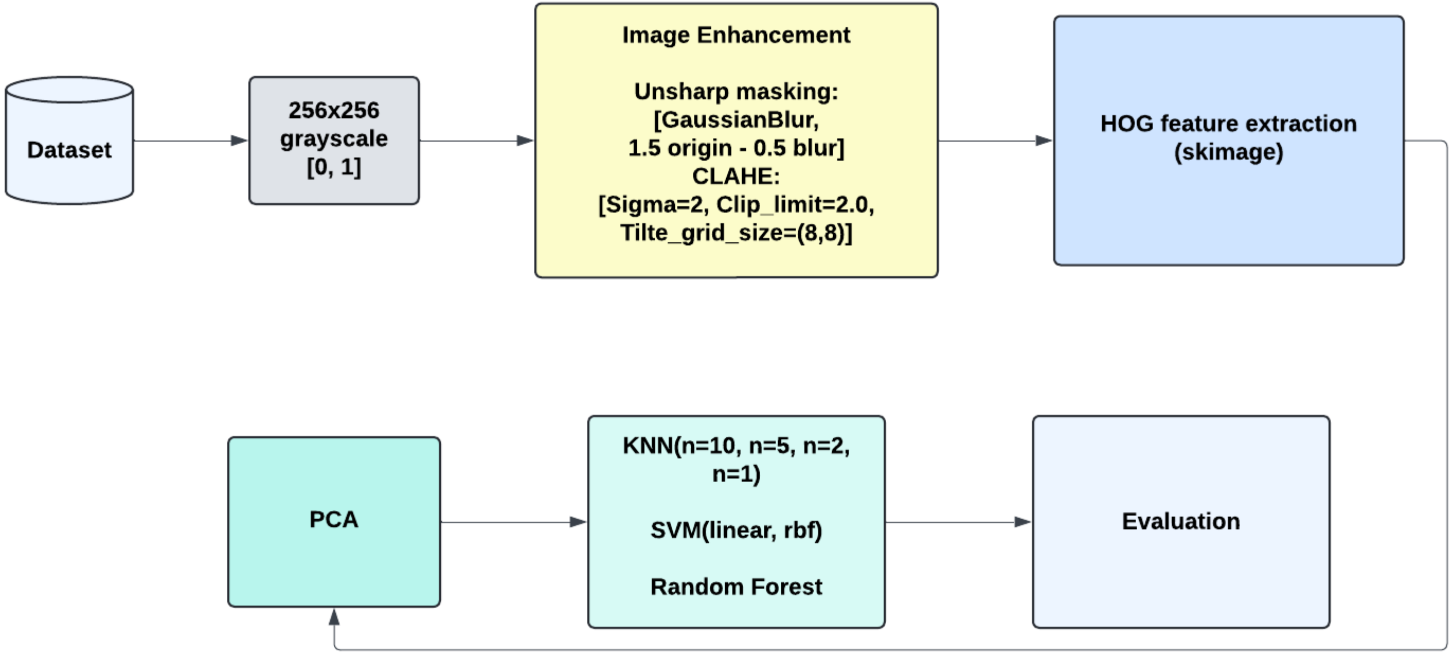
HOG feature extraction

HOG: Histogram of Oriented Gradients, first described by *Robert K. McConnell of Wayland Research Inc*. A feature descriptor technique commonly used in object detection and recognition tasks.

Purpose: capture local edge information, which are essential for shape and object recognition

Pipeline

Feature extraction + Training - Evaluation



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

Limitation of HOG

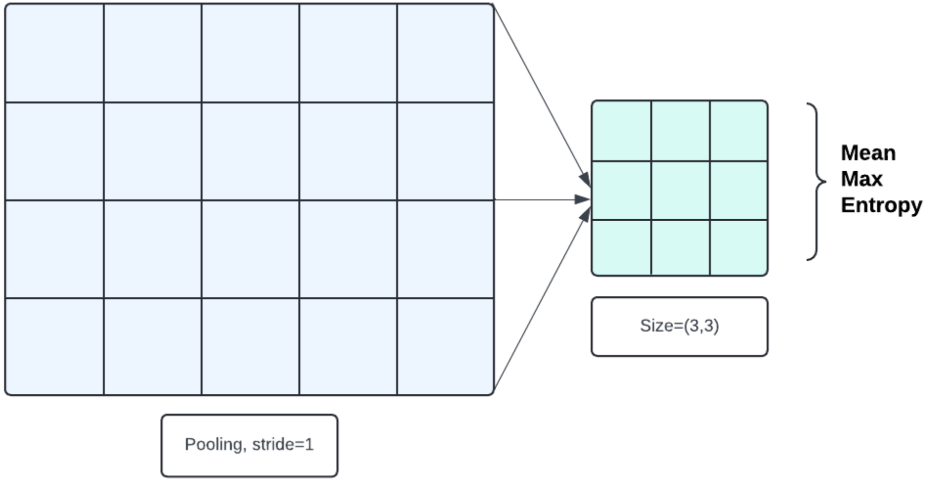
Curse of Tumor

Within the same tumor type, there can be many different shape depending on the different stages of the tumor.
Besides, different types of tumors may share a similar shape.

But, there is a **key insight** that:
Location of tumor is one of the Key Distinguishing Factors**.**
And, the **intensity of tumor** is frequently different from the rest.

Methodology (2)

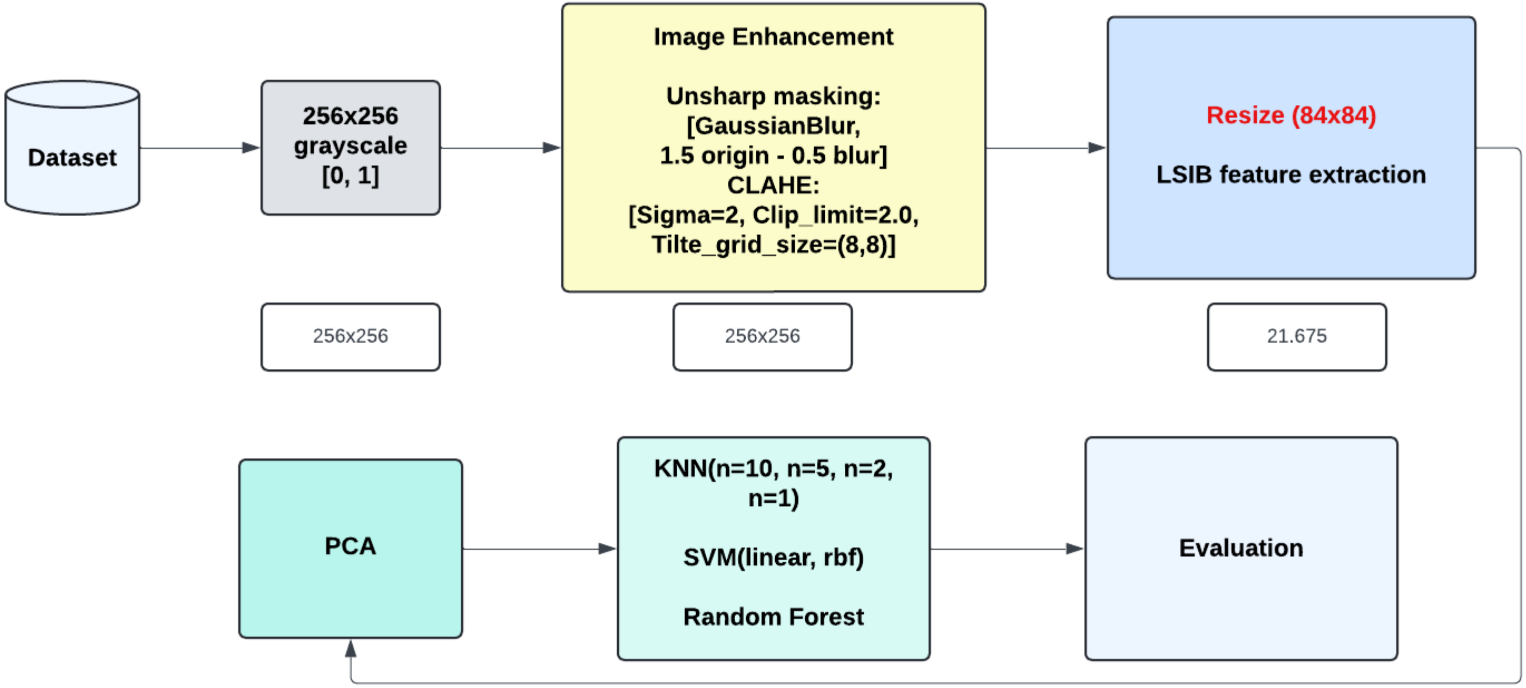
Local Statistics Intensity Based feature extraction



Purpose: capturing texture, contrast, and spatial relationships between different intensity distribution in images

Pipeline

Feature extraction + Training - Evaluation



LSIB illustration

Can be improved?

Combine LSIB with HOG

How to isolating the tumor region and capture broader spatial relationships between different parts of the image?	Focus specifically on the tumor region and extracting relevant features of tumor instead of the entire brain.

Fusion Dance

Segmentation based Classification

Combine LSIB and HOG

Combine Segmentation and Classification

Methodology (3)

Segmentation based Classification: Related work

Ramdas and Mohd
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 cites.

Methodology (3)

Related work: I&C + RCNN

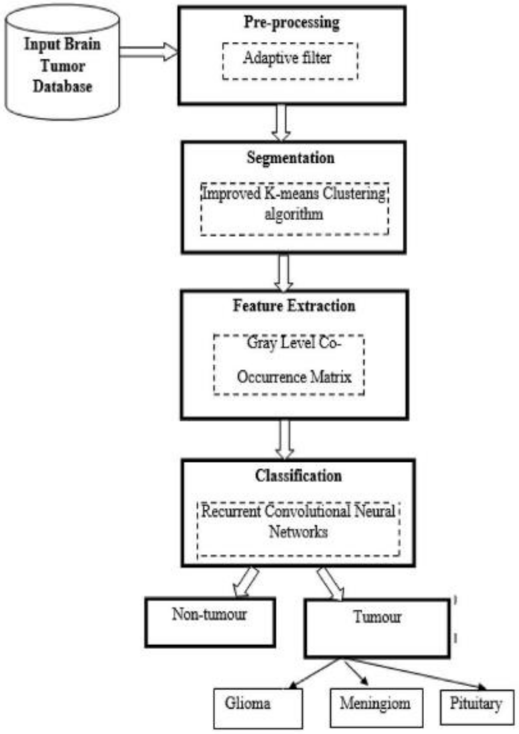


Fig. 2. Proposed methodology overview.

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

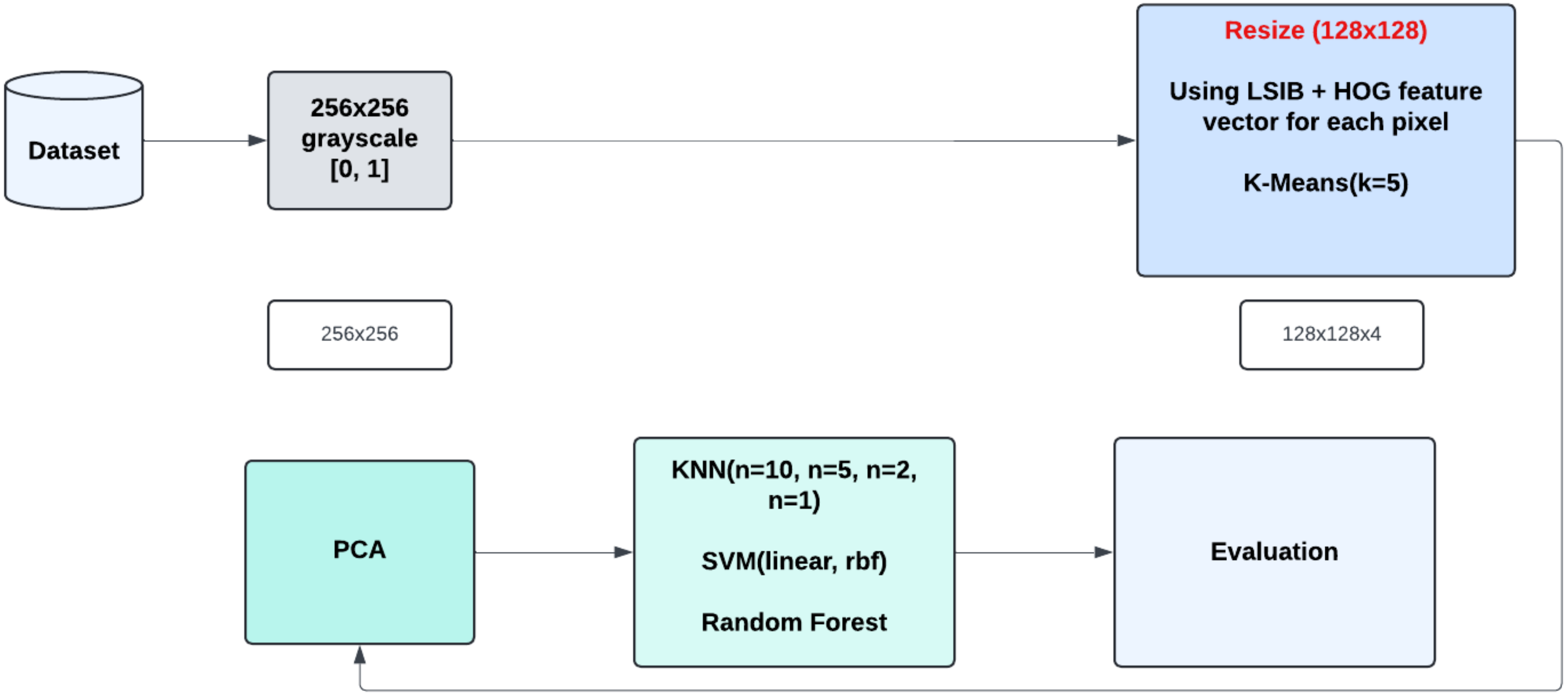
Step6: Compute K – means segmentation

Step7: Compute thresholding segmentation

Step8: Finally output will be a tumor region

Pipeline

Feature extraction + Training - Evaluation



Segmentation illustration

Evaluation Method

Mertrics

To meet the core aim of this research project, we use:

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.

$\text{Accuracy} = \dfrac{(TP + TN)}{(TP + FP + TN + FN)}$	$\text{F1 Score} = \dfrac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$

Evaluation Method

Dataset

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

- This dataset is a combination of the following three datasets: Figshare, Sartaj, and Br35H. This dataset contains 7023 images of human brain MRI images as a set of 2D slices, not 3D volume.

- The dataset are classified into 4 classes: glioma - meningioma - no tumor and pituitary.

- 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.

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

Evaluation Method

Dataset Distribution

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

Evaluation Method

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 (set up following sklearn library with K-Fold=4, and x5 time cost for all experiments).
- 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.

Result Experiment (1)

Comprehensive results using

HOG

Result Experiment (2)

Comprehensive results using LSIB

	KNN-10	KNN-5	KNN-2	KNN-1	SVM-ln	SVM-rbf	RF
mCV 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

Result Experiment (3)

Comprehensive results using Segmentation vs LSIB

		KNN-10	KNN-5	KNN-2	KNN-1	SVM-ln	SVM-rbf	RF
LSIB	mCV 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
Seg	mCV 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

Result Experiment (2*)

Comparision results using
Segmentation vs LSIB

		Top 3	Unique Top 3	The best
LSIB	mCV 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
Seg	mCV 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

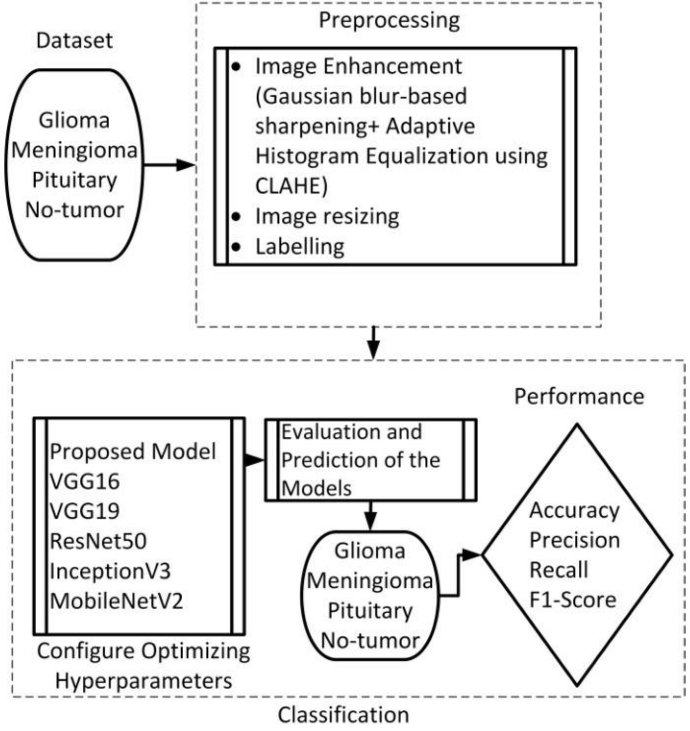
Result Experiment (3*)

Comparision results with Related work

Method	Dataset	CV accuracy	Accuracy	F1-score
Enh + HOG (the best)	BRMRI 2022			
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 2022	0.9739	0.9764	0.9750 0.9765

Result Experiment

Enh + CNN - 2023 paper



Xception FineTuning

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)

Research Finding

Conclusion

We found the effectiveness of capture local edge information, shape of tumor and also texture, spatial relationship (location), different intensity distribution of tumor region for Brain Tumor MRI classification using feature extraction such as HOG, LSIB.

Besides, combining them can be an better way for the accurate identification and classification of complex tumors. However, spatial relationship, different intensity distribution features seem to be more essential.

Segmentation based classification could be a novel way that help isolate the tumor region and focus on them instead of entire brain.

The experiment result shows potential of model resonation by an ML segmentation method.

Amid the explosion of DL and CNN, our research shows that understanding and creatively combining traditional ML methods still shows effectiveness and has essential application values.

Limitation Finding

Visualization

Recommendation

Future Research Direction