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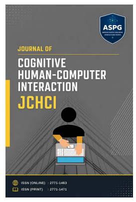

FULL LENGTH ARTICLE

Classification Segmentation and Visualization of Intracranial Hemorrhage in CT Brain Images

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ABSTRACT

Intracranial hemorrhage (ICH) poses a large chance to affected person fitness, regularly requiring set off diagnosis and intervention. In latest years, medical imaging techniques, specifically computed tomography (CT) scanning, have become critical tools for detecting and characterizing ICH. This paper offers a comprehensive review of state-of-the-art techniques for the segmentation, classification, and visualization of intracranial hemorrhage in CT brain images. The review encompasses conventional image processing strategies, machine-learning algorithms, and deep-learning strategies, highlighting their strengths, limitations, and capability applications in scientific exercise. It also discusses challenges associated with correct ICH detection and quantification, including artifacts, anatomical variations, and class imbalance. The segmented portion from each CT image is constructed into a single 3D volumetric structure and essential information such as region area, volume, and location are provided. Further, the classification accuracy between normal brain and ICH brain is 95.8%. Such 3D visualization, classification, and volumetric analysis of ICH can provide exact and necessary information to neurologists for treatment planning.

Keywords: Intracranial hemorrhage ▪ CT brain images ▪ Segmentation ▪ Classification ▪ Visualization ▪ Image processing ▪ Machine learning ▪ Medical imaging

1. INTRODUCTION

Intracranial hemorrhage (ICH) represents a critical medical condition characterized by bleeding inside the cranium. It encompasses various types, including epidural, subdural, subarachnoid, and intracerebral hemorrhages, each imparting unique challenges in prognosis and control [1, 2]. ICH can result from diverse etiologies, including trauma, vascular abnormalities, high blood pressure, coagulopathies, or underlying structural lesions. Regardless of the cause, prompt identification and precise localization of ICH are paramount for initiating timely interventions and improving patient consequences.

Medical imaging performs a pivotal function in the detection and characterization of intracranial hemorrhage. Among the available modalities, computed tomography (CT) imaging is a cornerstone in the diagnostic workflow for brain-associated pathologies. CT offers rapid acquisition, high spatial resolution, and the capability to visualize bony structures and smooth tissues with strong contrast. This makes CT especially suitable for assessing acute hemorrhagic activities in the brain and allowing clinicians to swiftly compare the extent and severity of bleeding.

Early detection of ICH is crucial for starting timely interventions, including surgical evacuation of hematomas or management of anticoagulant reversal agents that may enhance patient outcomes and reduce mortality. Correct localization and characterization of hemorrhagic lesions are essential for guiding treatment decisions and assessing prognosis. For example, distinguishing among different styles of ICH, such as traumatic versus spontaneous or intraparenchymal versus subdural hemorrhage, is crucial because management strategies may differ substantially.

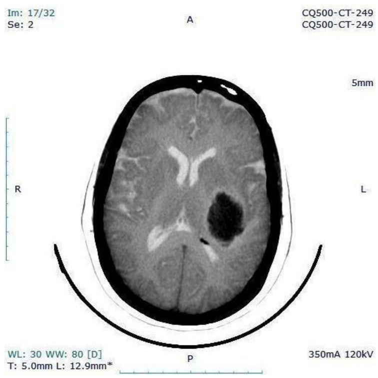


Figure 1. Intracranial hemorrhage CT brain image.

Intracranial hemorrhage is denoted as bleeding inside the skull, as demonstrated in Figure 1. It is a major cause of death and disability and is a subtype of stroke. ICH can occur spontaneously or after trauma. Spontaneous intracranial hemorrhage can be associated with different disease processes, while traumatic ICH can occur in any person who has suffered trauma. Patients on anticoagulation are at a substantially increased risk. Intracranial hemorrhage is an emergency in which rapid diagnosis is critically important because patients can deteriorate rapidly after symptom onset.

2. BACKGROUND AND RELATED WORK

Intracranial hemorrhage is a complex and potentially life-threatening condition that requires fast and correct diagnosis for suitable medical control. Researchers and clinicians have explored various methods to automate detection, segmentation, and classification of ICH lesions using medical imaging, especially CT imaging.

2.1 Previous Studies on ICH Detection, Segmentation, and Classification

Early attempts at automatic ICH detection relied on traditional image-processing strategies such as thresholding, edge detection, region growing, and morphological operations. These techniques exploit intensity differences between hemorrhagic and non-hemorrhagic tissues, but they may struggle when noise, artifacts, and anatomical variation affect the image.

Recent research has shifted toward machine learning (ML) and deep learning (DL) methods. ML algorithms, including support vector machines (SVMs), random forests, and gradient boosting machines, examine discriminative features from handcrafted descriptors and radiomic features extracted from CT images. Deep learning methods, especially convolutional neural networks (CNNs), U-Net, fully convolutional networks, and DeepLab, learn hierarchical features directly from raw image data, enabling more robust segmentation of hemorrhagic lesions [3, 4, 5, 6, 7].

2.2 Existing Methods and Barriers

Despite significant progress in automated ICH detection and analysis, several limitations persist. A common challenge is the lack of large-scale annotated datasets for training and validating machine-learning models. Public datasets may not fully capture the range of clinical scenarios encountered in practice. Another limitation is the generalizability of algorithms across imaging modalities, acquisition protocols, and patient populations. Interpretability also remains challenging for deep-learning models, which often operate as black boxes.

2.3 Advances in Clinical Imaging and Computational Strategies

Advances in clinical imaging technology have contributed to improved detection and characterization of ICH. Improvements in CT scanner hardware and acquisition strategies provide higher image quality and enable better visualization of subtle hemorrhagic regions. Meanwhile, computational strategies combine preprocessing, segmentation, classification, and visualization in integrated systems that can support clinical decision-making.

3. LITERATURE REVIEW

A wide range of approaches has been reported for hemorrhage detection, segmentation, volumetric analysis, and 3D reconstruction. Amelia et al. [8] used Otsu thresholding and morphological operations for CT-based cerebral hemorrhage volume calculation. Chan [1] studied computer-aided detection of small acute intracranial hemorrhage on CT. Dhawan et al. [2] investigated image analysis and 3D visualization of intracerebral brain hemorrhage.

Unsupervised clustering has also been used for brain CT segmentation. Lee et al. [9] explored unsupervised clustering approaches, while Ma et al. [10] optimized K-means clustering for head CT images. Singh et al. [11] proposed a hybrid fuzzy C-means and modified level-set method for hemorrhage segmentation, improving the delineation of hemorrhagic regions. Sumijan et al. [12] combined Otsu thresholding, feature-region methods, and mathematical morphology to calculate hemorrhage volume and reconstruct 3D brain hemorrhage images.

Recent work has emphasized deep learning. Guo et al. [3] proposed simultaneous classification and segmentation using a fully convolutional neural network. Hu et al. [4] used an encoder–decoder CNN for automatic intracerebral hemorrhage segmentation. Majumdar et al. [5], Patel et al. [6], and Qiu et al. [7] reported deep learning and semantic segmentation methods for hemorrhage identification in 3D non-contrast CT and head CT scans.

4. DATA ACQUISITION AND PREPROCESSING

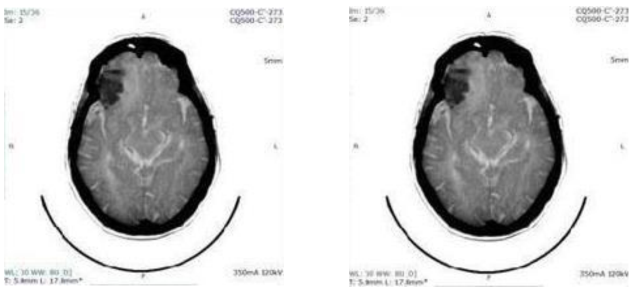
4.1 Description of the Dataset

The study leveraged a comprehensive dataset of CT brain images collected from multiple medical institutions and research repositories. The dataset was curated to include diverse instances, representing several ICH scenarios. Inclusion standards encompassed patients with acute and chronic ICH, as well as various degrees of hemorrhage severity, location, and etiology.

Each CT scan was accompanied by clinical metadata such as patient demographics, clinical history, and imaging findings including hemorrhage area and quantity. To facilitate algorithm development and assessment, the dataset was partitioned into training, validation, and testing subsets with careful attention to preserving a balanced distribution of positive and negative cases. Ground-truth annotations for hemorrhagic areas were delineated by radiologists or neuroimaging specialists and reviewed for accuracy and consistency.

4.2 Preprocessing Steps

The 2D sliced CT intracranial hemorrhage image is first represented in RGB format. Image resizing is necessary to process a fixed image size of 256×256. The resized RGB image is then converted into grayscale for image processing. The segmented portion from each CT image is constructed into a single 3D volumetric structure, and essential information such as region area, volume, and location are provided.



(a) Resized image (b) Grayscale image

Figure 2. Preprocessed CT intracranial hemorrhage image.

Figure 2(a) shows the resized image, and Figure 2(b) shows the grayscale conversion. An 8-bit grayscale image forms a matrix with values from 0 to 255, where 0 indicates black pixels and 255 indicates white pixels.

The preprocessing pipeline includes noise reduction, skull stripping, intensity normalization, and spatial resampling. Noise reduction mitigates digital noise, patient movement artifacts, and photon scatter. Skull stripping removes extracranial structures such as the cranium and soft tissues. Intensity normalization reduces variations caused by different scanners and acquisition protocols. Spatial resampling aligns voxel dimensions and orientations across the dataset.

5. SEGMENTATION OF INTRACRANIAL HEMORRHAGE

5.1 Traditional Methods

Traditional segmentation approaches for ICH rely on classical image-processing techniques. These methods typically involve thresholding, where pixels or voxels with intensity values above a threshold are classified as hemorrhagic and those below it are classified as non-hemorrhagic. Region-growing algorithms iteratively expand regions based on intensity similarity or spatial connectivity. Morphological operations such as erosion and dilation refine segmented regions and remove artifacts. The preprocessed image can be clustered by K-means, as shown in Figure 3.

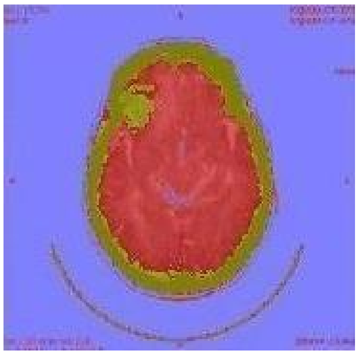
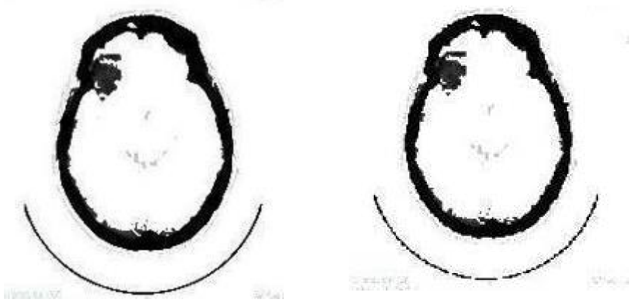


Figure 3. K-means clustered image.

Each clustered region from the K-means algorithm can contain the presence or absence of an ICH region, as shown in Figure 4. Connected components and their length values are used to select the ICH-present cluster. The length of the ICH region is smaller than the length of the absence cluster region.



(a) ICH absent region (b) ICH presented region

Figure 4. Separated clustered regions.

Figure 5. ICH-present clustered region.

The main aim is to segment the ICH region from the image. Figure 5 shows both ICH and skull components; therefore, skull components must be removed to isolate the hemorrhagic region accurately.

5.2 Machine-Learning and Deep-Learning Approaches

Machine-learning approaches use handcrafted features such as intensity, texture, shape, and spatial information extracted from CT images. These features can be classified by SVMs, random forests, or related algorithms. Deep-learning techniques learn discriminative representations directly from images. CNN-based segmentation frameworks can capture spatial context and have shown strong performance for heterogeneous lesion appearances and variable imaging protocols.

5.3 Evaluation Metrics for Segmentation

Segmentation quality can be assessed with overlap, detection, and boundary metrics. The Dice similarity coefficient (DSC) is defined as

$$\mathrm{DSC} = \frac{2\,|A \cap B|}{|A| + |B|}, \tag{1}$$

where A is the predicted mask and B is the ground-truth mask. The Jaccard index, or intersection over union (IoU), is

$$\mathrm{IoU} = \frac{|A \cap B|}{|A \cup B|}. \tag{2}$$

Sensitivity and specificity are calculated as

$$\text{Sensitivity} = \frac{TP}{TP+FN}, \qquad \text{Specificity} = \frac{TN}{TN+FP}. \tag{3}$$

Accuracy and precision are expressed as

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \tag{4}$$

$$\text{Precision} = \frac{TP}{TP+FP}. \tag{5}$$

Hausdorff distance quantifies the maximum distance between corresponding points in predicted and ground-truth masks, providing a measure of spatial discrepancy.

Table 1. Segmentation and classification metrics used for ICH analysis.

Metric	Purpose
Dice similarity coefficient	Overlap between predicted and ground-truth masks
Jaccard index / IoU	Normalized intersection of two masks
Sensitivity	Correct detection of hemorrhagic pixels or cases
Specificity	Correct identification of non-hemorrhagic pixels or cases
Accuracy	Overall correctness of segmentation or classification
Precision	Reliability of positive predictions

6. CLASSIFICATION OF INTRACRANIAL HEMORRHAGE

6.1 Classification Algorithms

SVM is a supervised learning algorithm that is effective for classification tasks, particularly in high-dimensional spaces. It works by finding the hyperplane that best separates different classes while maximizing the margin between them. SVMs can handle linear and non-linear classification problems through kernel functions. The aim is to create the best line or decision boundary that separates the n-dimensional space into classes, as illustrated in Figure 6.

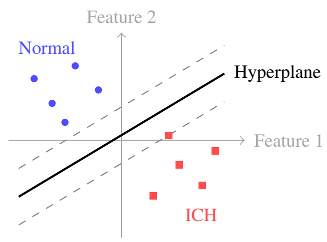


Figure 6. SVM hyperplane separating normal and ICH classes.

Random forest is an ensemble learning method that builds multiple decision trees during training. Each tree is trained on a random subset of the data and selects a random subset of features at each node. The final classification is determined by aggregating predictions of individual trees. CNNs are deep-learning models designed for images. They use convolutional layers to learn hierarchical feature representations, pooling layers to reduce spatial dimensions, and fully connected layers for classification [13, 14].

6.2 Feature Extraction and Selection

Traditional feature extraction methods manually compute features such as texture, intensity, or shape from images. These features capture information related to hemorrhage characteristics. With CNNs, features are learned automatically from raw pixel values. Convolutional layers extract simple patterns such as edges and progressively learn complex structures such as shapes and textures.

6.3 Performance Evaluation Metrics

Classification is evaluated using accuracy, precision, recall, specificity, F1 score, ROC curve, AUC, and confusion matrix. Accuracy measures the proportion of correctly classified samples. Precision measures the proportion of true positives among predicted positives, while recall measures the proportion of true positives correctly identified. The F1 score balances precision and recall:

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{6}$$

The confusion matrix summarizes true positive, false positive, true negative, and false negative predictions.

7. VISUALIZATION TECHNIQUES

7.1 2D Visualization Techniques

Overlay maps place color-coded masks on original CT images to visualize hemorrhage regions. Heatmaps use color gradients to indicate hemorrhage intensity or probability at each pixel. Contour drawing delineates hemorrhage boundaries, supporting precise localization and volume measurement. Slice-by-slice visualization enables detailed examination of hemorrhage morphology and relationships with surrounding structures.

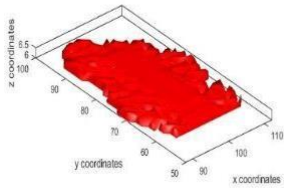
7.2 3D Visualization Techniques

Surface rendering generates 3D surface models of the skull and brain, with hemorrhage regions highlighted to provide spatial understanding of location and extent. Volume rendering displays the entire CT volume with different opacity levels assigned to hemorrhage regions. Concatenated images can be visualized as a 3D image using an isosurface method, as shown in Figure 7.

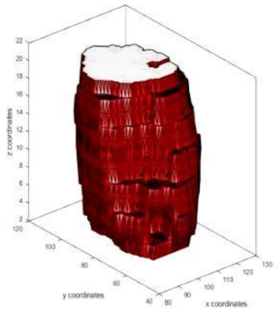
3D slice stacks display consecutive CT slices in a stack format, offering a volumetric view of hemorrhage distribution. Isosurface extraction identifies and renders surfaces in the CT volume that represent hemorrhage regions, supporting surgical planning and treatment evaluation.

7.3 Tools and Software for Visualization

Visualization can be performed with 3D Slicer, ITK-SNAP, OsiriX, ImageJ/FIJI, MATLAB, and Python libraries. These



(a) Isosurface 3D visualization



(b) Faces and vertices representation

Figure 7. 3D visualization using isosurface.

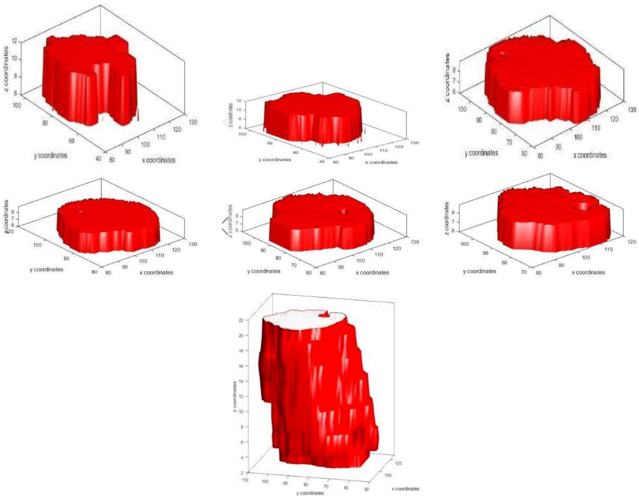


Figure 8. 3D visualization of ICH slices with 3 mm thickness.

tools provide medical image visualization, segmentation, volume rendering, plugin-based analysis, and custom workflows for automated hemorrhage detection and visualization. They support analysis of hemorrhage morphology, localization, and distribution.

8. INTEGRATION AND PERFORMANCE EVALUATION

8.1 Integration of Segmentation and Classification Methods

In medical imaging, integration of segmentation and classification methods plays a pivotal role in automating the analysis of complex structures such as ICH. Segmentation algorithms delineate regions of interest, while classification methods analyze these regions to determine hemorrhage type and severity. By combining segmentation and classification, clinicians gain detailed insight into the nature and extent of hemorrhage.

The system classifies two classes: grayscale normal CT brain images and ICH brain images. The gray-level co-occurrence matrix is used as a statistical method to calculate texture features of the segmented image. Twenty different feature values from each image are used as input to an SVM classifier. The scatter plot in Figure 9 provides a graphical representation of two features between two classes.

A confusion matrix is a performance measurement for the SVM classifier when the output has two or more classes, as shown in Figure 10. The reported classification accuracy between normal brain and ICH brain is 95.8%.

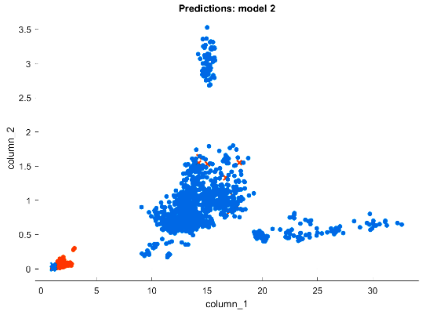


Figure 9. Scatter plot.

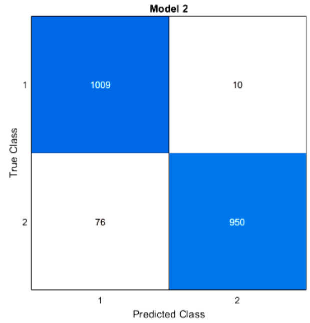


Figure 10. Confusion matrix.

8.2 Evaluation of the Combined System's Performance

Assessing the performance of an integrated system is crucial for validating its efficacy in clinical practice. Sensitivity measures the system's ability to correctly identify positive cases of ICH, ensuring that no true cases are missed. Specificity assesses accuracy in identifying negative cases and minimizing false alarms. Accuracy provides an overall measure of correctness. The Dice similarity coefficient quantifies agreement between segmentation results and ground-truth annotations.

8.3 Comparative Analysis with Existing Approaches

Traditional machine-learning methods such as SVMs and random forests have been widely used for ICH detection. Deep-learning techniques, particularly CNNs, have also shown promising results. Comparative analysis evaluates computational efficiency, accuracy, robustness to noise, and generalization to unseen data. Benchmarking against established methods shows the potential clinical impact of the integrated system and identifies directions for refinement.

9. CONCLUSION

Thus, intracranial hemorrhage CT brain images can be digitally acquired, segmented, classified, visualized in 3D, and analyzed volumetrically. ICH segmentation for all 2D slices from a single CT scan is performed using K-means clustering. Classification is then performed with an SVM classifier, and 3D visualization is proposed using an isosurface technique. These processes can be implemented using MATLAB.

The achieved results show that the proposed system provides effective segmentation and 3D visualization and can determine the area, volume, and depth of occurrence efficiently. The resultant output helps doctors determine hemorrhage type and depth of occurrence. Moreover, an easy tool that aids the surgeon in taking the proper course of action may support better therapeutic planning and reduced mortality.

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