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 modern requiring set off diagnosis and intervention. In latest years, the medical imaging techniques, specifically computed tomography (CT) scanning, have end up critical tools for detecting and characterizing ICH. This paper offers a complete evaluate comprehensive review of the state-of-the-art techniques for the segmentation, category, and visualization cutting-edge intracranial hemorrhage in CT mind pics. The evaluate encompasses numerous methodologies, consisting of conventional picture processing strategies, system cutting-edge algorithms, and deep brand new strategies, highlighting their strengths, limitations, and capability applications in scientific exercise. Additionally, it discusses the challenges associated with correct ICH detection and quantification, inclusive of the presence modern day artifacts, anatomical variations, and sophistication imbalance. Furthermore, the paper explores emerging tendencies in ICH research, which includes the combination trendy multimodal imaging information and the improvement trendy interactive visualization gear for enhanced medical choice-making. 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 a 3D visualization, Classification and volumetric analysis of ICH can provide the exact and necessary information to the neurologist which is essential for the treatment of ICH.

Keywords: Intracranial hemorrhage; CT mind images; Segmentation; Class; Visualization; photograph processing; Machine brand new; Deep modern day; Scientific imaging; Medical choice-making

1. Introduction

Intracranial hemorrhage (ICH) represents a critical medical condition characterized by bleeding inside the cranium. It encompasses various types, which includes epidural, subdural, subarachnoid, and intracerebral hemorrhages, each imparting unique challenges in prognosis and control [2-3]. ICH can end result from diverse etiologies, consisting of trauma, vascular abnormalities, high blood pressure, coagulopathies, or underlying structural lesions. No matter the underlying reason, prompt identification and precise localization of ICH are paramount for initiating timely interventions and improving affected person consequences.

Medical imaging performs a pivotal function in the detection and characterization of intracranial hemorrhage. Among the modalities to be had, Computed Tomography (CT) imaging sticks out as a cornerstone in the diagnostic workflow for brain-associated pathologies. CT offers numerous blessings over other imaging modalities, which includes rapid acquisition instances, high spatial

DOI: https://doi.org/10.54216/JCHCI.090103
Received: November 03, 2024 Revised: December 17, 2024 Accepted: January 14, 2025

decision, and the capability to visualize each bony structures and smooth tissues with incredible assessment decision. This makes CT especially properly-suitable for assessing acute hemorrhagic activities in the mind, allowing clinicians to swiftly compare the extent and severity of bleeding.

The importance of early detection and correct analysis of ICH cannot be overstated. Behind schedule or overlooked prognosis may lead to devastating outcomes, including neurological deficits, everlasting disability, or maybe demise. Consequently, developing dependable and efficient methods for the segmentation, category, and visualization of intracranial hemorrhage in CT brain snap shots is of extreme importance.

Early detection of ICH is crucial for starting up timely interventions, inclusive of surgical evacuation of hematomas or management of anticoagulant reversal dealers that could substantially enhance affected person consequences and reduce mortality charges. Moreover, correct localization and characterization of hemorrhagic lesions are essential for guiding remedy decisions and assessing analysis. As an example, distinguishing among exceptional styles of ICH (e.g., disturbing vs. Spontaneous, or intra parenchymal vs. Subdural) is crucial, as their management strategies can also differ drastically.

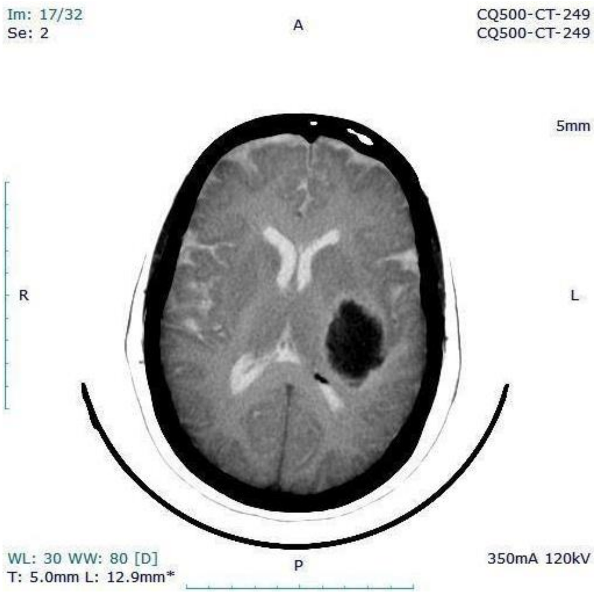

Figure 1. Intracranial hemorrhage CT brain image

Intracranial hemorrhage is denoted as bleeding inside the skull, as demonstrated in Figure 1. Intracranial hemorrhage is a most cause factor of death and disability and is a subtype of stroke. Intracranial hemorrhage can occur impulsively or in the locating of trauma. Spontaneous intracranial hemorrhage can be associated with a different process of diseases. Traumatic intracranial hemorrhage can happen to any person who has suffered trauma, but patients on anticoagulation are at a substantially increased risk of intracranial hemorrhage. Intracranial hemorrhage is an emergency with rapid diagnosis critically important to improve patient outcomes as patients often deteriorate rapidly within the initial onset of symptoms.

2. Background and Related Work

Intracranial hemorrhage (ICH) is a complex and doubtlessly life-threatening situation that requires fast and correct diagnosis for suitable scientific control. Over the years, researchers and clinicians have explored various methods to automate the detection, segmentation, and type of ICH lesions the use of medical imaging strategies, specifically computed tomography (CT) imaging.

A. Previous Studies on ICH detection, Segmentation, and Category:

Early tries at automatic ICH detection relied closely on traditional picture processing strategies, together with thresholding, edge detection, and morphological operations. At the same time as those techniques supplied a foundation for automatic evaluation, they regularly struggled with as it should

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be segmenting hemorrhagic lesions, mainly inside the presence of noise, artifacts, and anatomical versions.

In current years, there was a paradigm shift in the direction of machine studying (ML) and deep gaining knowledge of (DL) methods for ICH detection and evaluation. ML algorithms, which includes aid vector machines (SVM), random forests, and gradient boosting machines (GBM), had been employed to examine discriminative functions from handmade descriptors and radiomic features extracted from CT pix. Even as those methods have shown promising consequences, they frequently depend on predefined characteristic sets and might conflict with capturing the complex spatial relationships inside ICH lesions.

Deep mastering techniques, exactly convolutional neural networks (cnns), have emerged as effective gear for computerized clinical picture analysis, together with ICH detection and segmentation. CNN architectures, which includes U-internet, completely Convolutional Networks (fcns), and deeplab, have validated top notch skills in learning hierarchical features without delay from raw image information, enabling accurate and robust segmentation of hemorrhagic lesions. These DL-primarily based processes have proven superior overall performance as compared to conventional strategies, mainly in challenging eventualities with heterogeneous lesion traits and variable imaging protocols.

B. Existing methods and their barriers:

Despite the good sized development in automated ICH detection and analysis, several limitations persist. One commonplace challenge is the lack of massive-scale annotated datasets for schooling and validating system mastering fashions. Even as efforts were made to create publicly to be had datasets, which includes the RSNA Intracranial Hemorrhage Detection assignment dataset, those datasets may not completely capture the range of clinical eventualities encountered in real-world practice.

Every other hassle is the generalizability of present algorithms throughout exclusive imaging modalities, acquisition protocols, and patient populations. Many algorithms are skilled and evaluated on datasets from precise establishments or imaging protocols, also which can limit their applicability to other settings. Moreover, the interpretability of deep studying fashions stays a task, as those fashions often function as "black containers," making it difficult to apprehend the underlying choice-making method.

C. Advances in Clinical Imaging Generation and Computational Strategies:

Latest advances in clinical imaging generation have contributed to advanced detection and characterization of intracranial hemorrhage. Improvements in CT scanner hardware, inclusive of twin-power CT and iterative reconstruction strategies, have led to enhancements in picture high-quality, assessment decision, and artifact discount. Those improvements have facilitated the visualization of diffused hemorrhagic lesions and stepped forward the accuracy of automated detection algorithms.

At the computational the front, trends in deep gaining knowledge of architectures and education methodologies have improved development in automated ICH detection and segmentation. Switch mastering strategies, together with excellent-tuning pre-trained fashions on area-specific information, have enabled speedy improvement of high-performance models with constrained annotated information. Moreover, the integration of multimodal imaging information, along with CT perfusion, diffusion-weighted imaging (DWI), and magnetic resonance imaging (MRI), holds promise for enhancing the sensitivity and specificity of automatic ICH detection algorithms.

3. Literature Review

Danfeng Guo et al (2020) proposed that total of 1176 head CT scans were collected from the hospitals, with 581 ICH patients and 595 normal subjects. Each slicein these head CT images has a size of 512_512 pixels [4]. Divided the dataset into a random sample of 706 subjects for training, 235 for validation and 235 for testing, 3D/2D resnet18 and 3D U- Net were used as subject-level/slice-level classification task and segmentation task baseline models, respectively. Additionally, performed ablation experiments by evaluating the performance of: ichnet for the classification tasks only without the segmentation branch (ichnetcls), ichnet for the segmentation task only without classification branch (ichnetseg), ichnet without attention blocks. They used five metrics (accuracy, sensitivity, specificity, F1 score, and area under the curve (AUC)) to evaluate models' performance for the classification tasks, and used dice coefficient as the evaluation metric for the segmentation task. Multi-

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task ichnet generally outperforms the baseline models (3D/2D resnet18 for classification and 3D U-Net for seg) as well as single-task ichnet models (ichnetcls and ichnetseg) across all metrics. It should be also noted that the single-task ichnet model's performance is still notably better than the corresponding baseline model, indicating that convlstm module can be a more efficacious approach in capturing sequential information than directly utilizing 3D convolution. For the seg task, the use of attention mechanism also brings additional performance improvement but not as substantial as adding the class branch.

Kai Hu et al (2020) Focused on deep neural networks in order to segment ICH regions. Also they developed an encoder-decoder convolutional neural network (ED-Net) architecture to extract and integrate the multi-scale semantic feature and unified ICH feature respectively [5].

Pankaj Singh et al (2018) developed that a Diagnosis of haemorrhage is major task for the physicians because of vital mortality rate. This paper proposed a method for segmentation of intracranial haemorrhage on CT images [13]. In this proposed method tried to improve the accuracy of haemorrhage diagnosis, which can save lives of patients. To achieve this object a hybrid method of FCM and MDRLSE is used for the segmentation of intracranial haemorrhage. FCM clustering is used for initialization of level set function in MDRLSE. Experimental results of ICH segmentation show that proposed hybrid method is much accurate for the segmentation of hemorrhagic regions [6-7]. The results of ICH segmentation cooperate well with the expert's measurements. Doctors in clinical can use this proposed method for the diagnosis of haemorrhage.

Sumijan et al (2017) proposed this research provides a method for segmentation, extraction and 3D reconstruction image of the incision [14]. Merger Otsu method, feature region and Morphological can generate several things including: Algorithm cropping elliptical proposed models can accurately separate area of the skull and the brain from other areas in the image of a CT scan. These results greatly facilitate and accelerate the process of extraction of haemorrhage in the brain area. Combined Otsu method, the search and removal of objects as well as the area of mathematical morphology is very effective in segmenting and extracting areas of bleeding in the brain. Otsu algorithm is used to detect and Segmentation areas of brain haemorrhage and other areas that have a high intensity value. Search algorithm is developed to determine the position and area of each white area of Otsu algorithm results. Removal algorithm is used to identify and eliminate areas that are not part of the area Haemorrhage, so what is left is only the bleeding area. Mathematical morphology algorithm used to cover parts of the bleeding area lost by previous processes [8-9]. The area and volume calculation algorithm can calculate the area of a cerebral haemorrhage per slice and the volume of the entire slice through 3D reconstruction bleeding area. 3D reconstruction algorithm used brain haemorrhage area is referring to the algorithm linear interpolation between two adjacent slices.

Ameli et al (2017) proposed a Haemorrhage is seen from the image of the head scan, furthermore the image segmentation of head using the method of otsu. Otsu is one of the thresholding method [1]. The purpose of the linear method is to divide its gray level of graphic histogram into the two differences of regions automatically without the need of user's help to enter the threshold value. The Segmentation processes are performed by using the MATLAB code and the image used for segmentation is a CT scan image. CT head image with haemorrhage on slice 26 until slice 37 before segmentation [10-11]. The result of segmentation of otsu method can separate object with its background, that is brain haemorrhage and brain [12]. The next step is followed by morphological operations to improve the segmentation results and eliminate the noise and eliminate the undesirable area.

The result of segmentation with otsu method and morphological operation is binary image. The binary image is used for calculating the area of haemorrhage in the brain by summing all white objects with pixels of value is 1. The total area value obtained is still in pixel units, so as to convert it into mm2 units, then the result is divided by image spatial resolution is 2,7380 pixels/mm. The head image in brain haemorrhage can be well segmented, and to know the region and area of haemorrhage segmented can be seen from the visualization of the segmentation. Conclude that the use of otsu method and morphological operation for image segmentation process can be well implemented. The head image along with segmentation will help to enhance the performance of measuring the region of haemorrhage foe better visualization and segmentation. The output of Otsu method provides clarity of the process through the morphological operation which is implemented in this system.

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4. Data Acquisition and Preprocessing

A. Description of the Dataset:

Our look at leveraged a complete dataset inclusive of CT brain photographs amassed from more than one scientific establishments and research repositories. The dataset turned into meticulously curated to encompass a diverse array of instances, making sure a broad representation of intracranial hemorrhage (ICH) eventualities. The inclusion standards encompassed sufferers with each acute and continual ICH, in addition to various tiers of hemorrhage severity, place, and etiology.

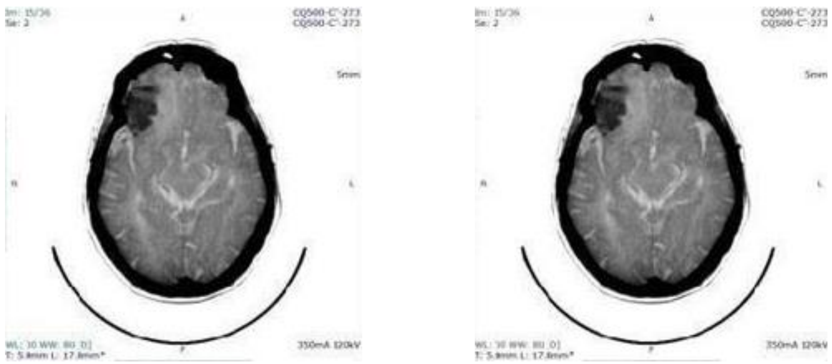
Each CT scan inside the dataset changed into followed through distinctive clinical metadata, such as patient demographics (age, gender), applicable clinical history (e.g., presence of hypertension, anticoagulant use), and pertinent imaging findings (e.g., hemorrhage area, quantity). Furthermore, to facilitate algorithm improvement and assessment, the dataset changed into partitioned into distinct subsets for schooling, validation, and testing, with careful attention given to preserving a balanced distribution of fantastic and negative instances throughout the subsets.

Floor truth annotations for hemorrhagic areas within the CT snap shots were meticulously delineated by using board-certified radiologists or neuroimaging specialists. Those annotations have been meticulously reviewed and established to make sure accuracy and consistency across the dataset. Special interest was paid to appropriately shooting the quantity and barriers of hemorrhagic lesions, accounting for variations in lesion morphology, size, and imaging characteristics.

Stringent measures have been undertaken to make sure affected person privacy and compliance with moral hints governing the usage of medical imaging data in studies. All affected person identifiers have been anonymized, and institutional evaluation board (IRB) approval changed into received in which relevant.

B. Preprocessing Steps:

2D sliced CT Intracranial haemorrhage image in RGB format. Image resizing is necessary to process a image and fix unique size of (256x256). Further the resized RGB image can be converted in to Gray scale image for performing 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. Further the classification accuracy between normal brain and ICH brain is 95.8%.



(a) Resized image (b) Grayscale image

Figure 2. Pre processed CT Intracranial hemorrhage

Image shown in Figure 2(a) can be resize into (256x256). Resized image in RGB can be converted into gray scale image shown in figure 2(b). Grayscale image being represented in 8-bit will form a matrix, the range of values can be of anything between 0 to 255. 0 specifies the black pixels parameter and 255 indicates the white pixels term and in between different shades of black to white will arise.

Prior to undertaking picture evaluation obligations, a series of preprocessing steps have been employed to standardize and decorate the excellent of the CT brain photographs:

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a. Noise reduction: CT pix are inherently susceptible to noise bobbing up from various sources, consisting of digital noise, affected person movement artifacts, and photon scatter. To mitigate these assets of noise, advanced denoising algorithms, including iterative reconstruction strategies or adaptive filtering techniques, were carried out to the uncooked CT pics. Those algorithms effectively suppressed noise whilst keeping crucial photograph features and information.
b. Cranium Stripping: The presence of extracranial systems, which include the cranium and soft tissues, can introduce confounding factors in automatic image analysis duties. To deal with this, robust cranium stripping algorithms have been employed to section the intracranial region from the encircling non-brain tissues.
c. Those algorithms applied superior morphological operations, depth thresholding, and location developing strategies to as it should be delineating the brain parenchyma at the same time as with the exception of extraneous structures.
d. Depth Normalization: CT pix acquired from exclusive scanners or imaging protocols may exhibit variations in intensity values, main to inconsistencies in picture look and contrast. To standardize the intensity traits throughout the dataset, intensity normalization techniques had been carried out. This worried rescaling the depth values to a commonplace range or employing histogram equalization strategies to align the depth distributions of the pictures.
e. Spatial Resampling: CT images frequently show off variations in voxel dimensions and orientations, that could impact the performance of subsequent picture evaluation algorithms. To make sure uniformity in voxel spacing and alignment across the dataset, spatial resampling techniques have been applied.

This concerned interpolating the photo voxels to reap isotropic voxel dimensions and constant orientation along the x, y, and z axes. By using carefully imposing these preprocessing steps, we aimed to optimize the CT pix for next analysis, ensuring strong and reproducible effects in computerized ICH detection, segmentation, and characterization responsibilities. Furthermore, those preprocessing measures have been vital for minimizing artifacts, enhancing image quality, and facilitating the development of clinically relevant picture analysis algorithms.

5. Segmentation of Intracranial Hemorrhage

A. Traditional Methods:

Traditional segmentation approaches for intracranial hemorrhage often rely on classical image processing techniques. These methods typically involve thresholding, where pixels or voxels with intensity values above a certain threshold are classified as hemorrhagic, and those below are classified as non-hemorrhagic. Region growing algorithms iteratively expand regions based on predefined criteria, such as intensity similarity or spatial connectivity. Additionally, morphological operations, such as erosion and dilation, are employed to refine the segmented regions and remove artifacts. The Pre-processed image can be cluster by using K-means cluster. The clustered image is shown in the Figure 3.

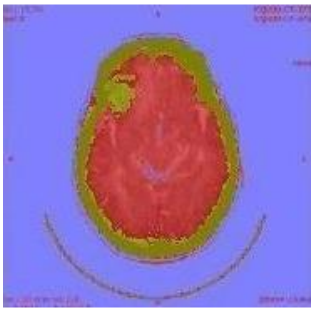

Figure 3. K means clustered image

Separate each clustered region from k means algorithm contains presence of ICH region and absence of ICH region shown in Figure 4.

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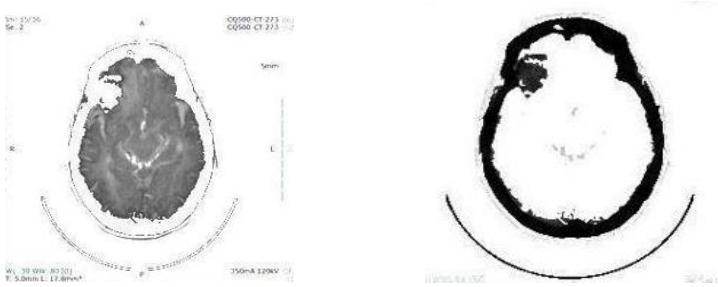

(a)ICH absent region (b) ICH presented region

Figure 4. Separated a Clustered region

From the separated clustered region using the connected components and its length value to select the ICH present clustered region is shown in Figure 5. Length of ICH region is less than the length of absence of ICH cluster region.

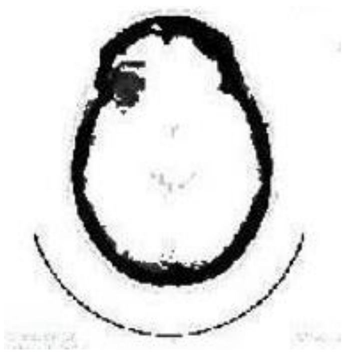

Figure 5. ICH present clustered region

Main aim is to segment a ICH region from the image. In Fig 5 image shows both ICH as well as Skull components. Need to remove the Skull region for efficient segmentation by using connected components. Skull region identify by using thresholding method.

B. Machine Learning (ML) Approaches:

Machine learning-based segmentation techniques leverage statistical learning algorithms to automatically identify and delineate intracranial hemorrhage regions within CT images. Supervised ML methods, such as support vector machines (SVM) and random forests, learn discriminative features from annotated training data to classify pixels or voxels as belonging to hemorrhagic or non-hemorrhagic regions. Unsupervised ML techniques, such as k-means clustering, partition the image into clusters based on feature similarity, with hemorrhagic regions emerging as distinct clusters.

C. Deep Learning (DL) Techniques:

Deep learning-based segmentation methods have emerged as state-of-the-art approaches for segmenting intracranial hemorrhage from CT images. Convolutional neural networks (CNNs) are particularly well-suited for this task due to their ability to learn hierarchical features directly from raw image data. Architectures like U-Net, Fully Convolutional Networks (FCNs), and DeepLab employ encoder-decoder structures to capture contextual information and generate pixel-wise segmentation masks [15-16]. DL-based approaches offer superior performance compared to traditional methods, as they can handle complex lesion morphologies and variations in imaging characteristics.

D. Evaluation Metrics Used for Assessing Segmentation Accuracy:

The DSC measures the spatial overlap between the predicted and ground truth segmentation masks. It is calculated as twice the intersection of the predicted and ground truth masks divided by the sum of their sizes. A DSC value of 1 indicates perfect overlap, while lower values indicate poorer segmentation accuracy.

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E. Jaccard Index (JI) or Intersection over Union (IoU):

The Jaccard Index (also known as IoU) measures the overlap between the predicted and ground truth segmentation masks, normalized by their union. It is calculated as the intersection of the predicted and ground truth masks divided by the union of the two masks. Similar to DSC, higher values indicate better segmentation performance.

F. Sensitivity and Specificity:

Sensitivity (true positive rate) measures the proportion of true hemorrhagic pixels or voxels correctly identified by the segmentation algorithm, while specificity (true negative rate) measures the proportion of true non-hemorrhagic pixels or voxels correctly identified. These metrics provide insights into the algorithm's ability to detect both positive and negative instances.

H. Accuracy and Precision:

Accuracy measures the overall correctness of the segmentation results, while precision measures the proportion of true positive predictions among all positive predictions. These metrics offer a comprehensive assessment of segmentation performance, considering both true positive and true negative instances.

I. Hausdorff Distance:

Hausdorff distance quantifies the maximum distance between corresponding points in the predicted and ground truth segmentation masks. It provides a measure of spatial discrepancy between the two masks, with lower values indicating better alignment and agreement. Hausdorff distance is particularly useful for evaluating spatial accuracy of segmentation algorithm.

By utilizing these evaluation metrics, researchers can quantitatively assess the performance of segmentation algorithms and compare their accuracy and robustness across different methodologies and datasets. Additionally, these metrics provide valuable insights into the strengths and limitations of segmentation algorithms, guiding further improvements and refinements in automated ICH detection and analysis.

6. Classification of Intracranial Hemorrhage

A. Classification Algorithms:

Support Vector Machine (SVM): 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 using different kernel functions.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that easily put the new data point in the correct category in the future. The best decision boundary is called a hyperplane shown in figure 6.

Random Forest: 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 for splitting at each node. The final value of classification is determined by aggregating the predictions of individual trees, often through voting or averaging.

Convolutional Neural Network (CNN): CNNs are deep learning models specifically designed for processing structured grid-like data, such as images [17-18]. They consist of convolutional layers that learn hierarchical representations of the features directly from input images. The Pooling layers being used to reduce spatial dimensions, and fully connected layers at the end will perform final classification based on its learned features.

B. Feature Extraction Methods and Feature Selection Techniques:

Handcrafted Features: Traditional feature extraction methods involve manually defining and computing specific features from the images, such as texture, intensity, or shape features. These features are often designed to capture relevant information related to the underlying characteristics of intracranial hemorrhage.

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Deep Learning-based Features: With CNNs, features are learned automatically from the raw pixel values of the images. Convolutional layers extract hierarchical representations of features, starting from simple patterns (e.g., edges) to more complex and abstract features (e.g., shapes, textures). These learned features are highly informative for classification tasks and often outperform handcrafted features.

C. Performance Evaluation Metrics for Classification Accuracy:

Accuracy: Accuracy measures the proportion of correctly classified samples out of the total number of samples. It provides an overall assessment of the classifier's performance.

Precision and Recall: Precision measures the proportion of true positive samples among all samples classified as positive, while recall (also known as sensitivity) measures the proportion of true positive samples that were correctly identified. These metrics are particularly useful when dealing with imbalanced datasets.

Specificity: Specificity measures the proportion of true negative samples that were correctly identified. It is especially important in medical applications to ensure that healthy cases are not misclassified as diseased. The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the classifier's performance, especially in situations where precision and recall have contrasting values.

Receiver Operating Characteristic (ROC) Curve and Area under the Curve (AUC): ROC curves visualize the trade-off between sensitivity and specificity across different threshold values. AUC quantifies the classifier's ability to distinguish between classes, with higher values indicating better performance.

Confusion Matrix: A confusion matrix summarizes the performance of a classification algorithm by tabulating the true positive, false positive, true negative, and false negative predictions.

These performance evaluation metrics provide a comprehensive understanding of the classification model's effectiveness in distinguishing between different classes of intracranial hemorrhage. By analyzing these metrics, researchers and clinicians can assess the strengths and weaknesses of the classification methods and make informed decisions about their applicability in clinical practice.

7. Visualization Techniques

A. 2D Visualization Techniques:

- Overlay Maps: Overlaying color-coded maps onto the original CT images allows for a straightforward visualization of hemorrhage regions. Different colors may represent different types or severity of hemorrhage.
- Heatmaps: Heatmaps utilize color gradients to indicate the intensity or probability of hemorrhage at each pixel. This method provides a visual representation of the distribution and extent of hemorrhage within the brain. Drawing contours around hemorrhage regions helps delineate their boundaries, aiding in precise localization and measurement of hemorrhage volume.
- Slice-by-Slice Visualization: Viewing individual CT slices with annotated hemorrhage regions enables detailed examination of hemorrhage morphology and its relationship with surrounding structures.

B. 3D Visualization Techniques:

- Surface Rendering: Generating 3D surface models of the skull and brain, with hemorrhage regions highlighted, provides an intuitive spatial understanding of hemorrhage location and extent.
- Volume Rendering: Rendering the entire CT volume with different opacity levels assigned to hemorrhage regions allows for a transparent visualization of surrounding tissues, facilitating the assessment of hemorrhage location in relation to adjacent anatomical structures. Concatenated image can be visualized in 3D image using Iso surface shown in Figure 7.

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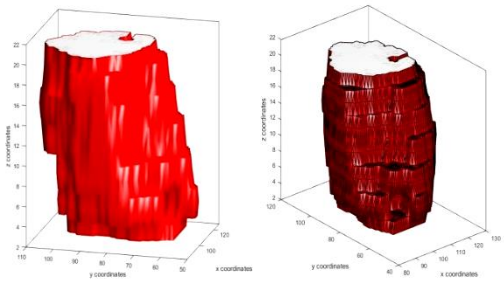
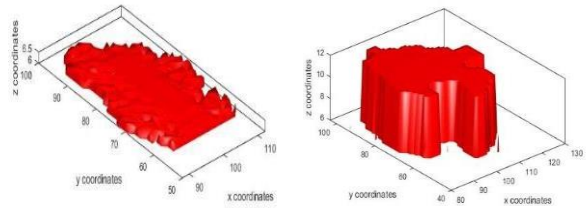


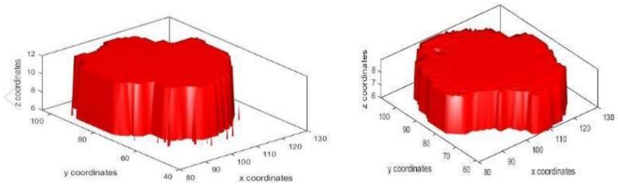
(a) Iso surface 3D visualization (b) Faces and Vertices Representation

Figure 7. 3D visualization using Iso surface

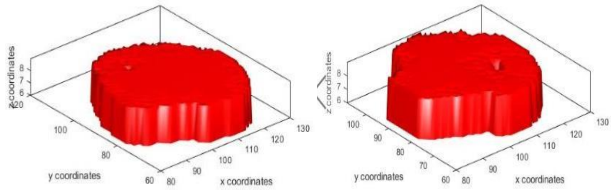
- 3D visualization of each slice with 3mm Thickness shown in Figure 8



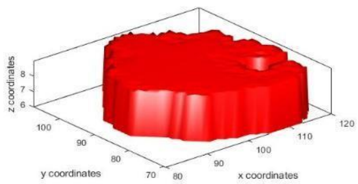
(a)ICH Slice 1 in 3D (b) ICH Slice 2 in 3D



(c)ICH Slice 3 in 3D (d) ICH Slice 4 in 3D



(e) ICH Slice 5 in 3D (f) ICH Slice 6 in 3D



(g) ICH Slice 7 in 3D

Figure 8. 3D Visualization of ICH slice with 3mm Thickness

- 3D Slice Stacks: Displaying consecutive CT slices in a 3D stack format offers a volumetric view of hemorrhage distribution, enabling clinicians to navigate through the volume and examine hemorrhage morphology from different perspectives.
- Isosurface Extraction: Identifying and rendering surfaces within the CT volume that represent hemorrhage regions offers a clear visualization of the spatial distribution of hemorrhage, aiding in surgical planning and treatment evaluation.

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C. Tools and Software for Visualization:

- 3D Slicer: This open-source software platform provides extensive tools for medical image visualization and analysis. It supports a variety of visualization techniques and enables customization to meet specific clinical needs.
- ITK-SNAP: Open-source software, ITK-SNAP specializes in segmentation and visualization of medical images. It offers intuitive tools for delineating hemorrhage regions and provides advanced visualization options.
- OsiriX: Widely used in the medical community, OsiriX is comprehensive software for MacOS that offers advanced visualization capabilities for CT, MRI, and other imaging modalities. It enables interactive exploration of CT volumes and facilitates the identification of hemorrhage regions.
- ImageJ/FIJI: These open-source software packages offer a wide range of image processing and analysis tools, including plugins for medical image visualization. They provide flexibility and extensibility for custom visualization workflows.
- MATLAB: MATLAB is a powerful tool for medical image processing and visualization. With built-in functions and toolboxes, it allows for the development of custom visualization techniques and integration with other analysis tools.
- Python Libraries: Python libraries such as SimpleITK, PyRadiomics, and PyVista offer capabilities for medical image visualization and analysis. They provide a flexible and efficient platform for developing custom visualization solutions and integrating with deep learning frameworks for automated hemorrhage detection and visualization.

These visualization techniques and tools are essential for interpreting CT brain images and aiding clinicians in the accurate diagnosis and treatment of intracranial hemorrhage. They enable detailed analysis of hemorrhage morphology, localization, and distribution, ultimately improving patient care and outcomes.

8. Integration AND Performance Evaluation

A. Integration of Segmentation and Classification Methods:

In medical imaging, the integration of segmentation and classification methods plays a pivotal role in automating the analysis of complex structures like intracranial hemorrhages (ICH). Segmentation algorithms delineate regions of interest within images, outlining potential areas of hemorrhage. These regions, however, lack context regarding the type or severity of hemorrhage. This is where classification methods come in. They analyze the segmented regions, discerning nuances like the type (e.g., epidural, subdural) and severity (e.g., mild, moderate, severe) of hemorrhage. Integrating these methodologies ensures a comprehensive understanding of ICH cases. For instance, a segmented region might indicate the presence of hemorrhage, but without classification, its clinical significance remains uncertain. By combining segmentation and classification, clinicians gain detailed insights into the nature and extent of hemorrhage, aiding in accurate diagnosis and treatment planning.

- Classification is a technique that classifies the two-class such as Grayscale normal CT brain image and ICH brain image.
- Gray Level Co-occurrence Matrix is a statistical method that calculates Texture Feature of the segmented image.
- Acquired 20 different Feature's value of each image to be input for Support Vector Machine (SVM) classifier.
- Scatter plot is a graphical representation as well as classification of two Features between two classes shown in Figure 9.

DOI: https://doi.org/10.54216/JCHCI.090103
Received: November 03, 2024 Revised: December 17, 2024 Accepted: January 14, 2025

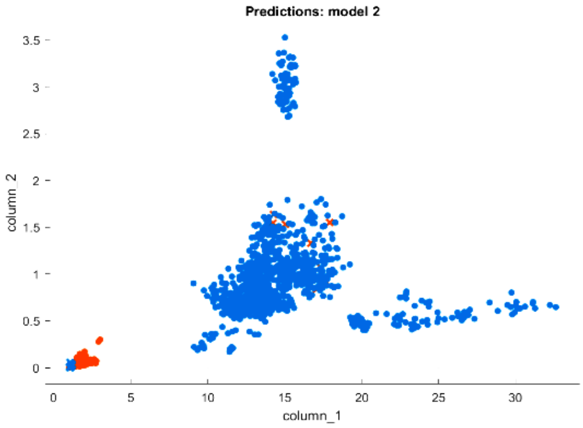

Figure 9. Scatter plot

- Confusion matrix shown Figure 10 is a performance measurement for Support Vector Machine Classifier where output can be two or more classes.

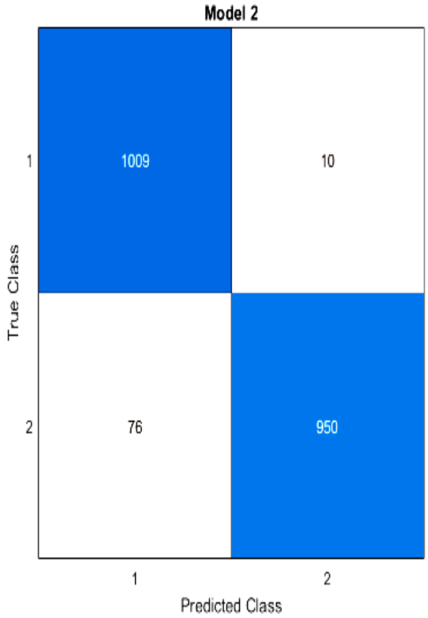

Figure 10. Confusion matrix

B. Evaluation of the Combined System's Performance:

Assessing the performance of an integrated system is crucial for validating its efficacy in clinical practice. Various metrics are employed to gauge different aspects of performance. Sensitivity measures the system's ability to correctly identify positive cases of ICH, ensuring that no true cases are missed. Specificity assesses the system's accuracy in identifying negative cases, minimizing false alarms. Accuracy provides an overall measure of correctness, indicating the system's reliability across both positive and negative cases. Additionally, the Dice similarity coefficient quantifies the agreement between the system's segmentation results and ground truth annotations, reflecting the system's ability to accurately delineate hemorrhage regions. By comprehensively evaluating these metrics, clinicians can assess the integrated system's reliability, sensitivity, and specificity, crucial for its adoption in clinical workflows.

C. Comparative Analysis with Existing Approaches:

Innovation in medical imaging is iterative, with new methodologies constantly emerging. Hence, it's essential to compare the performance of the integrated system with existing approaches to demonstrate its superiority or competitiveness. Traditional machine learning methods, such as support vector

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machines or random forests, have been widely used for ICH detection. Deep learning techniques, particularly convolutional neural networks (CNNs), have also shown promising results in recent years. Comparative analysis involves evaluating factors like computational efficiency, accuracy, robustness to noise, and generalization to unseen data. By benchmarking the integrated system against established methods, researchers can showcase its advancements and potential clinical impact. Additionally, highlighting its strengths and limitations in comparison to existing approaches informs future research directions and facilitates the continuous refinement of medical imaging algorithms.

9. Conclusion

Thus, the Intracranial Hemorrhage CT brain image to be digitally acquired, segmented, classified, 3D visualization and volumetric analysis can be done. ICH segmentation for all 2D slices from a single CT scan done by K means clustering method, Further classification done by SVM classifier, and Finally proposed a 3D visualization using iso surface technique. These processes can be done by using the MATLAB tool. The achieved results show that proposed system is a good segmentation, 3D Visualization and found the area, volume, depth of occurrence efficiently. The resultant output helps a doctor to determine the type of hemorrhage and its depth of occurrence. Moreover, an easy tool that can aid the surgeon to take the proper course of action can help reduce to provide better therapeutic planning and reduced mortality rate.

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DOI: https://doi.org/10.54216/JCHCI.090103

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