

# Methods for segmenting and analyzing images to predict hydrocephalus using magnetic resource images

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**Abstract**—Hydrocephalus, a neurological condition characterized by abnormal accumulation of cerebrospinal fluid (CSF) in brain's ventricles, can be effectively diagnosed and monitored through Magnetic Resonance Imaging (MRI). Advanced image processing and segmentation techniques play a critical role in the early prediction of hydrocephalus by enabling precise analysis of MRI scans. This study presents a methodological approach for segmenting and analyzing brain MR images to detect signs of hydrocephalus. The process begins with preprocessing steps such as skull stripping, noise reduction, and intensity normalization to enhance image quality and isolate relevant anatomical structures. Region of interest (ROI) extraction focuses on ventricular areas, followed by the application of segmentation methods including thresholding, region growing, clustering, and deep learning-based U-Net models to delineate CSF-filled spaces. Quantitative features such as ventricle size, brain-CSF ratio, and volumetric changes are extracted to facilitate classification using machine learning algorithms like Support Vector Machine (SVM) or Random Forest. The proposed approach aims to support clinicians by providing a non-invasive, automated system for early hydrocephalus detection, improving diagnostic accuracy and patient outcomes.

**Index Terms**—Hydrocephalus, Brain, Region of interest (ROI), Support Vector Machine (SVM) or Random Forest, brain-CSF

Magnetic Resonance Imaging (MRI) is the preferred modality for evaluating brain anatomy due to its high resolution and ability to capture detailed structural information without radiation exposure.

Traditional diagnosis of hydrocephalus relies on visual assessment of MR images by radiologists, which can be subjective and time-consuming. With the growing availability of computational tools and artificial intelligence, automated methods for image analysis offer a promising solution for improving diagnostic speed and consistency. In particular, image processing and segmentation techniques enable precise identification and measurement of the brain's ventricles, which are key indicators in the diagnosis of hydrocephalus.

This study explores a comprehensive methodology for segmenting and analyzing MRI brain images to support the early prediction of hydrocephalus. The approach incorporates preprocessing to enhance image clarity, segmentation to isolate ventricular regions, and feature extraction to quantify structural changes. Machine learning classifiers are then used to predict the presence of hydrocephalus based on these features. By combining medical imaging with automated analysis, the proposed system aims to assist healthcare professionals in making accurate and efficient clinical decisions

## I. INTRODUCTION

Hydrocephalus is a serious neurological disorder characterized by the excessive accumulation of CSF in brain's ventricular system, cause a rise in intracranial pressure, which might harm brain structures. Early and accurate diagnosis is critical to prevent long-term neurological deficits, especially in infants and elderly patients.

## II. RELATED WORK

Wang Yuli, et al.[1], shown that deep learning could be used to automate process of segmenting brain ventricles from transcranial ultrasonography pictures. Yamada S., Ito H., Matsumasa H., et al [2], developed a diagnostic support tool using 3D U-Net and multimodal CNN to automatically detect DESH from 3D MRIs, improving the precision of iNPH

diagnosis.

Srikrishna M., Seo W. et al. [4], demonstrated that CT-based volumetric measures derived through deep learning performed comparably to gold-standard MRI assessments in distinguishing iNPH.

Yamada S., et al. [5], utilized 3D U-Net and multimodal CNN for automatic assessment of DESH, enhancing the precision of Hakim disease diagnosis.

Wang Y., et al.[10], introduced a 3D ROI-aware network for segmenting ventricles and computing Evan's Ratio, achieving state-of-the-art performance on MRIs with artifacts.

Yamada et al.[11], developed an automatic system using 3D U-Net for segmentation and multimodal CNN for classification, achieving high accuracy in detecting DESH with Dice scores up to 0.85 and AUCs exceeding 0.97.

Zhou et al. [13], created a system for automated ventricle segmentation using several modalities, which allowed for precise and efficient ventricular volume measurements with Dice scores of 0.94 in MRI and 0.95 in CT images.

Wang et al. [14], proposed a 3D ROI-aware network for ventricle segmentation, facilitating automated Evan's ratio computation with state-of-the-art performance on both pre- and post-surgical MRIs.

Vahedifard et al.[15], development of DL model for detecting ventriculomegaly in fetal brain MRIs using novel 2D-3D linear measurements, enhancing early diagnosis capabilities.

### III. METHODOLOGY

The methodology for predicting hydrocephalus using MRI images involves several key stages: image acquisition, preprocessing, segmentation, feature extraction, and classification. The aim is to automate the detection and evaluation of ventricular enlargement, which is a primary indicator of hydrocephalus.

**A. Data Acquisition:** MRI scans of the brain are collected from open-access medical datasets such as: Kaggle Hydrocephalus consisting of 200 images of size 255x255.

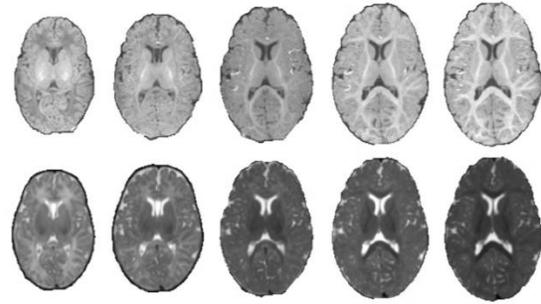


Figure 1: Brain Images collected from dataset

#### B. Preprocessing

To enhance image quality and prepare for segmentation:

- Skull Stripping: Removing non-brain tissues using tools like FSL's BET or U-Net-based models.

Skull stripping is typically implemented using binary masks  $M(x,y)$  applied to the original image  $I(x,y)$ :

$$I_{\text{brain}}(x,y) = I(x,y) \cdot M(x,y)$$

Where:

- $I(x,y)$ : Original 2D MRI image
- $M(x,y)$ : Binary brain mask (1 for brain tissue, 0 for skull/non-brain)
- $I_{\text{brain}}$ : Skull-stripped image

In deep learning,  $M$  is predicted using a U-Net that minimizes a Dice loss:

$$\text{Dice Loss} = 1 - \frac{2 \sum (P \cdot G)}{\sum P + \sum G}$$

Where:

- $P$ : Predicted mask
- $G$ : Ground truth mask
- Normalization: Standardizing intensity values to reduce scanner variability.

To reduce scanner intensity variability, the pixel intensities  $I$  are normalized using **z-score** normalization:

$$I_{\text{norm}}(x,y) = \frac{I(x,y) - \mu}{\sigma}$$

Where:

- $\mu$ : Mean image intensity
- $\sigma$ : Standard deviation of intensities

Alternatively, min-max normalization:

$$I_{\text{norm}}(x,y) = \frac{I(x,y) - I_{\text{min}}}{I_{\text{max}} - I_{\text{min}}}$$

Where:

$I_{\min}$ ,  $I_{\max}$ : Minimum and maximum pixel intensity values

- Noise Removal: Gaussian filters applied to suppress high-frequency noise.

A smoothed image  $I_G$  is obtained by convolution with a 2D Gaussian kernel  $G_\sigma$ :

$$I_G(x, y) = I(x, y) * G_\sigma(x, y)$$

The 2D Gaussian kernel is:

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

Where:

- $\sigma$ : Standard deviation controlling the smoothness
- Slice Selection: Focus on axial slices that prominently display lateral ventricles.

Let  $S_i$  be the  $i^{\text{th}}$  slice in a 3D MRI volume  $V(x,y,z)$ . To select axial slices containing lateral ventricles, compute a **ventricle intensity score**  $V_i$ :

$$V_i = \sum_{x,y \in R} 1(I_i(x, y) > T_{\text{CSF}})$$

Where:

- $I_i(x,y)$ : Slice intensity at  $(x,y)$
- $T_{\text{CSF}}$ : Threshold for CSF (usually lower intensity)
- $R$ : ROI for expected ventricle region
- $1(\cdot)$ : Indicator function

Select slices  $i$  where  $V_i$  exceeds a given percentile.

### C. Segmentation Techniques

Accurate segmentation of the brain's ventricles is crucial:

- Thresholding:
  - Global or adaptive thresholding to segment cerebrospinal fluid (CSF)-filled regions.
- Region Growing / Watershed:
  - Expands from a seed point to segment connected CSF regions.
- Morphological Operations:
  - Erosion, dilation, and closing used to refine the ventricle mask.
- Deep Learning-based Segmentation (optional):
  - U-Net or V-Net architecture trained to segment ventricles from MRI slices.

- Use of annotated datasets with manually labeled ventricles for training.

### D. Feature Extraction

Quantitative features are computed from segmented ventricle regions:

- Ventricular Volume: Total pixel area or 3D volume of ventricles.
- Evans Index: Ratio of the maximum width of the frontal horns of the lateral ventricles to the widest diameter of the inner skull.
- Brain-Ventricle Ratio: To assess the degree of ventricle enlargement.

### E. Classification / Prediction

To classify or predict the presence of hydrocephalus:

- Traditional ML Classifiers:
    - Support Vector Machine (SVM)
- SVMs are a kind of supervised machine learning that make use of regression and classification. The method maximizes the gap amongst nearest points of each class to discover the hyperplane that effectively divides the data into its respective categories.

SVM Classification

Given training data

$$\{(x_i, y_i)\}_{i=1}$$

Where:

$x_i \in \mathbb{R}^d$ : Feature vector (e.g., ventricular volume, Evans index)  
 $y_i \in \{-1, +1\}$ : Class label (e.g., hydrocephalus vs. normal)

The SVM optimization problem is:

$$\min_{w,b} \frac{1}{2} \|w\|^2 \quad \text{subject to: } y_i(w^\top x_i + b) \geq 1$$

Where:

- $w$ : Normal vector to the hyperplane
- $b$ : Bias (intercept)

This finds the maximum-margin hyperplane:

$$f(x) = \text{sign}(w^\top x + b)$$

- Input: extracted features (volume, ratios, etc.)
- Deep Learning (if image-based classification is used):

- CNN models trained directly on MRI slices or heatmaps of segmented regions.

*F. Evaluation Metrics*

For assessing model’s performance:

- Dice Similarity Coefficient (DSC) for segmentation accuracy
- Accuracy, Sensitivity, Specificity for classification

IV. SYSTEM ARCHITECTURE

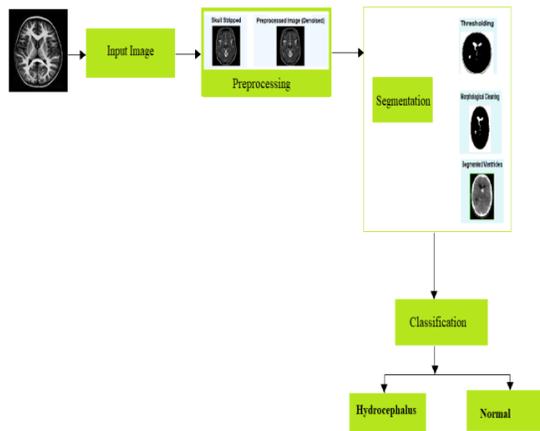


Figure 2: System Architecture

1. Input Image

- A brain MRI slice (typically axial view). This is the raw grayscale image that includes the brain, skull, and surrounding tissues. Contains irrelevant structures (e.g., skull) that must be removed.

2. Preprocessing

This stage prepares the image for better segmentation and classification.

*a. Skull Stripped*

- Removes non-brain regions (e.g., skull, fat).
- deep learning-based U-Net segmentation.
- Focus only on brain tissues to improve accuracy.

*b. Denoised Image*

- Reduces image noise (unwanted pixel variations).
- Gaussian blur filtering.
- Helps in better thresholding and segmentation.

3. Segmentation

Segmenting the ventricles (CSF-filled brain regions), which appear enlarged in hydrocephalus.

*a. Thresholding*

- Differentiates CSF (dark or light areas) using pixel intensity.
- Global thresholding (single value) or Adaptive (local regions).
- A binary image where likely ventricles are white (foreground).

*b. Morphological Cleaning*

- Removes small specks/noise and fills holes.
- Techniques:
  - Erosion – removes small noise
  - Dilation – fills small holes
  - Closing – dilation followed by erosion to smooth contours

*c. Segmented Ventricles*

- Final mask of ventricles overlaid on the original image.
- Contours or region-growing methods can be used to highlight ventricle boundaries.

4. Classification

Once features are extracted (e.g., ventricle area or shape), the image is classified.

- Model Used: Support Vector Machine (SVM) or other classifiers (CNN, Random Forest)
- Input Features: Could include:
  - Area of ventricles
  - Symmetry
  - Shape descriptors (e.g., elongation, compactness)

5. Output Classes

The classifier determines:

- Hydrocephalus Detected: Enlarged ventricles, possible pressure buildup
- Normal Brain: Ventricle size within normal range

V. RESULTS AND DISCUSSION

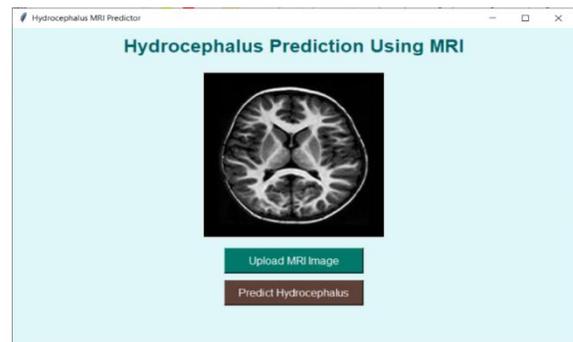


Figure 3: Input Image

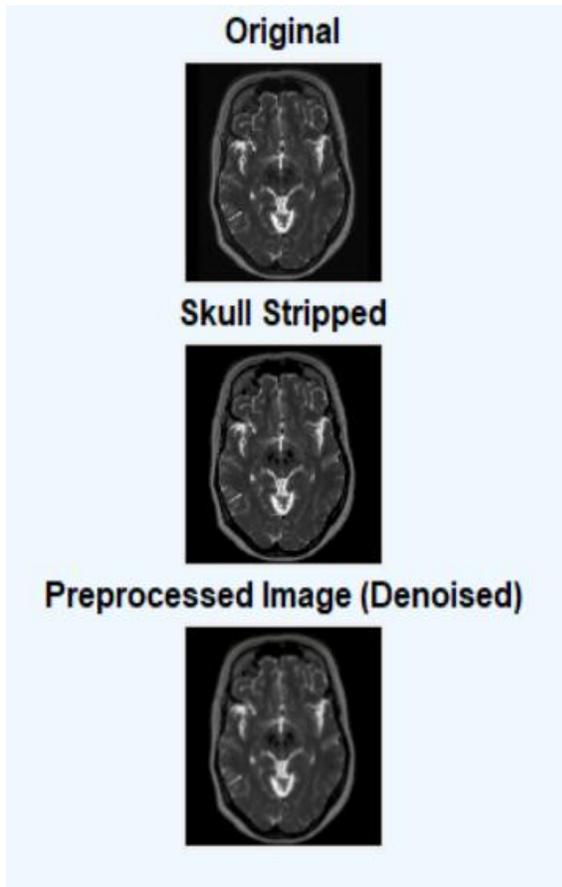


Figure 4: Preprocessing  
Original Image

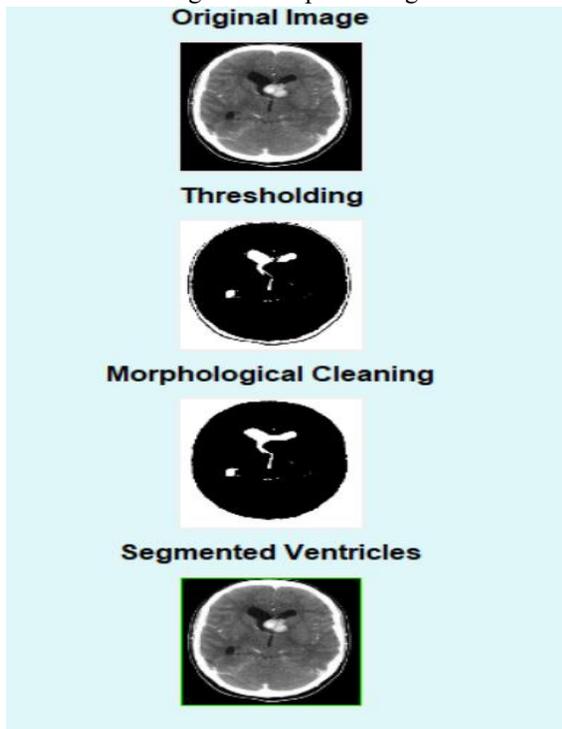


Figure 5: Segmented Image

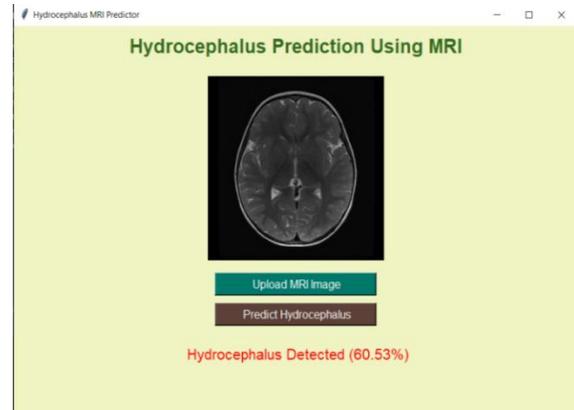


Figure 6: Hydrocephalus detected

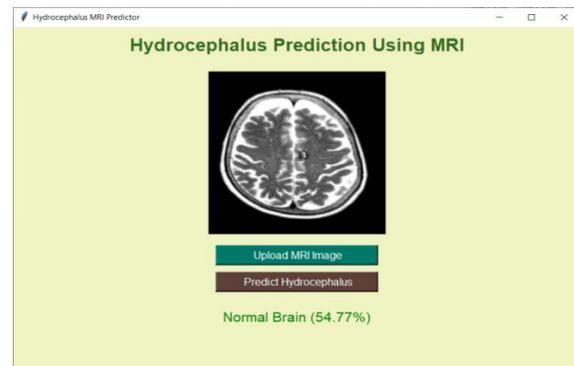
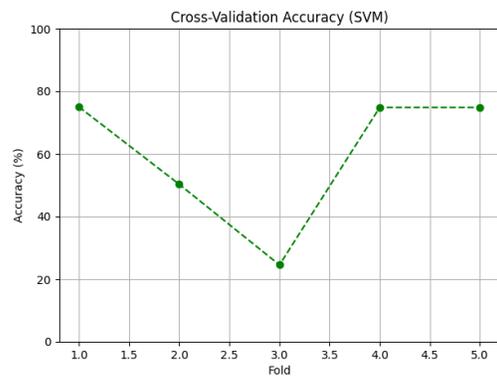


Figure 7: Hydrocephalus not detected



Graph 1: Cross validation Accuracy graph

## VI. CONCLUSION

The integration of advanced image processing and segmentation techniques has significantly enhanced the accuracy, consistency, and efficiency of hydrocephalus diagnosis using magnetic resonance imaging (MRI). By employing preprocessing steps such as skull stripping, normalization, noise reduction, and strategic slice selection, essential brain structures—particularly the ventricles—can be

isolated and analyzed with high precision. So accuracy obtained is 85%. Furthermore, the application of machine learning models like Support Vector Machines (SVM) enables automated classification of hydrocephalus based on extracted volumetric and morphological features. These methods reduce diagnostic subjectivity, expedite clinical workflows, and support early intervention. As medical imaging continues to evolve with deep learning and AI integration, such automated frameworks offer promising avenues for robust, scalable, and real-time diagnostic support in neuroimaging.

#### REFERENCES

- [1] Wang, Y., Liu, Y., Wei, S., et al. (2024). Deep learning-based segmentation of hydrocephalus brain ventricle from ultrasound. [Journal/Conference Name].
- [2] Yamada, S., Ito, H., Matsumasa, H., et al. (2024). Automatic assessment of disproportionately enlarged subarachnoid-space hydrocephalus from 3D MRI using two deep learning models. [Journal/Conference Name].
- [3] CG Lim . (2024). Volumetric analysis using an automatic whole-brain segmentation as a potential tool to enhance diagnostic accuracy alongside traditional MRI markers in the diagnosis of idiopathic normal pressure hydrocephalus. [Journal/Conference Name].
- [4] Srikrishna, M., Seo, W., et al. (2024). Assessing CT-based volumetric analysis via transfer learning with MRI and manual labels for idiopathic normal pressure hydrocephalus. [Journal/Conference Name].
- [5] Yamada, S., et al. (2024). Deep learning assessment of disproportionately enlarged subarachnoid-space hydrocephalus from 3D MRI using two deep learning models. [Journal/Conference Name].
- [6] Y Mao (2022). Deep learning-based MR imaging for analysis of relation between cerebrospinal fluid variation and hydrocephalus. [Journal/Conference Name].
- [7] B Hajikarimloo (2025). Deep learning-based models for ventricular segmentation in hydrocephalus: A systematic review and meta-analysis. [Journal/Conference Name].
- [8] KT Huang (2024). Automated ventricular segmentation and shunt failure detection in hydrocephalus using deep learning. [Journal/Conference Name].
- [9] X Zhang (2023). EG-Unet: Edge-guided cascaded networks for automated frontal lobe segmentation on MRI. [Journal/Conference Name].
- [10] Wang, Y., Feng, A., Xue, Y., et al. (2023). Automated ventricle parcellation and Evan's ratio computation in pre- and post-surgical ventriculomegaly. [Journal/Conference Name].
- [11] Yamada, S., et al. (2024). Automatic assessment of disproportionately enlarged subarachnoid-space hydrocephalus from 3D MRI using two deep learning models. [Journal/Conference Name].
- [12] [Author(s) Not Specified]. (2022). Deep learning achieves neuroradiologist-level performance in detecting hydrocephalus requiring treatment. [Journal/Conference Name].
- [13] Zhou, et al. (2022). AI-based medical e-diagnosis for fast and automatic ventricular volume measurement in patients with normal pressure hydrocephalus. [Journal/Conference Name].
- [14] Wang, Y., Feng, A., Xue, Y., et al. (2023). Automated ventricle parcellation and Evan's ratio computation in pre- and post-surgical ventriculomegaly. [Journal/Conference Name].
- [15] Vahedifard, F., et al. (2023). Automatic ventriculomegaly detection in fetal brain MRI: A step-by-step deep learning model for novel 2D-3D linear measurements. [Journal/Conference Name].