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Ahsanullah University
of Science and Technology

Dept. of Computer Science and Engineering

Brain Tumor Detection Using Convolutional Neural Network

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HELLO!

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INTRODUCTION

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- In the field of Medical Image Analysis, research on Brain tumors is one of the most prominent ones
- Tumor segmentation is one of the most arduous task
- Primary brain tumors occur in around 250,000 people a year globally, making up less than 2% of cancers[1]

[1]. "Chapter 5.16" *World Cancer Report 2014. World Health Organization. 2014. ISBN 978-9283204299. Archived from the original on 02 May 2019.*

MOTIVATION

- ✓ Well adaptation of automated medical image analysis in the perspective of Bangladesh
- ✓ Early detection of Brain Tumors
- ✓ Reducing the pressure on Human judgement
- ✓ Build a User Interface which can identify the cancerous cells

CHALLENGES

- Device Independent
- Real-time in erratic background
- Segmenting tumors conjoined with the skull
- Reducing processing time by scaling the hidden layers

RESEARCH DOMAIN

Problem

- Segmentation of the tumorous cells
- Detection of the Tumor
- Extract extensive features from the tumor

How we can implement the problem?

  - Basic Image Processing techniques was used for segmentation
  - Using Convolutional Neural Network based detection

BACKGROUNDS

BRAIN TUMOR

- tumor cells remain undifferentiated in the image
- cells contain abnormal nuclei
- abnormal cells form within the brain
- many dividing cells: disorganized arrangement
- destroy healthy brain cells by invading them
- tumor may grow from neuroma, meningioma, craniopharyngioma or glioma

Types of Brain Tumor

Brain Tumor

- Benign
- Malignant

Benign

- non cancerous
- grows slowly: do not spread into other tissues
- have clear borders

Malignant

- brain cancers
- grows rapidly and invades healthy brain tissues
- distorted borders

BACKGROUND STUDIES

Existing Works

- Devkota et al. 2017
  - "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction"
- Song et al. 2016
  - "A Novel Brain Tumor Segmentation from Multi-Modality MRI via A Level-Set-Based Model"
- Dina et al. 2012
  - "Automated Brain Tumor Detection and Identification using Image Processing and Probabilistic Neural Network Techniques"
- Zahra et al. 2018
  - "Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images"

A REVIEW

Brain Tumor Segmentation Techniques on Medical Images - A Review[2]

- A total of 52 papers had been reviewed including Machine learning and Deep learning methods
- The whole review divided in Layer based, Region based, Edge based, Thresholding based segmentation techniques etc.
- Clustering technique was used in majority of the articles
- For Classification, K-Means, Fuzzy C-Means algorithm had been used

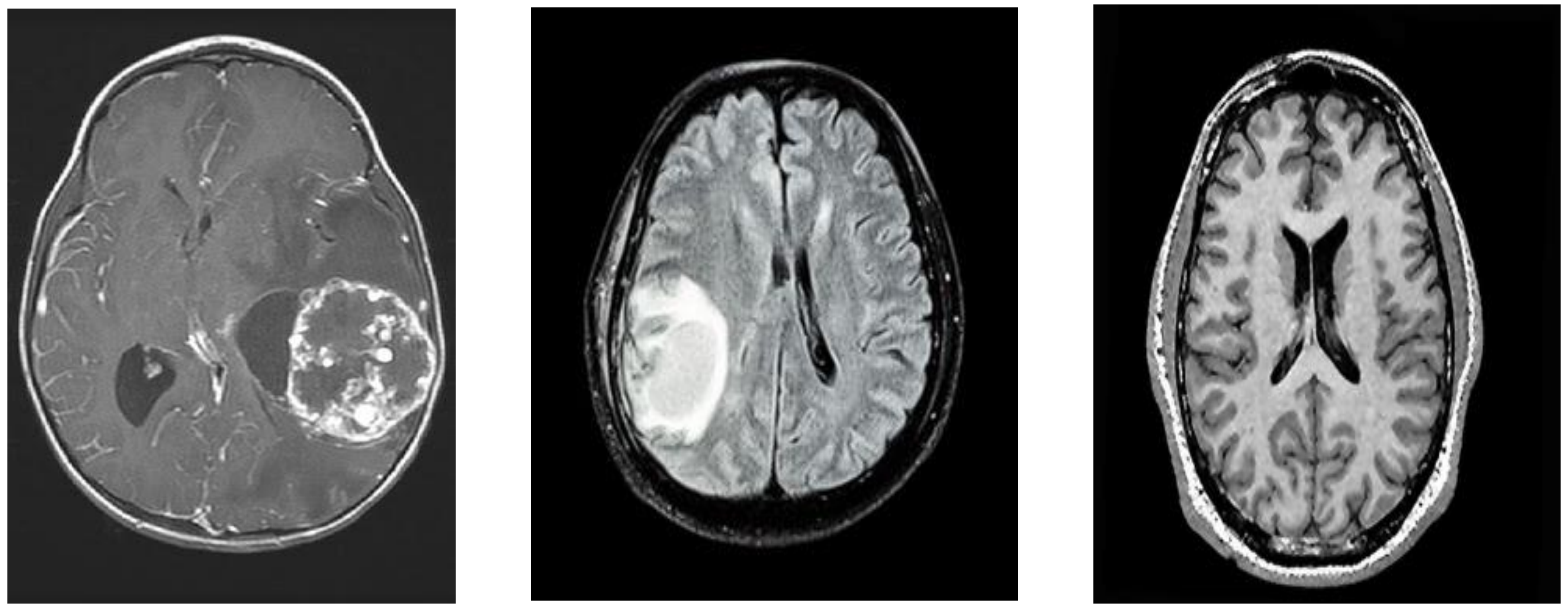
[2]. Faisal Muhammad Shah , Tonmoy Hossain , Mohsena Ashraf, Fairuz Shadmani Shishir , MD Abdullah Al Nasim , Md. Hasanul Kabir, "Brain Tumor Segmentation Techniques on Medical Images - A Review", INTERNATIONAL JOURNAL OF SCIENTIFIC & ENGINEERING RESEARCH, VOLUME 10, ISSUE 2, FEBRUARY-2019, ISSN 2229-5518.

Dataset

Dataset

- BraTS'13 data[3][4]
- Total MRI Image: 217
- Break down intro two category: class-0 and class-1
- All the MRI images are clinically-acquired pre-operative multimodal scans of HGG and LGG
- Described as- T1, T1Gd, T2 and FLAIR volumes

Some Examples



[3] Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, Burren Y, Porz N, Slotboom J, Wiest R, Lanczi L, Gerstner E, Weber MA, Arbel T, Avants BB, Ayache N, Buendia P, Collins DL, Cordier N, Corso JJ, Criminisi A, Das T, Delingette H, Demiralp Γ, Durst CR, Dojat M, Doyle S, Festa J, Forbes F, Geremia E, Glocker B, Golland P, Guo X, Hamamci A, Iftekharuddin KM, Jena R, John NM, Konukoglu E, Lashkari D, Mariz JA, Meier R, Pereira S, Precup D, Price SJ, Raviv TR, Reza SM, Ryan M, Sarikaya D, Schwartz L, Shin HC, Shotton J, Silva CA, Sousa N, Subbanna NK, Szekely G, Taylor TJ, Thomas OM, Tustison NJ, Unal G, Vasseur F, Wintermark M, Ye DH, Zhao L, Zhao B, Zikic D, Prastawa M, Reyes M, Van Leemput K. "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)", IEEE Transactions on Medical Imaging 34(10), 1993-2024 (2015) DOI: 10.1109/TMI.2014.2377694

[4] Bakas S, Akbari H, Sotiras A, Bilello M, Rozycki M, Kirby JS, Freymann JB, Farahani K, Davatzikos C. "Advancing The Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features", Nature Scientific Data, 4:170117 (2017) DOI: 10.1038/sdata.2017.117

METHODOLOGY (Segmentation)

Proposed Method for tumor segmentation and classification using traditional classifiers

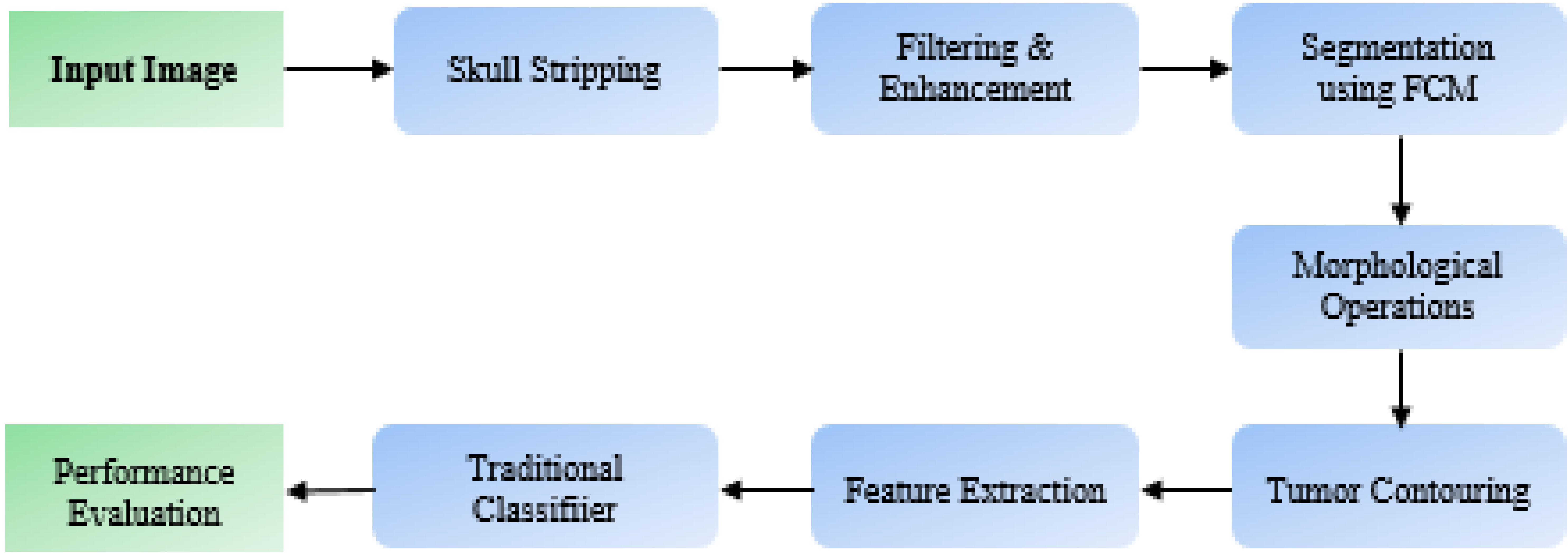


Fig 1: Proposed methodology for classification using Traditional Classifiers

Elaborated proposed methodology

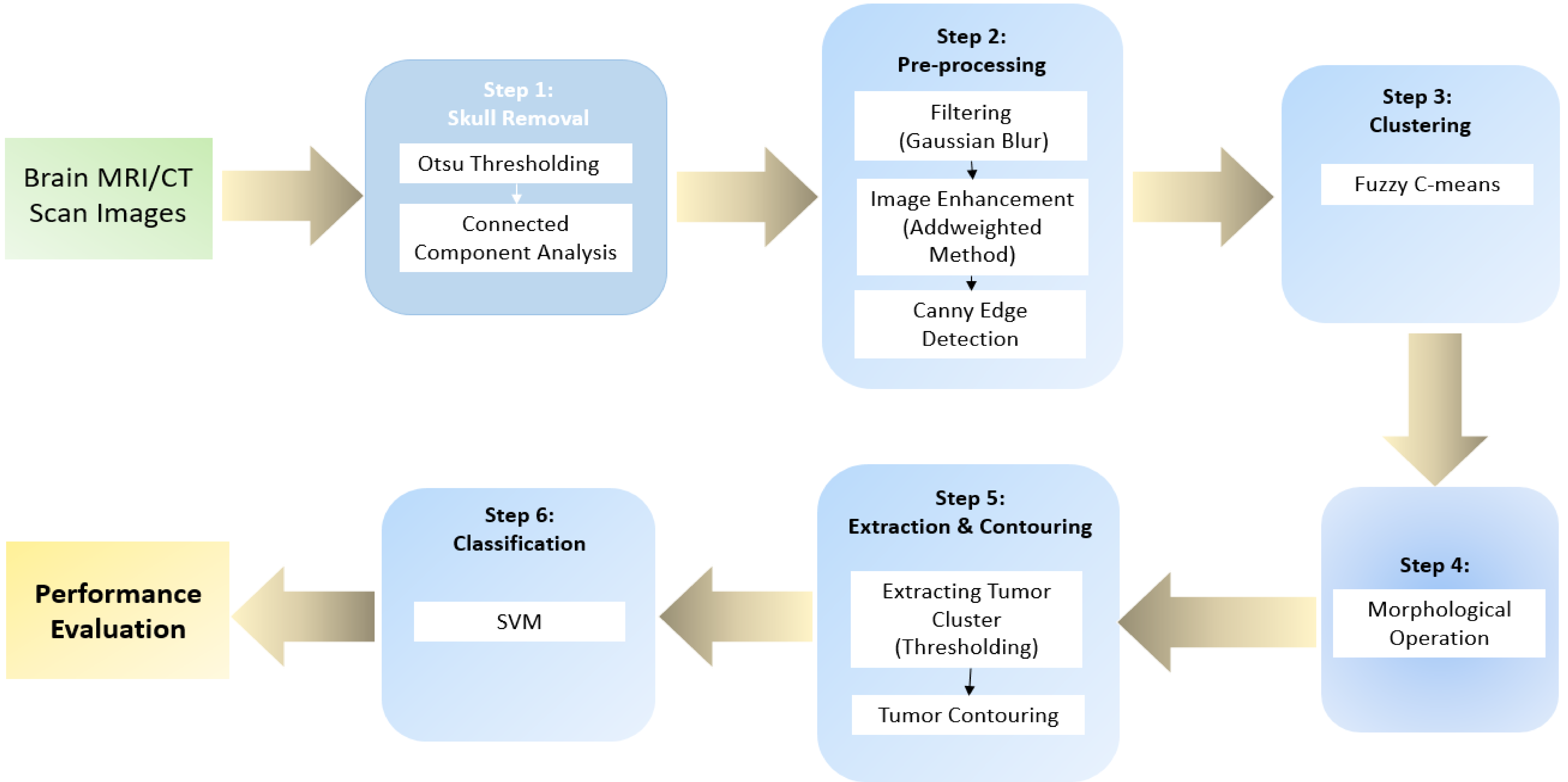


Fig 2: elaborated proposed methodology

Skull Stripping

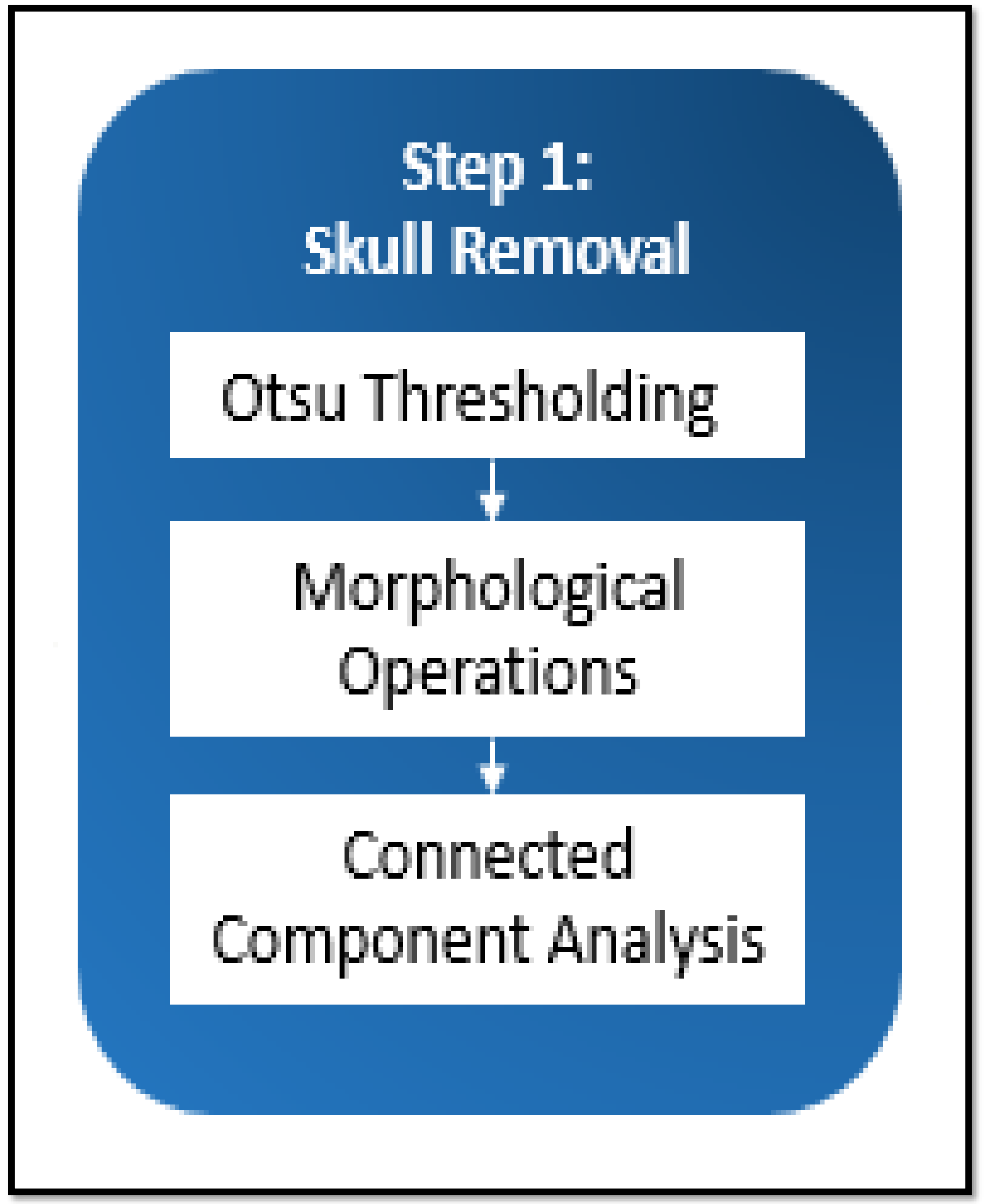


Fig 3: process of skull removal

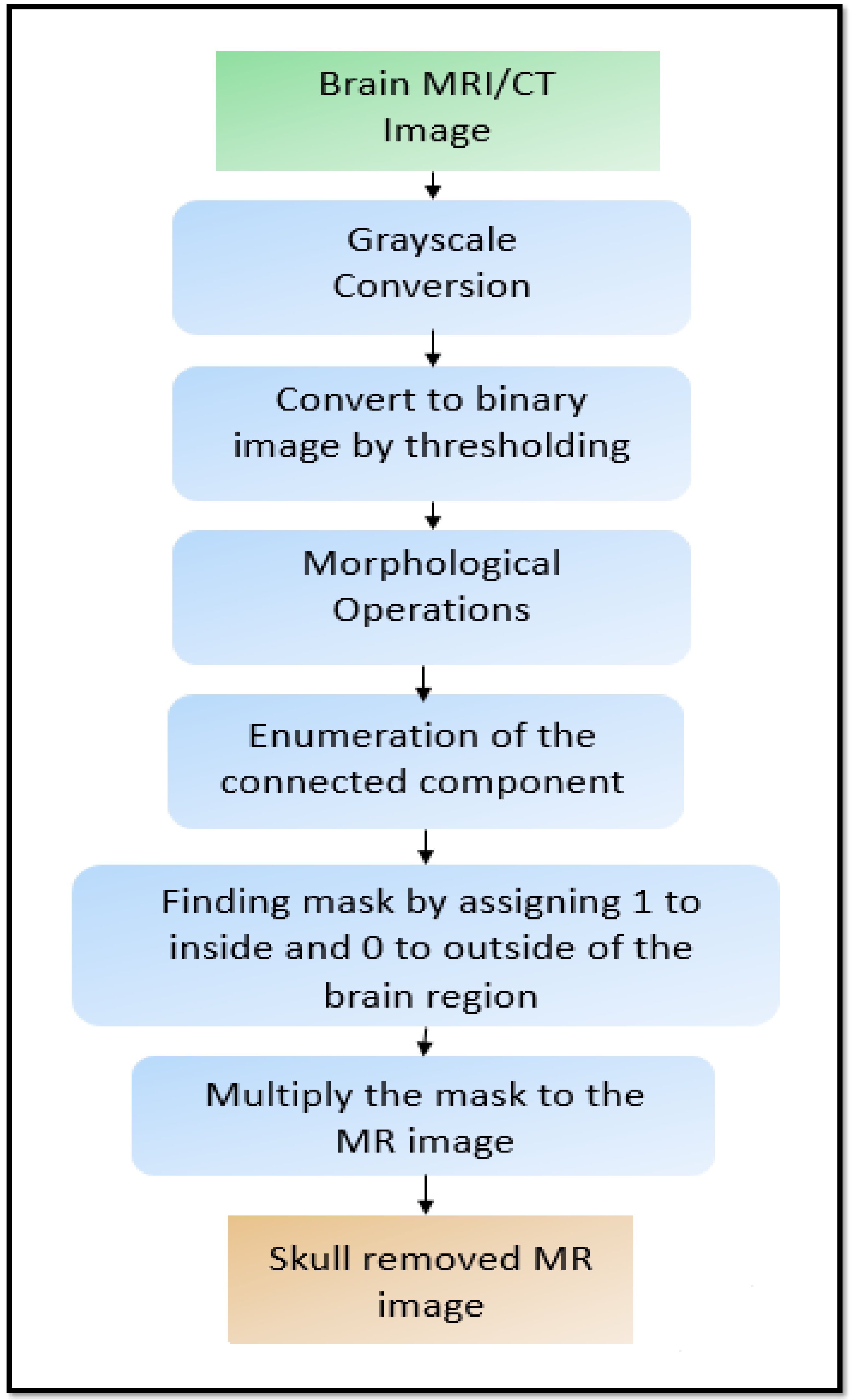


Fig 4: elaborated process of skull removal

Skull Stripping

- Converted our MRI Images into Grayscale
- OTSU Thresholding was applied for binarization
- Erosion operation had been performed before applying connected component analysis
- Each maximal region of connected pixels (not separated by boundary) is called a connected component. We found the largest component which is the skull
- We found the mask by assigning 1 to inside and 0 to outside of the brain region
- Multiplied the mask to T1, T2 and FLAIR images

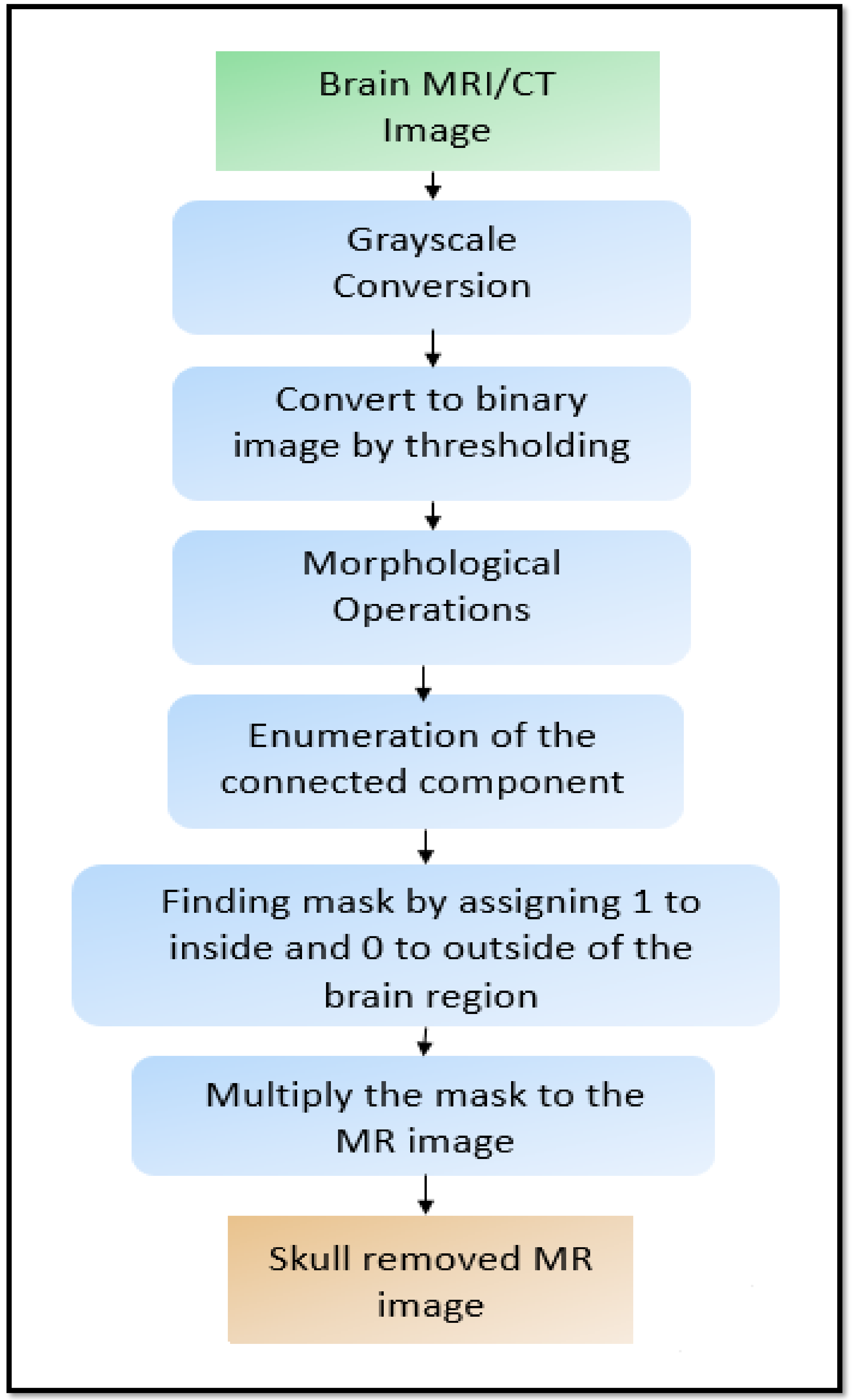


Fig 5: elaborated process of skull removal

Skull Stripping

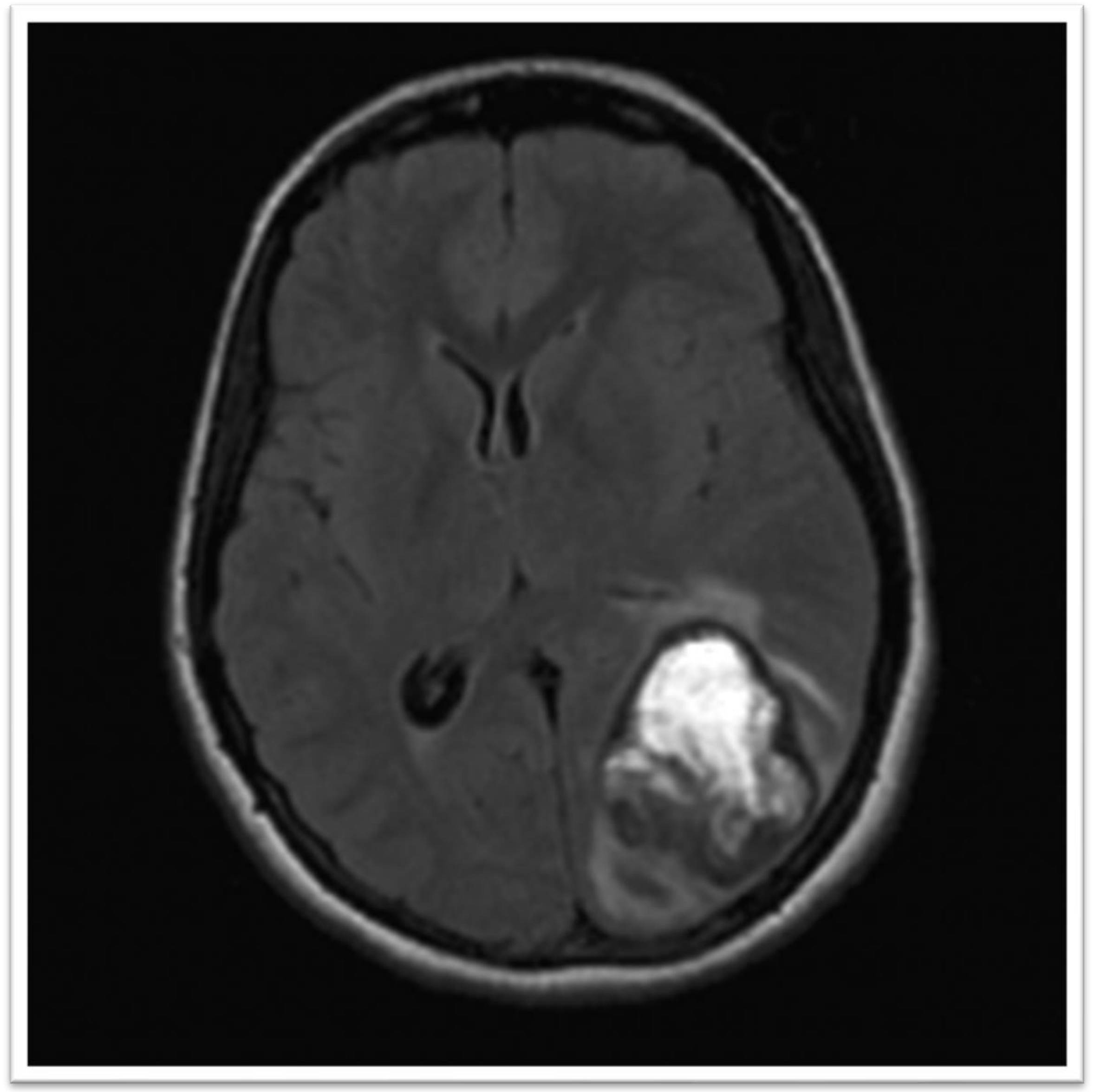


Fig 6.1: input image

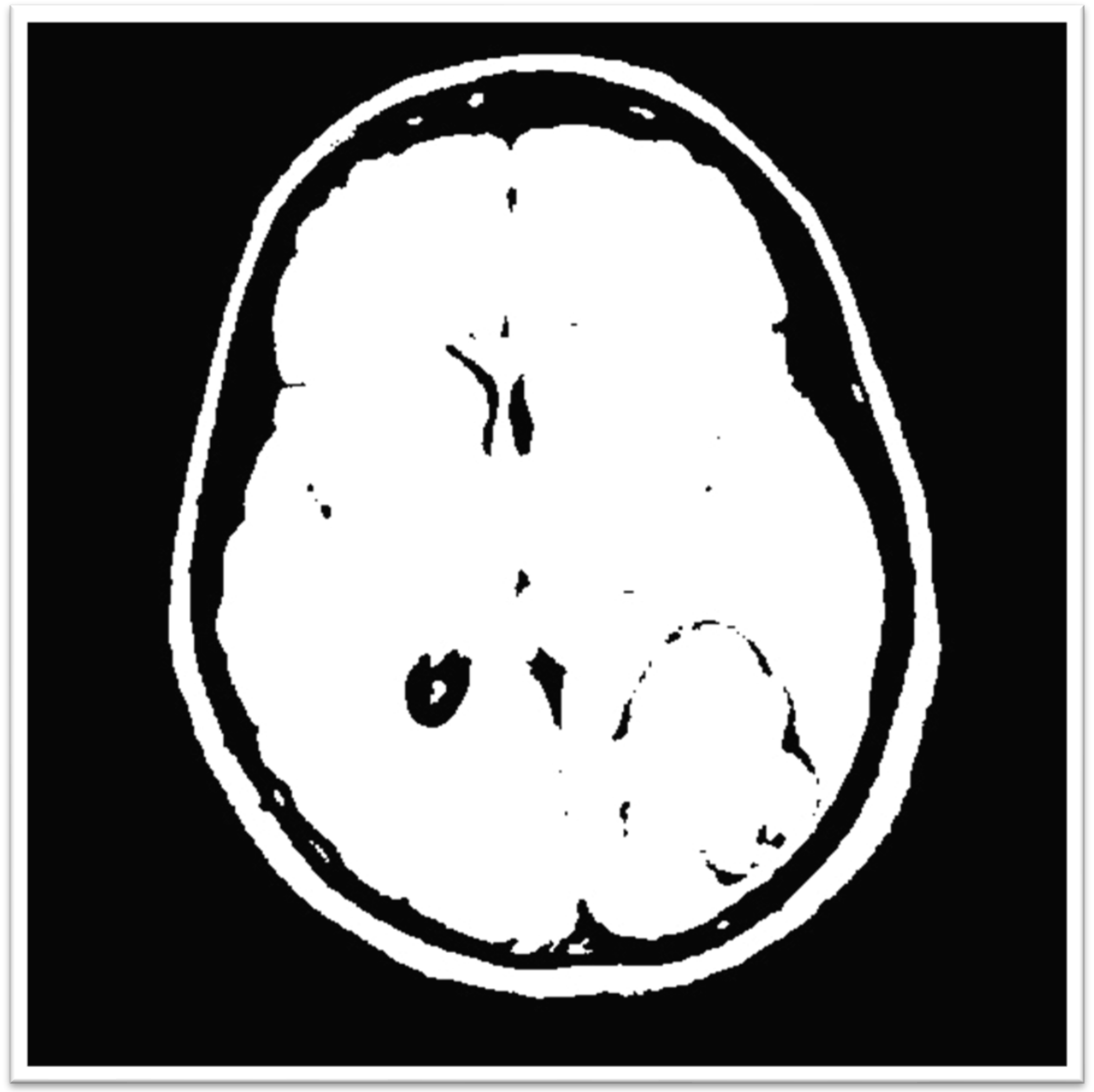


Fig 6.2: thresholded image

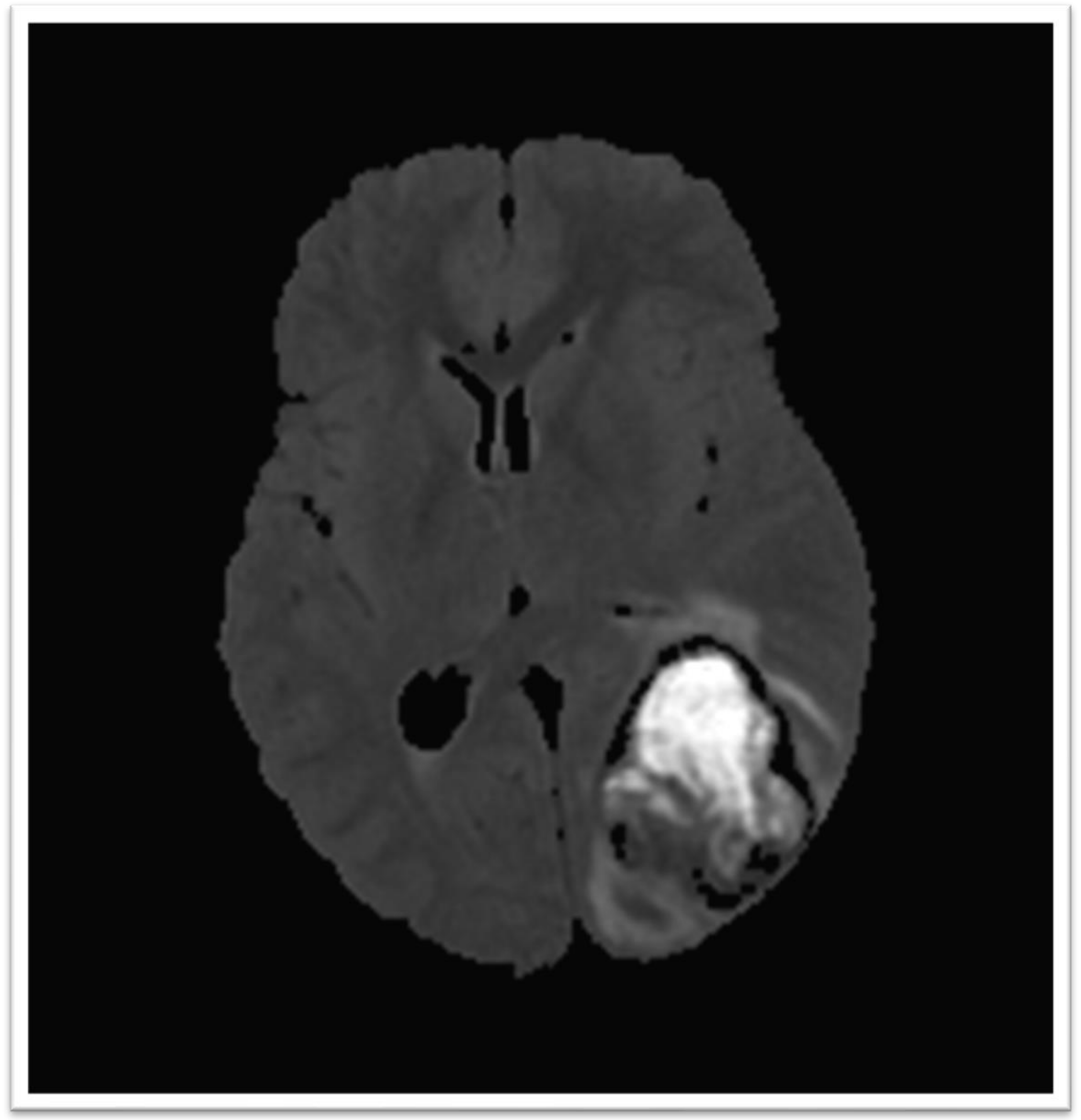
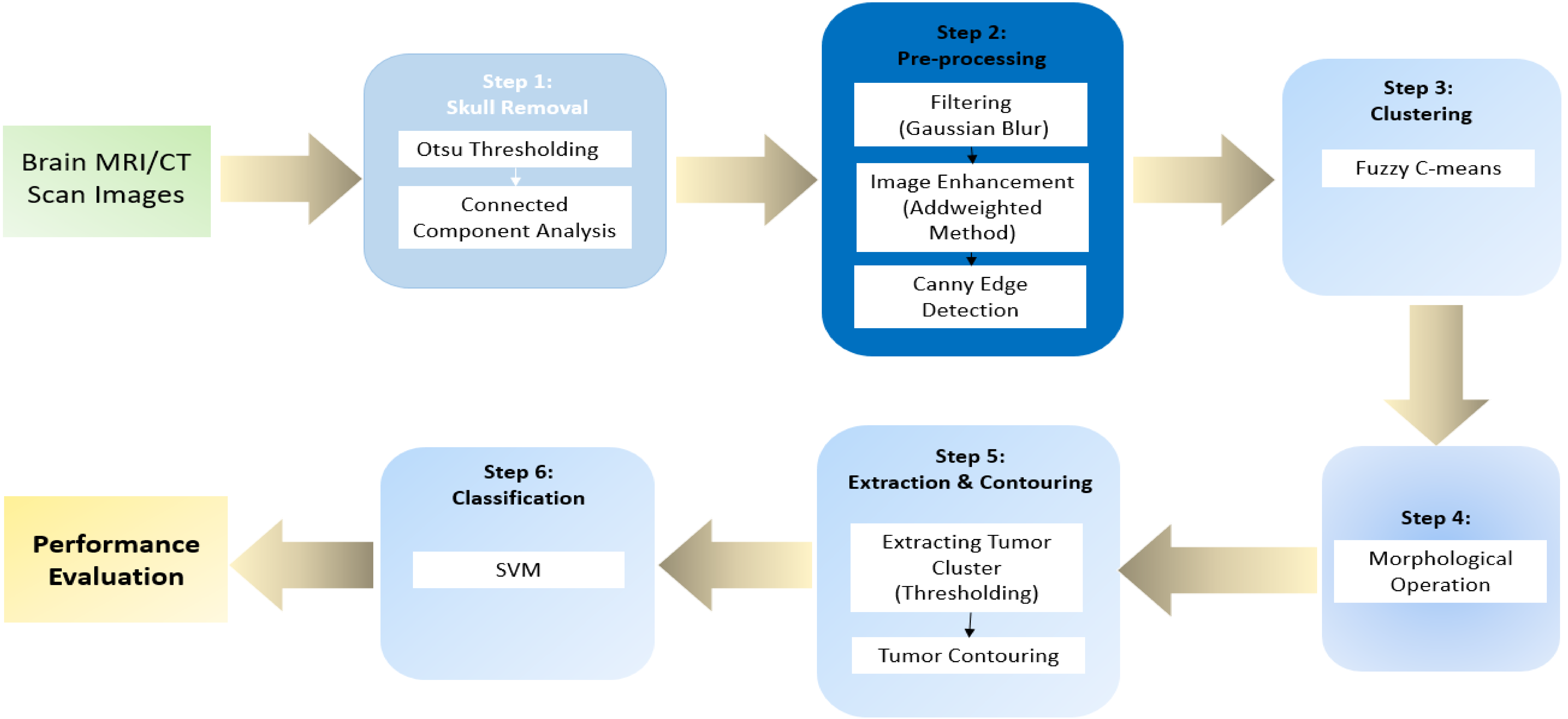


Fig 6.3: skull removed image

Fig 6: steps of skull stripping

Pre-Processing



Pre-Processing

- Median filter gives us the most prominent result among the filters
- For enhancing the image quality, we used the add-weighted method
- Applied the Canny Edge Detection method for detecting the edges

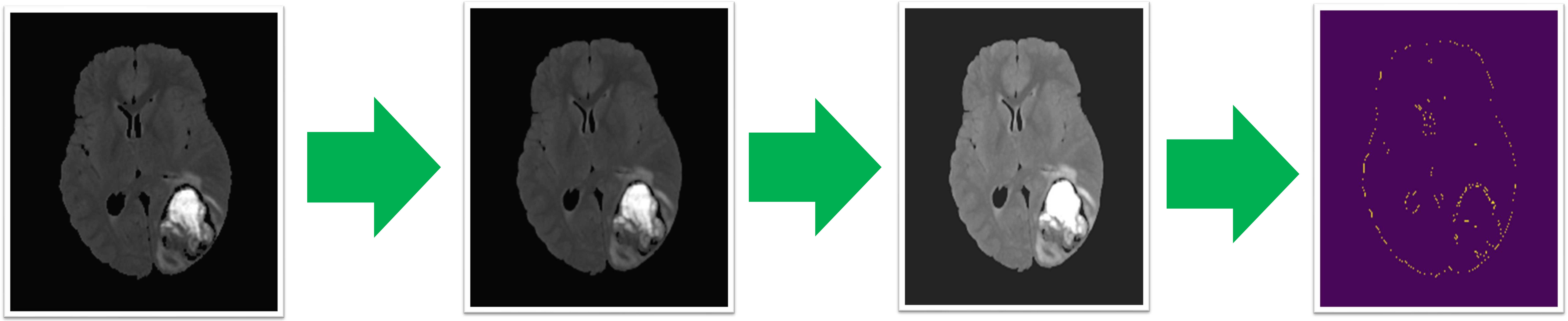
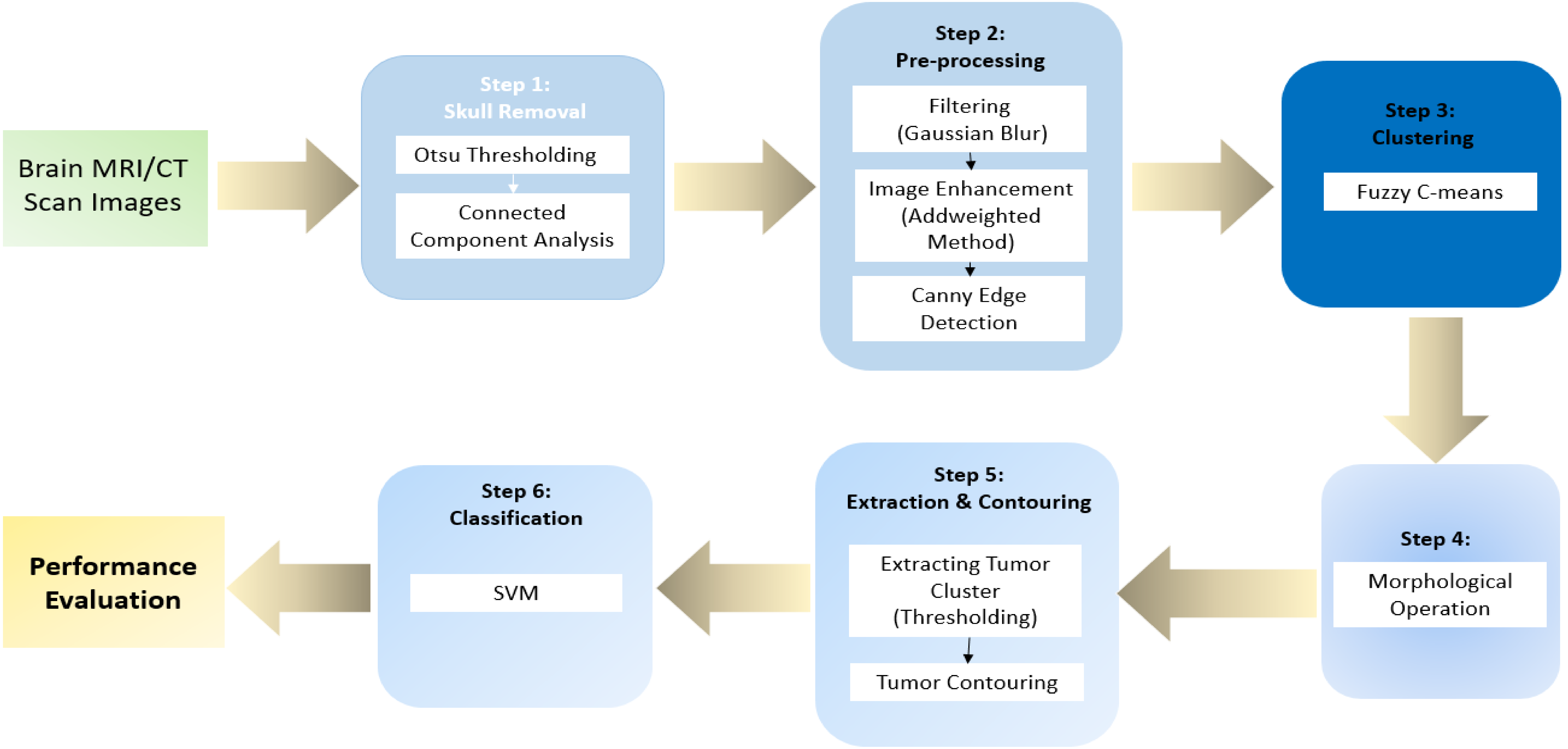


Fig 7.1: skull removed MRI | Fig 7.2: gaussian Blur Filter | Fig 7.3: enhanced MRI | Fig 7.4: edge detection MRI

Fig 7: steps of pre processing

Segmentation Using FCM



Segmentation Using FCM

- A method of clustering which allows one piece of data to belong to two or more clusters
- Involves assigning data points to clusters
- Items in the same cluster are as similar as possible
- Items belonging to different clusters are as dissimilar as possible

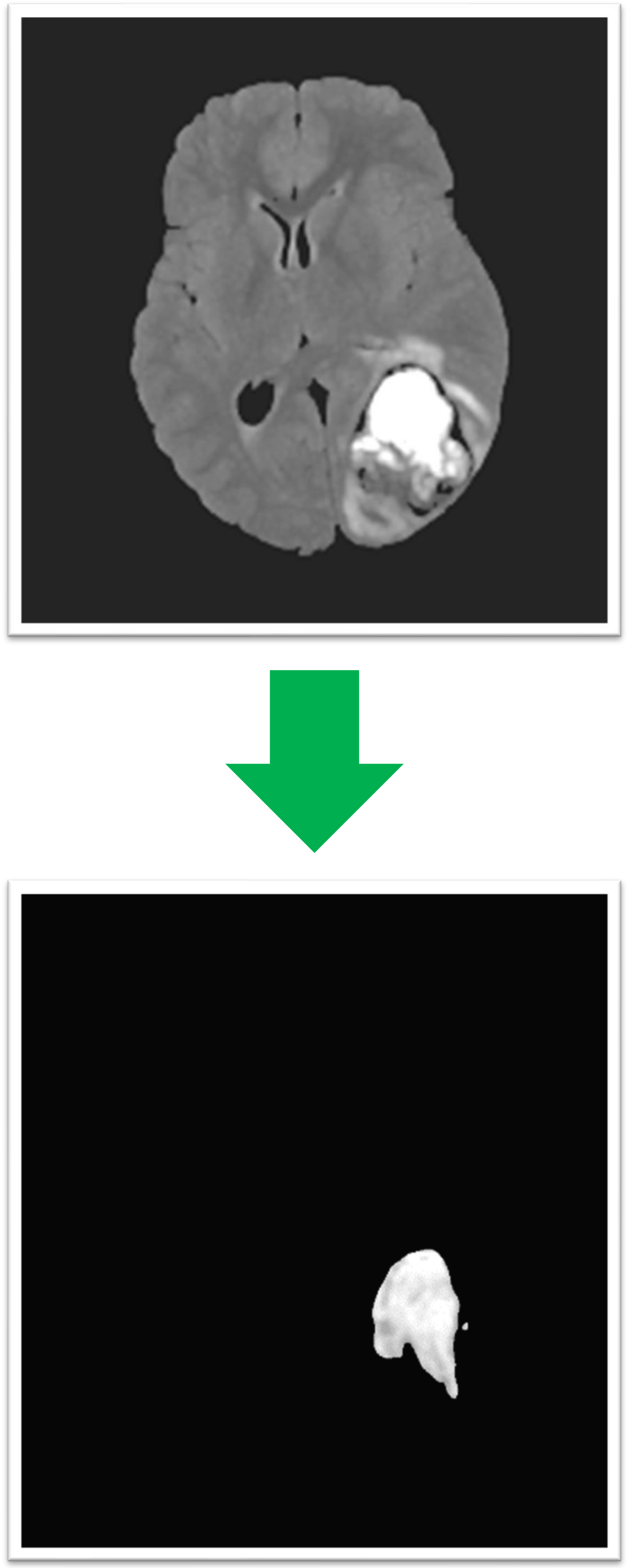
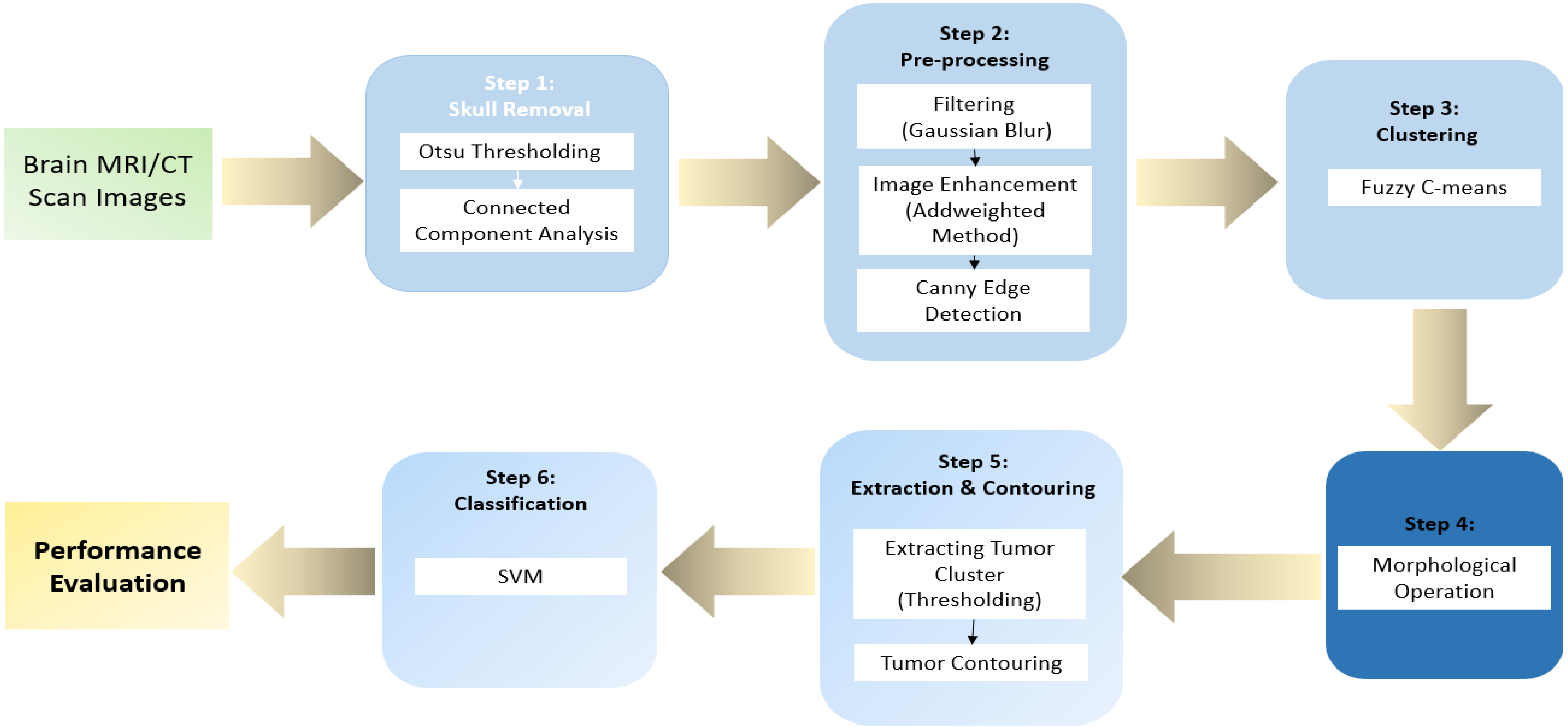
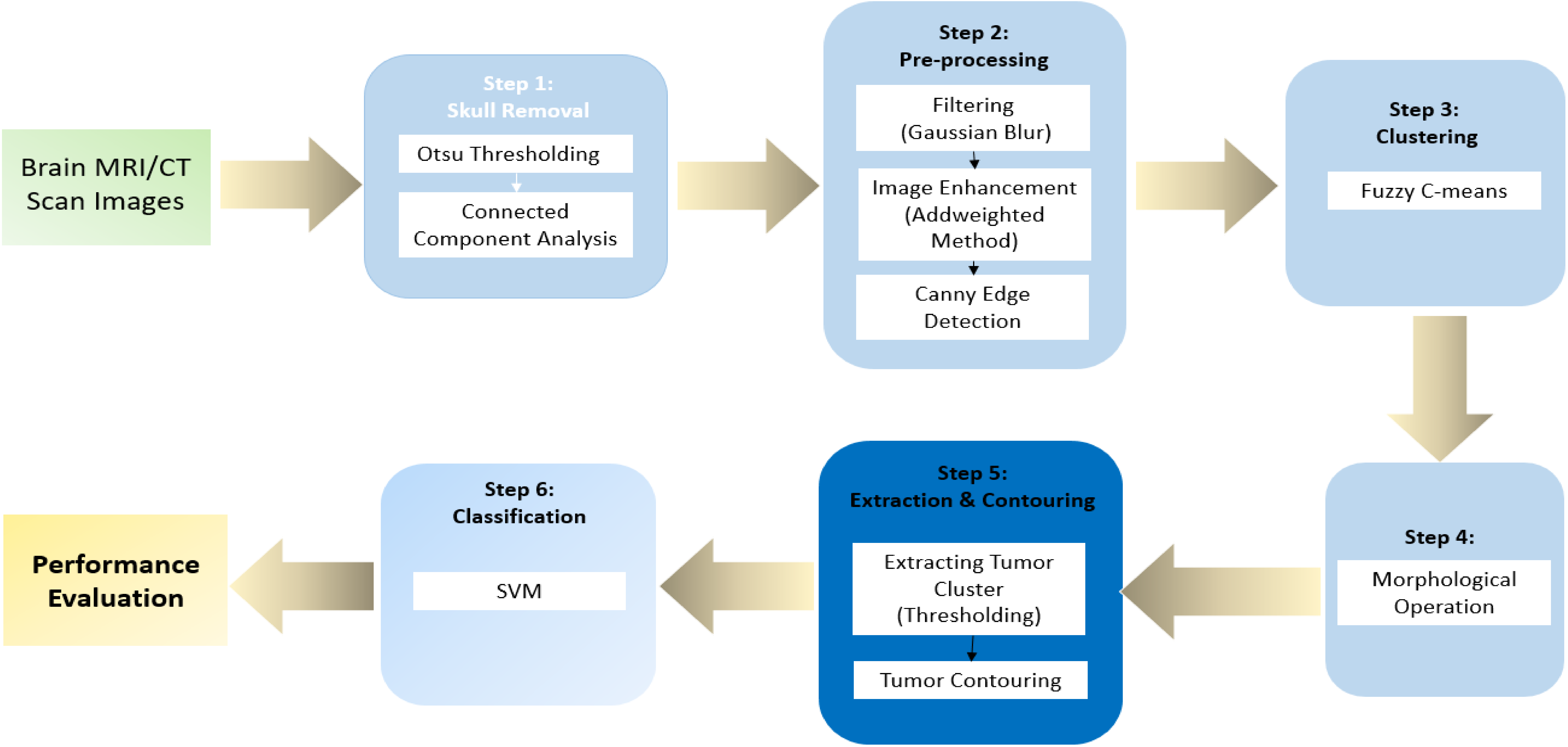


Fig 8: segmented tumor

Morphological Operation



Tumor Contouring



Tumor Contouring

- Contours can be explained simply as a curve joining all the continuous points (along the boundary), having same color or intensity
- Used the cv2.findContours( ) method for finding the contours

Fig 9.1: segmented MRI

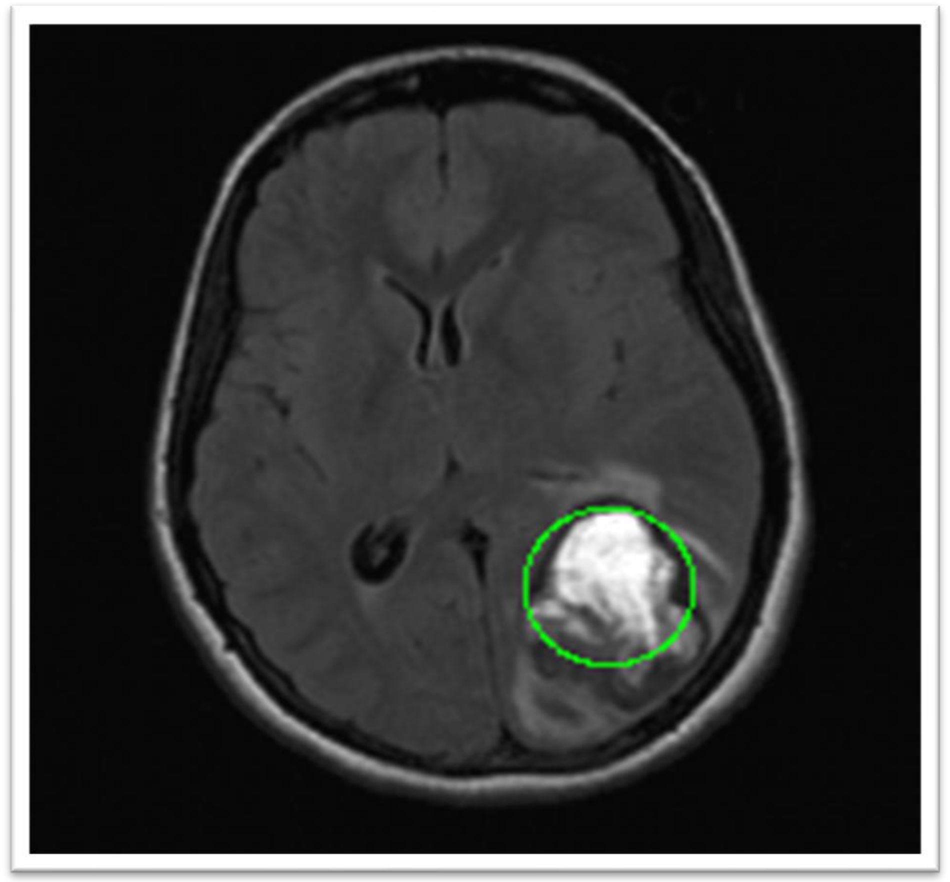


Fig 9.2: contoured tumor MRI

Fig 9: steps of tumor contouring

Traditional Classifier

We adopt six traditional Classifier

- K-Nearest Neighbor
- Logistic Regression
- Multilayer Perceptron
- Naïve Bayes
- Random Forest
- Support Vector Machine

Traditional Classifier

	TP	TN	FP	FN	Accuracy
K-Nearest Neighnour	56	3	4	3	89.39
Logistic Regression	56	2	5	3	87.88
Multilayer Perception	59	0	7	0	89.39
Naïve Bayes	47	5	2	12	78.79
Random Forest	58	1	6	1	89.39

Table I: confusion metrics of the classifiers

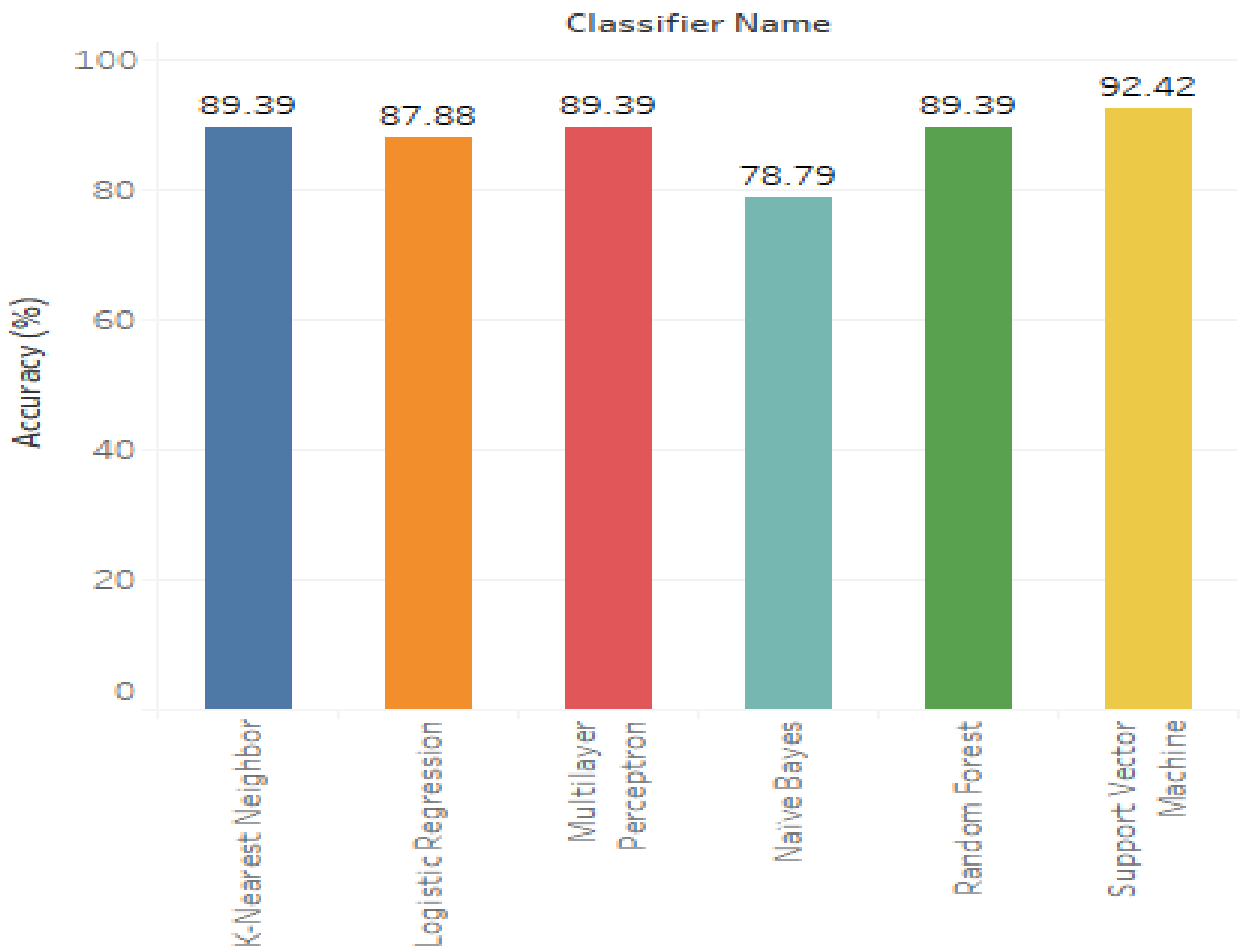


Fig 10: accuracy of the classifiers

Traditional Classifier

Classifier Name	Dice Score	Jaccard Index	Precision	Recall
K-Nearest Neighbour	0. 941	0.889	0.933	0.949
Logistic Regression	0.933	0.875	0.918	0.949
Multilayer Perception	0.944	0.894	0.894	1.000
Naïve Bayes	0.870	0.770	0.959	0.797
Random Forest	0.943	0.892	0.903	0.983
SVM	0.959	0.921	0.935	0.983

Table II: Performance Metrics of the classifiers

METHODOLOGY (CNN)

A Five-Layer CNN developed for tumor detection

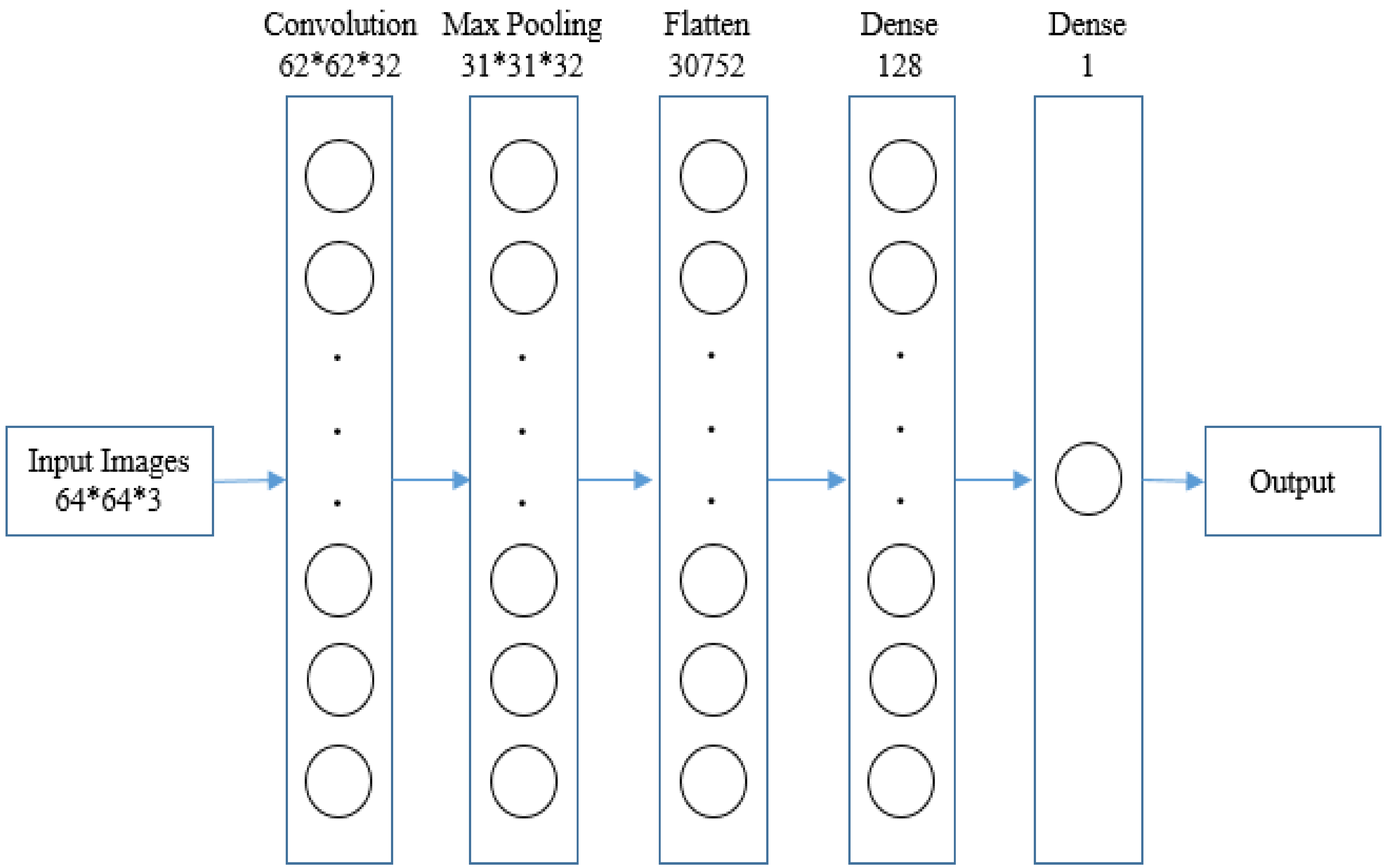


Fig 11: Proposed Methodology for tumor detection using 5-Layer Convolutional Neural Network

Convolution Layer

- The Beginning Layer
- Converting all the images into 64*64*3 homogeneous dimension
- Convolutional kernel of 32 convolutional filters of size 3*3 with the support of 3 tensor channels
- **Activation function: ReLU**

Max Pooling Layer

- Because of overfitting Max Pooling layer was introduced
- MaxPooling2D for the model
- Runs on 31*31*32 dimension
- Pool size is (2, 2)
- **Output: Pooled feature map**

Flatten

- Pooled feature map is work as the input
- Transformed the whole matrix into a single column vector
- Fed to the neural network for processing

Fully Connected Layers

- Two fully connected layers were employed Dense-1 and Dense-2 represented the dense layer
- The single obtained vector goes as an input
- Dense function was applied in Keras
- 128 nodes in the hidden layer
- For better Convergence ReLU and sigmoid function is used as an Activation function in the 1st and 2nd dense layer respecticely

Workflow of the Model

- Complete workflow is divided into 7 steps

Working Flow Devised for Proposed Methodology

1. Load the input dataset
2. Adding a Convolution Layer with 32 convolutional filter
3. Passing the Convolutional kernel into the Max Pooling layer
4. Pooled feature map is used to get the single column vector
5. Processing of the vector in dense layer with 128 nodes
6. Final dense layer applying Sigmoid as the Activation function
7. Validation stage and Performance evaluation

Fig 12: working flow of the proposed CNN Model.

Hyper-parameter values

- The hyper-parameters are divided into two stages- initialization and training

Stage	Hyper-parameter	Value
Initialization	bias	Zeros
	Weights	glorot_uniform
Training	Learning rate	0.001
	beta_1	0.9
	beta_2	0.999
	epsilon	None
	decay	0.0
	amsgrad	False
	epoch	10
	Batch_size	32
	steps_per_epoch	80

Table III: HYPER-PARAMETER VALUE OF CNN MODEL

Evaluation Process

- We devised an algorithm for the performance evaluation of our proposed model

Algorithm 1: Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig 13: algorithm of the performance evaluation

Performance of the proposed model

- Trained our model into two stage- 70:30 and 80:20 splitting ratio
- **Accuracy: 97.87%**

No	Training Image	Testing Image	Splitting Ratio	Accuracy (%)
1	152	65	70 : 30	92.98
2	174	43	80 : 20	97.87

Table IV: performance of the proposed CNN model

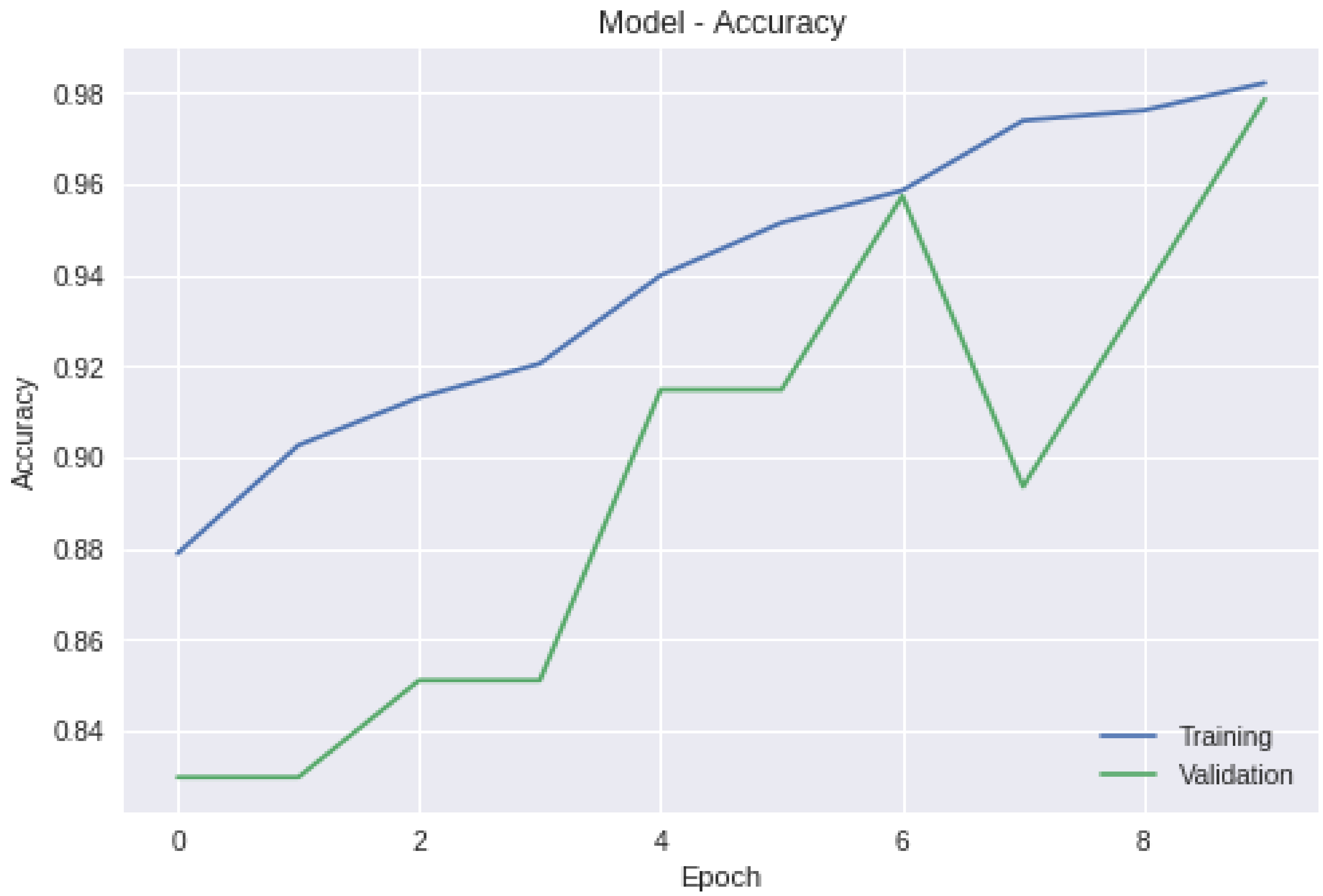


Fig 14: training and validation graph

FUTURE PLAN

Future Plan

- Work on 3D images
- Build our own dataset based on Bangladeshi patients
- Try to detect the grade and stage of the tumor
- Try to predict the location of the tumor from 3D images

THANK YOU!

Any Question!