Contribution to an Advanced Clinical Aided Tool Dedicated to Explore ASPECTS Score of Ischemic Stroke

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***Abstract*—The Alberta Stroke Program Early CT Score (ASPECTS) is a simple and reliable systematic method used to quantify and explore acute ischemic stroke. It was initially developed to standardize the assessment of the early ischemic changes' extent within the Middle Cerebral Artery (MCA). The ASPECTS assessment has been increasingly incorporated into treatment decision-making and has been used in several randomized clinical trials for endovascular treatment decision-making. The e-ASPECTS software is a tool for the automated use of ASPECTS. The purpose of this paper is twofold: The first objective is to present an advanced clinical that streamlines the extraction of ASPECTS regions of interest. This tool aids neuro-physicians by automating the segmentation Department process through preprocessing steps involving skull bone stripping, edge detection, and thresholding. The second objective is to propose an automated semi-quantitative method using Non-Contrast Computed Tomography (NCCT), enabling neuro-physicians to accurately diagnose and evaluate acute ischemic stroke. This comprehensive approach improves the exploration, diagnosis, and evaluation of acute ischemic stroke, bolstering clinical decision-making and treatment strategies. Experimental results were promising and depicted an interesting accuracy level ranging from 0.81 (internal capsule) to 0.98 (caudate), with a greater agreement for cortical areas. The proposed automated ASPECTS method presents an independent predictor for clinical practice and ischemic core judgment and treatment selection.**

***Keywords*—acute ischemic stroke, Non-Contrast Computed Tomography (NCCT) image, Alberta Stroke Program Early CT Score (ASPECTS) score diagnosis**

I. INTRODUCTION

Stroke remains a predominant contributor to global mortality and disability rates. Each year, approximately 800,000 individuals are afflicted by stroke, equating to almost one occurrence every four seconds [1]. Swift treatment initiation from symptom onset correlates significantly with improved patient outcomes [2]. Consequently, Computed Tomography (CT), renowned for its speed and widespread accessibility, has emerged as the primary imaging modality for assessing patients with acute Ischemic Stroke (AIS) [3, 4].

The Alberta Stroke Program Early CT Score (ASPECTS), formulated in 2000, partitions the middle cerebral artery territory into ten pre-defined anatomical zones to evaluate strokes, as introduced by Barber *et al.* [5]. A topographic scoring system divides the middle cerebral artery territory into 10 regions within two prespecified levels, i.e., the ganglionic level and the supra ganglionic level (Fig. 1). However, scanning to identify early signs of ischemia by human ASPECTS have considerable interrater variability, which is, among other factors, influenced by rater experience [6]. Consequently, such scoring variability has a disadvantage of negatively affecting the ischemic core judgement and treatment selection. Therefore, an automated ASPECTS score calculation method is needed to assist neuro-physicians in exploring and quantifying early ischemic brain damage.

In the last ten years, the application of Artificial Intelligence (AI) techniques has significantly influenced the field of stroke image analysis by automating the diagnostic process, enhancing diagnostic accuracy, and improving prognosis predictions [7]. Automated lesion

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identification or segmentation is a crucial component of precision medicine, and recent machine learning techniques have shown promising results in automatic diagnosis. Substantial headway has been achieved in lesion segmentation for Acute Ischemic Stroke (AIS) employing techniques such as Diffusion-Weighted Imaging (DWI) [8]. Furthermore, there has been the development of automatic ASPECT scoring systems tailored for the AIS region and comparisons were made between the human scorers and e-ASPECTS [9, 10] Noteworthy achievements also encompass the detection of the hyperdense middle cerebral artery sign through CT scans [11], the automated quantification of cerebral edema [12], and even the prediction of lesion final shapes [13].

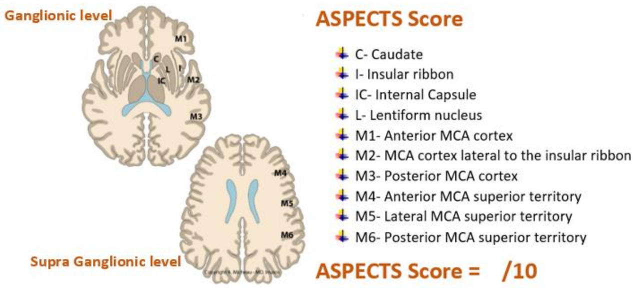


Fig. 1. Regions of ganglionic level and supra ganglionic level of ASPECTS score.

Considering these advancements, automatic diagnosis and ASPECT scoring of AIS using Non-Contrast CT (NCCT) would be a valuable tool in an era where faster thrombolysis is recommended. However, there is currently no proposed AI model for automatic ASPECT scoring based on NCCT.

Recently, Deep Learning (DL) methods have been introduced for detecting Early Ischemic Changes (EIC) and interpreting ASPECTS with promising results [14, 15]. However, there are limited well-established DL approaches for NCCT ASPECTS scoring, and most of the existing studies are single-centered, with a focus only on evaluating model efficiency rather than its performance in clinical emergency situations. Hence, further investigation is required to determine the DL model's performance in clinical scenarios. Our research was therefore inspired from ASPECTS territories and so to reinforce investigation of this pathology.

The study is structured into two primary segments. The first segment introduces an advanced approach that facilitates the extraction of all ASPECTS regions. This innovative approach holds the potential to offer neuro-physicians a clearer visual understanding of stroke-related areas, encompassing both normal and abnormal ASPECTS regions. The conventional clinical method involves manually demarcating ASPECTS regions using Digital Imaging and Communications in Medicine (DICOM) visualization software such as Radiant [16]. This process allows specialists to meticulously scrutinize ASPECTS regions on both hemispheres, enabling them to gauge the extent of damage and identify lesions [17]. However, this visually reliant approach is time-intensive and reliant on the operator's skillset [18].

In contrast, our study presents a novel approach that obviates the need for viewer software, streamlining the visualization of regions of interest while mitigating time constraints and imprecisions associated with manual assessment. Our method directly facilitates brain image exploration through the automated segmentation of ASPECTS regions. Furthermore, this tool plays a pivotal role in the advancement of automated ASPECTS score estimation. It tackles the automated segmentation phase, extracting the seven ASPECTS regions at the ganglionic level and the three ASPECTS regions at the supra-ganglionic level (Fig. 1). This automated approach not only enhances precision and efficiency but also contributes to the overall objective of developing a reliable method for ASPECTS scoring.

The study's distinctive contributions can be encapsulated as follows:

- Automated ASPECTS Segmentation: The study pioneers a clinically validated approach for the automated segmentation of ASPECTS regions. This innovation automates a process that was traditionally executed manually, thereby streamlining and enhancing the accuracy of ASPECTS assessment.
- Uncovering Subtleties in CT Images: The methodology employed uncovers intricacies within CT stroke images that may not be discernible to the human eye. By elucidating these subtleties, the approach provides a more comprehensive understanding of stroke-related areas, aiding neuro-physicians in making informed and rapid treatment decisions.
- Enhanced Stroke Exploration: The introduced approach empowers neuro-physicians to efficiently detect lesions and promptly make well-informed treatment choices. This real-time capability holds the potential to significantly improve patient outcomes.
- Precision-Focused Clinical Support Tool: The proposed tool is meticulously designed to elevate stroke exploration outcomes. By providing neuro-physicians with a robust and automated means of delineating ASPECTS Regions of Interest (ROIs), it aids in decision-making and enhances the precision of diagnoses.
- Automated ASPECTS Score Development: The study takes a significant step toward the development of an automated ASPECTS scoring system. This system leverages the physician's approach of contrasting dissimilarities between brain hemispheres to detect abnormalities. This novel tool has the potential to revolutionize early ischemic stroke detection, enhancing clinical efficiency and accuracy.
- Efficient Stroke Detection: The automated ASPECTS score system represents a pivotal advancement in early is chemic stroke detection. By automating a process that typically involves subjective comparison, the system offers a highly efficient means of assessing stroke severity and guiding appropriate treatments.

In the subsequent phase of the study, an automated ASPECTS score system is introduced. This system is rooted in the principle applied by physicians to identify abnormality through contrasting the differences between the brain's left and right hemispheres. The potential of this automated ASPECTS score system lies in its ability to facilitate early ischemic stroke detection, thereby significantly elevating clinical efficiency and diagnostic accuracy.

The paper is organized as follows: In Section II, we present the segmentation of ASPECTS ROIs. Section III presents proposed methodology for the automated ASPECTS score. Results are reported in Section IV. We further discuss some key issues in Section V and finally draw conclusions in Section VI.

II. ASPECTS Regions of Interest (ROI)

In the initial phase of this research, we introduced a semi-automated methodology designed to segment and extract all ASPECTS regions. This innovative approach serves a dual purpose. Firstly, it offers neuro-radiologists a comprehensive reference for visualizing all stroke-related areas, encompassing both normal and abnormal ASPECTS regions. Secondly, it plays a pivotal role in supporting medical assistance systems within the realm of radiology by facilitating the extraction of ASPECTS Regions of Interest (ROIs) from CT brain images.

A. Proposed Methodology

As depicted in Fig. 2, the proposed approach is composed of five steps:

- Importing CT image,
- Skull stripping,
- Edge detection process,
- Threshold segmentation of ASPECT regions, and finally results in both hemispheres.

The workflow can be broken down into several key steps. First, we began by importing the ischemic stroke image into our system. Following this, a critical step involved the removal of non-brain structures, effectively extracting the brain tissues. This preparatory stage significantly facilitated the subsequent segmentation process.

In the third step, we employed an edge detection method to create a mask that would guide our segmentation process. This mask was instrumental in identifying the precise boundaries of the areas of interest. With the mask in place, we proceeded to the fourth step, which involved the application of a thresholding process. This step allowed us to delineate the ten distinct regions of ASPECTS within the image.

Finally, after completing the segmentation process, we obtained the results, which included the ASPECTS regions in both hemispheres. This outcome represented a comprehensive breakdown of the ischemic stroke image, aiding in the assessment and diagnosis of the condition.

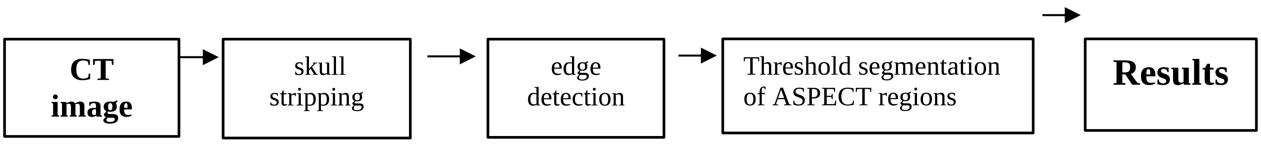


Fig. 2. The proposed approach.

- **Skull stripping**

The skull stripping procedure, an essential component of our algorithm, was effectively deployed to eliminate non-brain structures. This encompassed the removal of skull, bone, and eye structures. This preprocessing step was of paramount importance as it contributed to the accuracy of stroke region detection within the brain [19]. By ridding the image of extraneous tissues, we significantly enhanced the precision of our subsequent segmentation results.

To focus exclusively on cerebral tissues, we harnessed the power of Deep Learning (DL) in conjunction with a UNet architecture. This approach has demonstrated effectiveness in similar applications, and we found it to be particularly suited for our objectives. Our initial efforts involved processing the multiple slices of CT scans drawn from a diverse patient database. This approach offered notable advantages, as DL models tend to thrive with substantial input data. Each scan provided multiple slices for analysis, contributing to the overall accuracy and effectiveness of our tissue extraction process [20]. The UNet architecture, originally developed by Olaf Ronneberger, Philipp Fischer, and Thomas Brock in 2015, was initially created for cell segmentation in microscopic images. Since then, it has gained widespread recognition and is frequently employed to tackle image segmentation challenges [20]. The UNet architecture consists of two fundamental components: the encoder (responsible for narrowing) and the decoder (responsible for widening), which combine to form a U-shaped structure. The encoder's primary objective is to transform the input image into a format conducive to segmentation. It accomplishes this through a series of mathematical operations, typically leveraging convolutional neural networks.

In our proposed architecture, illustrated in Fig. 3, the encoding path comprises four distinct blocks. Each block features convolutional layers, with these layers typically being 2D convolutional layers. These 2D convolutional layers are crucial components that perform mathematical convolutions, a process that describes how one function is altered by another. The first convolutional layer encompasses 256 feature maps, the second comprises 128 feature maps, the third involves 64 feature maps, and the final one integrates 32 feature maps. It's important to note that all of these convolutional layers employ kernels with a size of 3×3.

Furthermore, we incorporated a ReLU Activation layer into the architecture. The Rectified Linear Unit (ReLU) Activation function is a key component in neural networks, introducing non-linearity and addressing the vanishing gradients issue. This activation function introduces non-linearity by defining the output of a neuron as a non-linear function of its input [21]. In our architecture, and in modern neural networks in general, we employ the rectifier function, which is analogous to a single-half-period rectifier in electrical engineering. ReLU defines neurons using the following Eq. (1) [22]:

$$f(x) = \max(0,x) \tag{1}$$

This activation function plays a pivotal role in enhancing the expressiveness of neural networks, making them well-suited for a wide range of tasks, including image segmentation and feature extraction. Following the encoding phase, we incorporated a crucial operation: max pooling, utilizing a 2×2 kernel. Max pooling is a method employed to extract the most significant features within the data. This operation involves selecting the maximum value from the feature map based on the filter size and stride parameters.

At the heart of our architecture lies the bottleneck layer, often referred to as the "Bridge." This component plays a vital role in reducing the number of parameters in the network, mitigating the risk of overfitting. It consists of 2D convolutional layers, with each of them featuring 512 feature maps and 3×3 kernels. This layer marks the point in the network where the spatial resolution of the feature maps is at its minimum and serves as a bridge connecting the encoder and decoder blocks.

The decoder block, an integral element of the U-Net architecture, carries out the reverse process of the encoder. This phase encompasses four individual blocks. Before each block, there is an up-sampling operation applied to the feature maps from the lower levels, followed by a 2D convolution layer, a ReLU activation function, and concatenation with the corresponding feature maps from the encoding path. Each block comprises two 2D convolutional layers, each followed by a ReLU activation function. Upon reaching the final level of the decoding path, we employ a 1×1 convolution and a Sigmoid activation layer to transform the multi-channel feature maps into the desired output. In this stage, we utilized a deep learning approach to eliminate non-cerebral tissues, isolating only the brain tissues of interest.

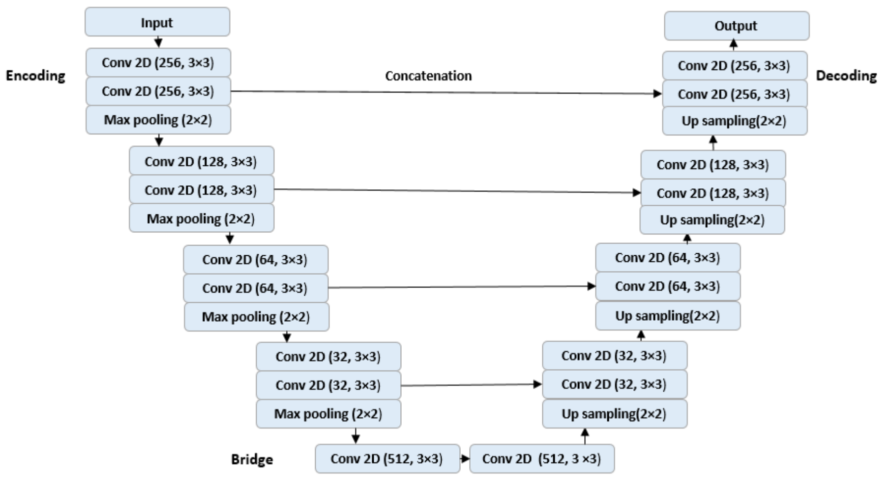


Fig. 3. UNET architecture.

- **Thresholding and edge detection technique**

Following the skull stripping phase, a pivotal aspect of our proposed approach is the application of the edge detection method. Initially, we initiated the process by extracting the ASPECTS regions' mask, guided by a template demarcated by a neuro-radiologist. To accomplish this, we employed the Simple Chain Approximation (SCA) method, as detailed in [23].

The Simple Chain Approximation (SCA) method is an optimal technique utilized in image processing and computer vision. It serves the purpose of detecting object boundaries or contours in a simplified, chain-like manner. This method relies on a series of line segments, often referred to as chains or polygons, to approximate complex shapes. SCA proves instrumental in reducing redundancy by retaining only the essential points that define the contour, rather than storing every single point comprising the contour.

Subsequently, we applied the thresholding technique, as described in [24], to extract a binary mask representing the ASPECTS regions of interest. In particular, we made use of the binary thresholding method to establish a binary representation of the image. This thresholding process effectively converted a grayscale image into a binary image, facilitating the SCA technique's extraction of ASPECTS areas. Furthermore, the thresholding technique was instrumental in eliminating irrelevant areas, resulting in a binary mask characterized by a black background and a white foreground, specifically delineating the ASPECTS regions.

Finally, for each ASPECTS area of interest, we obtained the corresponding image by multiplying the binary mask with the original image. This process allowed us to precisely isolate and visualize the regions of significance within the image.

B. Reference Standard and Clinical Motivation

ASPECTS functions as a semi-quantitative scoring system, primarily utilized for early ischemic change assessment based on Non-Contrast Computed Tomography (NCCT) images. ASPECTS serves as a robust predictor of functional outcomes [5], enabling swift diagnosis of ischemic lesions and aiding in the selection of potential candidates for intravenous and intra-arterial therapies. Furthermore, it plays a pivotal role in forecasting the thrombolytic effect and long-term prognosis [4].

This topographic scoring system effectively divides the Middle Cerebral Artery (MCA) territory into ten predefined anatomical areas. Each of these ten areas is assigned a value of one point, resulting in a total score of 10 points. Point subtraction is carried out for each area exhibiting early ischemic changes. The final score derived from this process serves as a dependable predictor of clinical outcomes and aids in the selection of appropriate treatment strategies.

Traditionally, a reference standard for ASPECTS area extraction is established through visual assessment by a neuro-physician. Although tools like Radiant [16] provide efficient DICOM viewing capabilities, they are limited to viewing and lack additional functionalities (Fig. 4). Moreover, this standard approach is time-consuming and reliant on visual inspection [6].

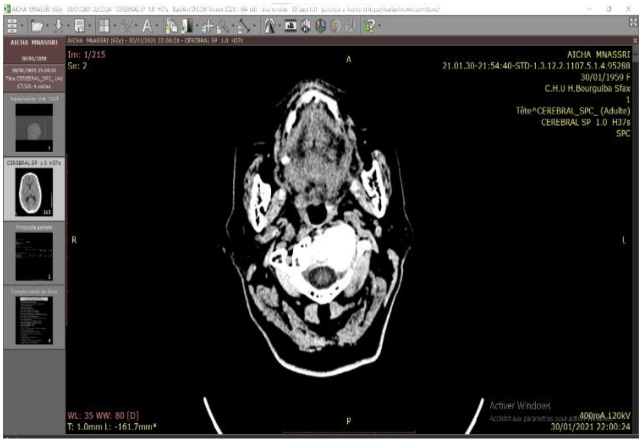


Fig. 4. Radiant slice.

Hence, our proposed approach has been meticulously developed to automate the segmentation of ASPECTS regions within the ischemic stroke scoring system. This method streamlines the process of brain segmentation in CT scan regions, closely mirroring the actions of a human expert, while significantly reducing the time and variability associated with manual assessment.

III. AUTOMATED ASPECTS METHOD

The objective of this part of the study was to develop an objective and automated ASPECT Score estimation system which will resolve the problem of scoring variability issue among medical experts.

A. Proposed Method

Illustrated in Fig. 5, our proposed method unfolds through a sequence of 5 distinct steps aimed at estimating the automated ASPECTS score:

1. Importing CT Image: The initial step involves the importation of the CT image into the system.
2. Skull Stripping: As elucidated in Section II, this step involves skull bone stripping of the CT stroke image, which is crucial for accurate and precise detection of ASPECTS regions.
3. Segmentation of each ASPECTS Region of Interest (ROI): Following skull stripping, we move on to the segmentation of ASPECTS regions in both hemispheres. This step involves isolating and delineating the areas of interest. (Section II)
4. GLCM Feature Extraction: Subsequently, the Gray-Level Co-Occurrence Matrix (GLCM) features of each region are extracted. This step serves to detect lesions by comparing the GLCM features of each ASPECTS ROI with its corresponding contralateral region.
5. Comparison and Score Estimation: This pivotal phase involves comparing the extracted features and leveraging them to estimate the ASPECTS score. Our approach is anchored in the medical principle applied by physicians who identify abnormalities by contrasting differences between the brain's left and right hemispheres.

The ASPECTS score, an essential tool in analyzing hypoattenuation in different brain areas, does not manifest as a sign but rather serves as an analytical instrument. It is particularly valuable for assessing subtle changes, such as the loss of grey-white matter differentiation, which is among the earliest parenchymal changes following ischemic onset. Each of the ten affected areas is assigned a value based on the degree of hypoattenuation and contributes to the decision-making process for patient clinical outcomes. To explore these hypoattenuation levels effectively, we employ a texture feature extraction method within the ROIs of stroke images. This technique plays a critical role in unveiling disparities between both hemispheres in the CT image and in the detection of lesions.

B. GLCM Features Extraction and Score Calculation

The exploration of texture features within the regions of the CT stroke image in both hemispheres involves the extraction of second-order statistical features. To delve into the texture features of the stroke ROI, we employed the GLCM method [25], which is widely utilized in medical images for texture analysis.

In this context, discrepancies in image pixel intensities serve as texture features, and the co-occurrence matrix proves to be a robust foundation for such texture analysis. This matrix is generated by calculating the pairwise statistics of image pixel intensities. The GLCM encompasses a range of second-order statistical texture features, which we harnessed and extracted using this technique.

The process of computing a gray-level co-occurrence matrix entails identifying the occurrences of pairs of gray levels separated by a specified distance 'd' in a defined direction characterized by a displacement vector (dx, dy) [26].

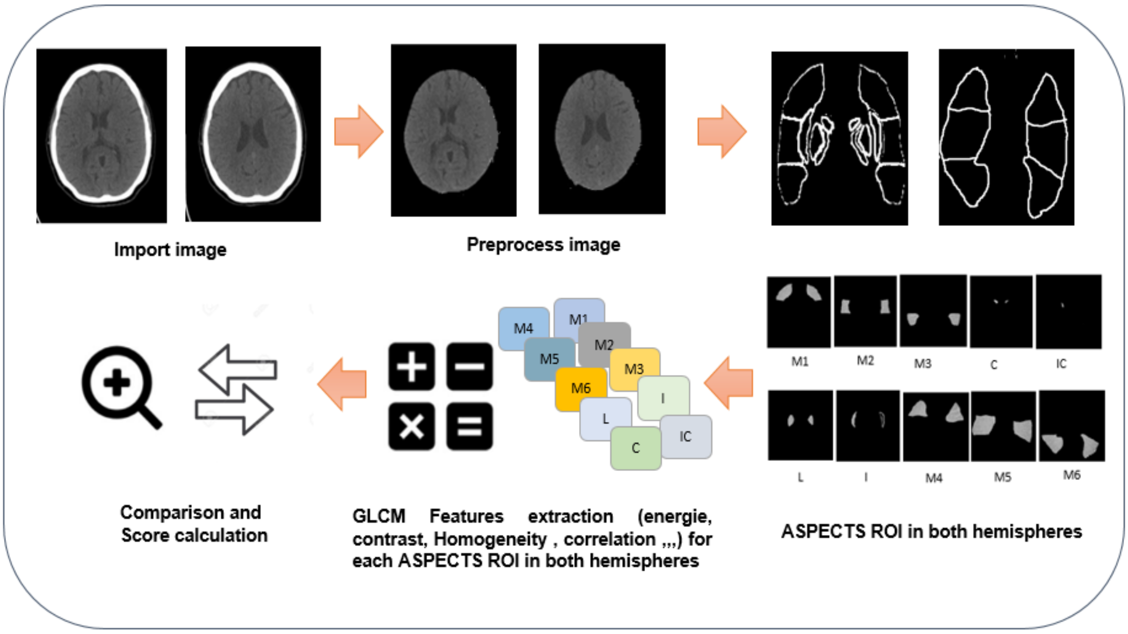


Fig. 5. Flow diagram of the automated ASPECTS score method.

To formalize the calculation of the GLCM for an image 'I' with dimensions $N \times M$, the following steps are undertaken:

$$GLCM_{\,dx,dy}(i,j) = \sum_{n=1}^{N}\sum_{m=1}^{M}\begin{cases}1, si\ I(n,m) = i\ et\ I(n+dx, m+dy) = j\\ 0, sinon\end{cases} \quad (2)$$

This method, applied to the CT stroke image regions, effectively uncovers and quantifies various texture features that play a critical role in the analysis and detection of anomalies.

where i and j are the gray levels of the reference pixel and the neighboring pixel respectively, n and m are to the coordinates of the pixels in the image I.

The co-occurrence matrix is characterized by G $(i, j \mid d, \Theta)$ where i and j define gray level values at a distance d with an angle Θ. Rows and Columns of the GLCM are identical. GLCM represents an importing method that helps well explore the bringing out of the textural differentiation of an image.

Fig. 6 shows how to calculate GLCM matrix with $\Theta = 0$ and $d = 1$. In the output GLCM, Element (4, 1) takes the value of 1 because there is only one instance in the image where two horizontally adjacent pixels have the values 4 and 1. Element (2, 3) in the GLCM contains the value 2 because there are two instances in the image where two horizontally adjacent pixels have the values 2 and 3.

The size of the GLCM matrix is Ng×Ng, where Ng is the maximum gray level of the region of interest.

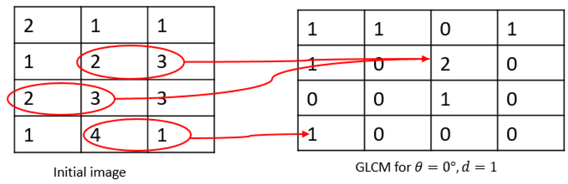


Fig. 6. Principle of co-occurrence matrix.

For this study, Energy, contrast, homogeneity, correlation, dissimilarity and ASM are calculated for four directions (0°, 45°, 90°, 135°) and for a distance of 1 pixel. A distance of 1 means that the GLCM is computed for pixel pairs that are 1 pixel apart in the specified direction. The angle is defined to assess the direction of texture. We will focus on and discuss the proposed GLCM features. These features are described as follows:

- Energy: Energy, also known as uniformity or angular second moment, measures the sum of squared elements in the GLCM. It represents the orderliness of the texture, with higher values indicating more homogeneity.

$$\text{Energy} = \sum_i \sum_j P_{i,j}^2 \quad (3)$$

- Contrast: This feature quantifies the variation in pixel intensity between neighboring pixels in the image. It is calculated as the sum of the absolute differences in pixel intensities for pairs of pixels at a specified offset.

$$\text{Contrast} = \sum_i \sum_j P_{i,j}\ (i-j)^2 \quad (4)$$

- Homogeneity: Homogeneity quantifies the closeness of pixel intensity values in the GLCM. It is computed as the inverse of the sum of squared differences between pixel pairs

$$\text{Homogeneity}=\sum_i \sum_j \frac{P_{i,j}}{1+(i-j)^2} \quad (5)$$

- Correlation: Correlation is a measure of how correlated the pixel intensities are between pairs of pixels at a specified offset. It provides information about the linear dependence between pixel values.

$$\text{Correlation}=\sum_i \sum_j P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2\sigma_j^2)}}\right] \quad (6)$$

- Dissimilarity (Entropy): Entropy reflects the randomness or disorder in the texture. Higher entropy values indicate more complex and less uniform textures.

$$\text{Dissimilarity}=\sum_i \sum_j P_{i,j}|i-j| \quad (7)$$

- ASM: measures the uniformity of the distribution of gray level in the image

$$\text{ASM}=\sum_i \sum_j \{p(i,j)\}^2 \quad (8)$$

where $P_{i,j}$: probability of occurrence in the pair gray levels i, j (normalized GLCM),
The standard deviation of the normalized inputs for the reference pixel of value *i* as follows:

$$\sigma_i = \sum_i P_{i,j}(i-\mu_i)^2 \quad (9)$$

The standard deviation of the normalized inputs for the neighboring pixel of value *j* as follows:

$$\sigma_j = \sum_i P_{i,j}(j-\mu_j)^2 \quad (10)$$

The brain image was partitioned into two equal hemispheres, with one hemisphere encompassing the abnormal area and the other containing the normal region. It's noteworthy that medical statistics indicate that strokes predominantly occur in one hemisphere [27]. Hence, the ASPECTS scoring method, which divides CT brain images into ten distinct regions, assigns a score of 1 point to each of these regions, resulting in a total score of 10 points.

Our approach revolves around the extraction and comparison of GLCM features from the ROIs of the left side with those from the right side, as depicted in Fig. 7. Essentially, for each hemisphere of the brain, we calculate and store the GLCM features of each ROI in vectors denoted as ($\overrightarrow{L_n}$: left side, $\overrightarrow{R_n}$: right side). Subsequently, we engage in a bilateral comparison of these features for each ASPECTS ROI and its corresponding contralateral region. Specifically, for each region, we calculate the difference between the vector of the left side ($\overrightarrow{L_n}$) and the vector of the right side ($\overrightarrow{R_n}$) to identify the abnormal region.

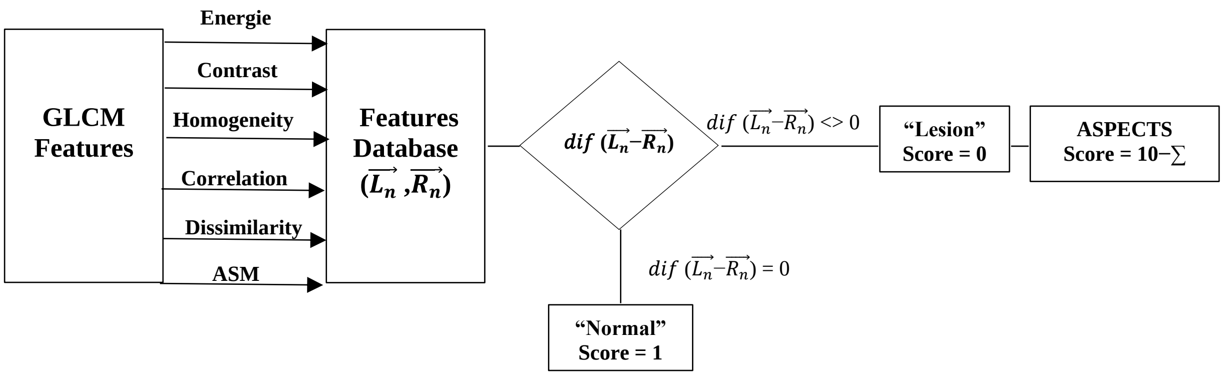


Fig. 7. GLCM feature extraction phase of our proposed method.

Our strategy offers three potential outcomes to determine the presence of abnormal regions:

- If the dif ($\overrightarrow{L_n}-\overrightarrow{R_n}$) is equal to zero, the region is classified as normal and the assigned ASPECTS score is equal to 1.
- If the dif ($\overrightarrow{L_n}-\overrightarrow{R_n}$) is negative: the presence of a lesion in the left hemisphere and the assigned ASPECTS score is zero.
- If the dif ($\overrightarrow{L_n}-\overrightarrow{R_n}$) is positive: the presence of a lesion in the right hemisphere and the ASPECTS score assigned is zero.

Then, for each area with signs of early ischemic change, one point is subtracted from that initial score.

$$\text{ASPECTS score} = 10-\sum_{i=1}^{10}(\text{dif}\,(L_n-R_n\,) \,!= 0) \quad (11)$$

IV. Results

A. Data

The dataset utilized in this experimental study was procured from Habib-Bourguiba University Hospital (CHU-HB Sfax-Tunisia) and is comprised of 22 CT stroke images. This database is focused on cases displaying early ischemic brain damage. The patients included in this research spanned an age range from 56 to 80 years.

The images in the dataset were acquired as slabs, and the number of axial slices varied, ranging from 2 to 22, contingent on the patient. These slices maintained a spacing of 5 mm and exhibited dimensions of 512×512. The CT scan images in the dataset possessed a resolution of 0.5 mm.

In the preprocessing stage, a ground truth segmentation mask was applied to the multiple slices for each patient. Furthermore, for scoring assessment, the ASPECTS score was determined manually by two neuro-radiologists. In cases of disagreement between the two radiologists, a third neuro-radiologist was consulted to adjudicate the final score. This meticulous approach ensures the accuracy and reliability of the ASPECTS score in the dataset, serving as a valuable resource for the experimental evaluation of our proposed method.

B. Experimental Results

The initial segment of this study is dedicated to the extraction of ASPECTS areas from CT brain images, thereby facilitating the detection of ischemia and enhancing the accuracy of stroke diagnoses for subsequent treatment decisions. The proposed method primarily consists of two key components: preprocessing and the segmentation of ASPECTS regions.

First, employing the UNET approach, we successfully isolated only the brain tissues, as demonstrated in Fig. 8. This figure illustrates the results of skull stripping for a stroke CT scan, including both the original image and the skull stripping outcomes. Notably, the Dice Similarity Coefficient was approximately 0.49 for this process. Skull stripping is a vital step in accurately identifying stroke regions within the brain, representing an essential preparatory phase for subsequent segmentation.

Second, the images obtained from the preprocessing stage are subjected to decomposition and reconstruction using edge detection and thresholding techniques. These processes are integral to the extraction of ASPECTS regions in both hemispheres. Fig. 9 displays the segmented ASPECTS regions' mask results after the thresholding process, which can be applied to segment any CT brain stroke image.

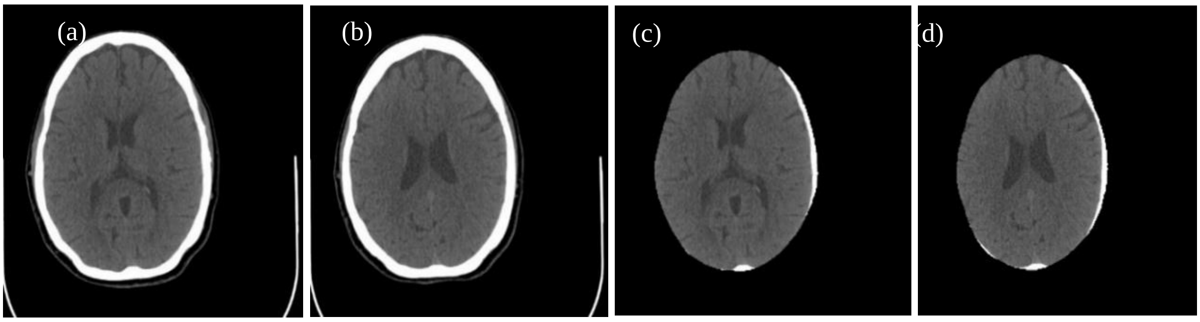


Fig. 8. The preprocessing stage: (a) ganglionic level before preprocessing, (b) supra ganglionic level before preprocessing, (c) ganglionic level after preprocessing, (d) supra ganglionic level after preprocessing.

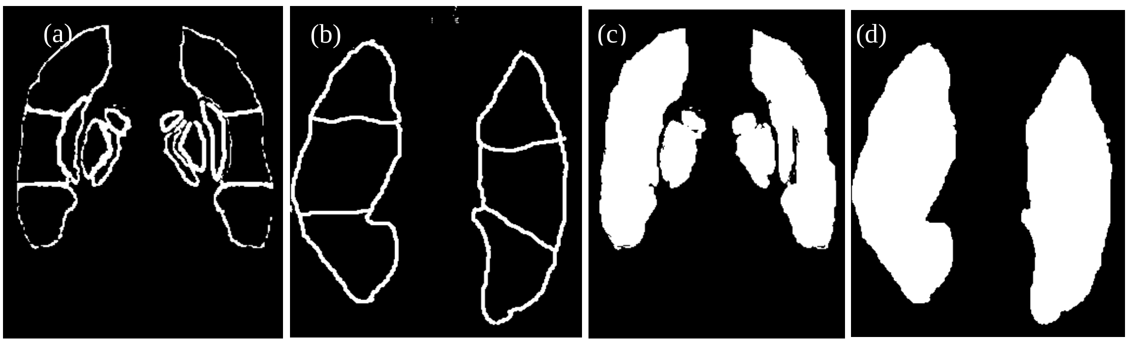


Fig. 9. Mask of ASPECTS regions, (a)&(c) regions of ganglionic level, (b)&(d) regions of supra ganglionic level.

The segmented stroke ASPECTS ROIs are revealed in Fig. 10 for both the Ganglionic level and the supra Ganglionic level, depicting the results for a stroke patient. In Figs. 11 and 12, each ASPECTS ROI is showcased individually for the CT scan example at both the Ganglionic and supra Ganglionic levels. This delineation ensures the distinction of various ASPECTS regions, including Caudate (C), Lentiform (L), Internal Capsule (IC), Insula (I), and the various cortex regions {M1, M2, M3, M4, M5, M6}. These regions are extracted in both hemispheres, left and right.

The figures underscore that the proposed approach enhances diagnosis, offering a clear visualization of the regions of interest without the need for viewer software like Radiant [16]. This method streamlines brain image exploration through ASPECTS region segmentation, enabling neuro-physicians to efficiently detect lesions and, ultimately, improve stroke treatment outcomes. The results affirm that the proposed method holds promise for integration into medical aid systems within the field of radiology for the extraction of ASPECTS ROIs in CT brain images.

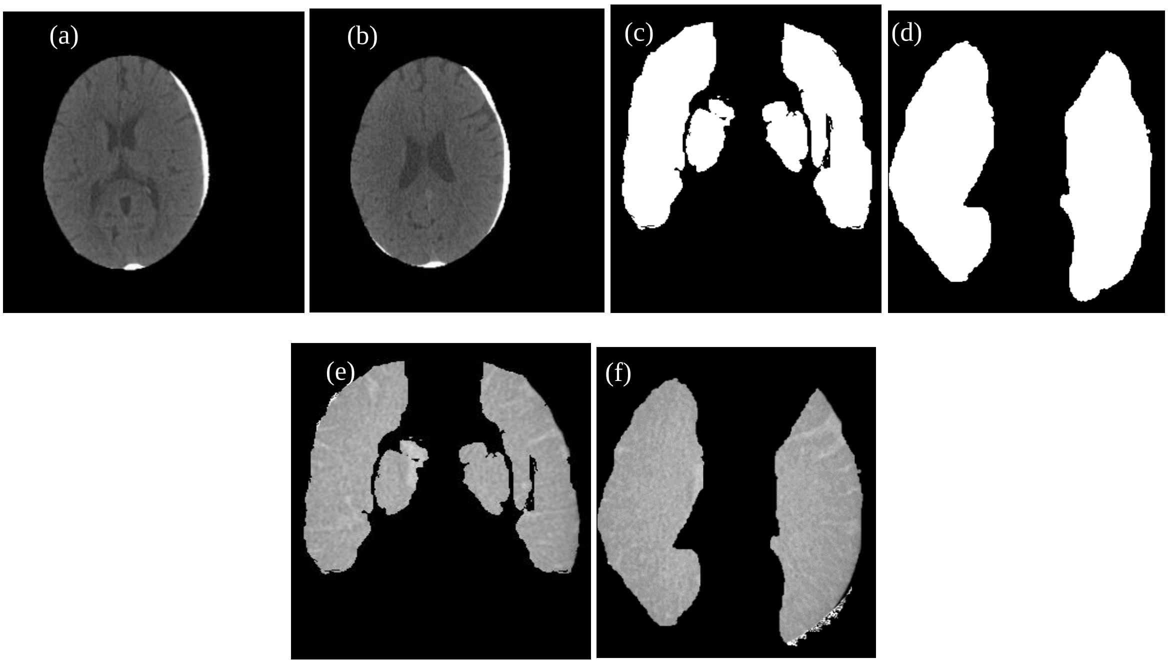


Fig. 10. The ASPECTS ROIs: (a)&(b): Original image, (c)&(d) Mask of ASPECT ROIs (Ganglionic level/ supra ganglionic level), (e) result of segmentation ASPECTS regions (ganglionic level), (f) result of segmentation ASPECTS regions (supra ganglionic level).

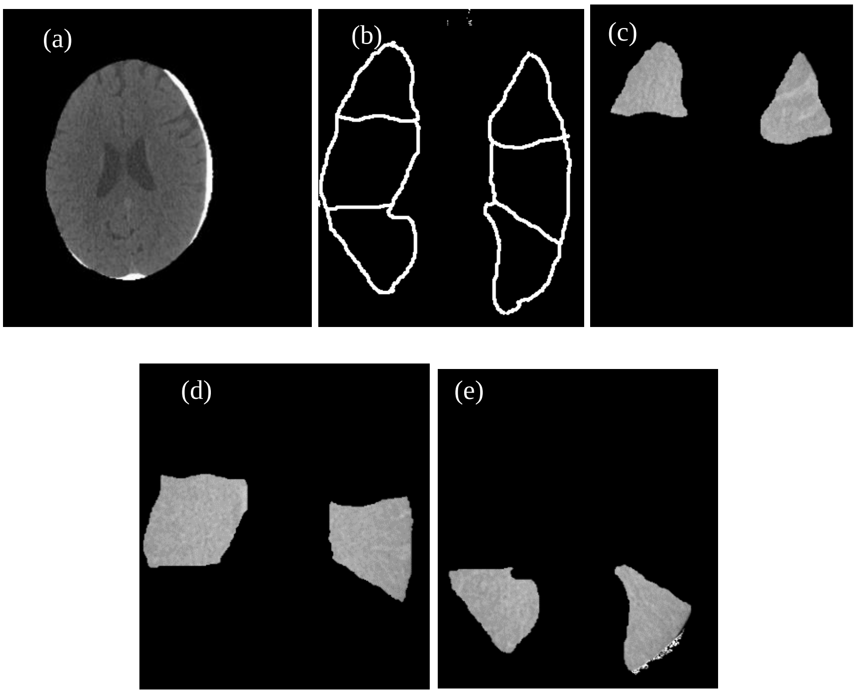
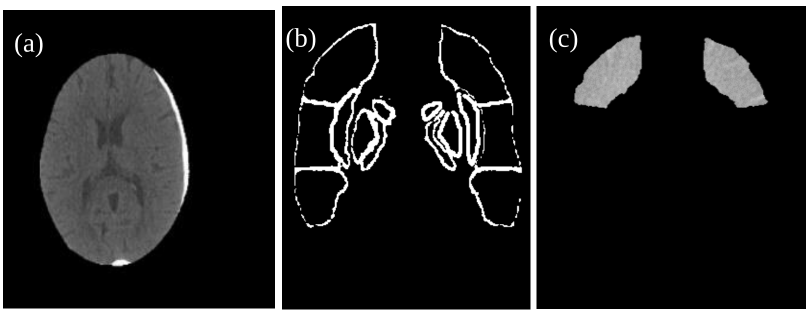


Fig. 11. Result of segmentation ASPECTS regions (supra ganglionic level): (a) Original image of supra ganglionic level, (b) Mask, (c) result of M4 area, (d) result of M5 area, (e) result of M6 area.



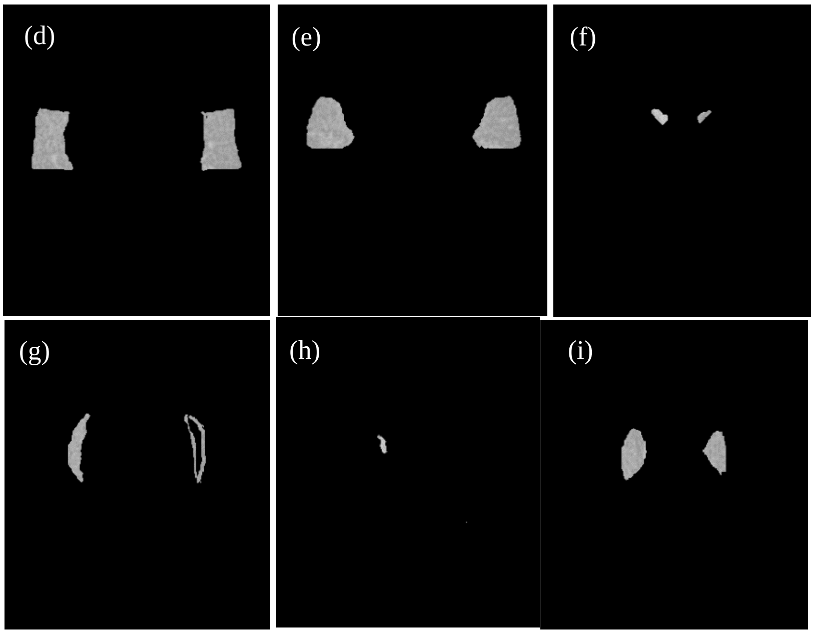


Fig. 12. Result of segmentation ASPECTS regions (ganglionic level): (a) Original image of ganglionic level, (b): Mask, (c) result of M1 area, (d) result of M2 area, (e) result of M3 area, (f) result of caudate C area, (g) result of insular ribbon I area, (h) result of Internal capsule IC area, (i) result of lentiform nucleus L area.

C. Evaluation

The famous saying, "Time is brain", encapsulates the critical importance of swift medical attention for individuals displaying stroke symptoms. With every passing minute during a stroke, approximately 1.9 million brain cells are lost. This stark reality underscores the urgency of timely care and intervention.

The first segment of this study is dedicated to the precise segmentation of various ASPECTS regions associated with strokes. This segmentation process significantly enhances the ability of neurologists to detect ischemia and make rapid and consistent treatment decisions.

Table I presents a comparative analysis of the computational time required for each scan when assessed by two Readers, both neuro-radiologists using DICOM viewer, and our proposed automated method. The experimental results reveal notable achievements, with our automated method delivering a remarkable computational time of approximately 2 to 3 min for each scan. In contrast, the clinician reader, when employing the DICOM viewer, requires significantly longer, ranging between 8 and 14 min.

These findings underscore the potential of the model developed in this study to provide a swift assessment of the ASPECTS score. It may serve as an invaluable ancillary tool, aiding physicians in making urgent clinical decisions and improving the overall efficiency of stroke diagnosis and treatment.

TABLE I. COMPUTATIONAL TIME FOR EACH SCAN

Manual method & automatic method	Time (minutes)
Clinician Reader 1	08–11
Clinician Reader 2	09–14
Our Automated method	**02–03**

In the second part of this framework, an automated ASPECTS score was estimated. The idea is to compare the characteristics of the corresponding ROIs. Therefore, for each area, we calculated the difference between the left side GLCM features $\overrightarrow{L_n}$ and the right side GLCM features $\overrightarrow{R_n}$ to identify the abnormal region. The results of the second stage of our method are compared to the results of the manual score of two neuro-radiologists for 22 testing images. Table II shows a performance comparison between our automated ASPECTS and the manual assessment for each region. The performance of our model was improved by an accuracy of 0.57 in quantifying the total ASPECTS score.

TABLE II. ACCURACY FOR INDIVIDUAL ASPECTS REGIONS BETWEEN MANUAL AND AUTOMATED ASPECTS

Regions	Accuracy
M1	0.95
M2	0.90
M3	0.95
IC	0.81
L	0.86
I	0.96
C	0.98
M4	0.95
M5	0.95
M6	0.95
Total ASPECTS	**0.57**

Table III provides a comparative analysis of the performance of each automated ASPECTS area extracted from NCCT images. It's important to note that the limited inclusion of only one recent study in this comparison is primarily due to the scarcity of works that have tested performance on a per-region basis. Furthermore, contemporary automated ASPECTS programs predominantly rely on deep learning methods that are trained on extensive datasets. In contrast, our proposed method was evaluated on a relatively small dataset comprising 22 patients.

The study conducted by Neuhaus *et al.* [10] compared the e-ASPECTS program with manual scoring by neuroradiologists for all 10 individual ASPECTS regions. The level of accuracy in their study ranged from 0.74 (insula) to 0.94 (M3), while the coefficient for the total ASPECTS score was 0.40.

In contrast, the advanced semi-quantitative method proposed in 2023 yielded an intriguing level of accuracy, ranging from 0.81 (internal capsule) to 0.98 (capsule), with particularly strong agreement for cortical areas. Notably, our results demonstrated a higher accuracy in quantifying the total ASPECTS score compared to the study by Neuhaus *et al.* [10]. This comparison suggests that our proposed approach enhances the efficiency and accuracy of early infarct stroke exploration for each ASPECTS area.

TABLE III. PERFORMANCE COMPARISON FOR EACH ASPECTS ROI

	Ain Neuhaus *et al.*	**Our proposed method**
M1	0.87	0.95
M2	0.84	0.90
M3	0.94	0.95
IC	0.91	0.81
L	0.78	0.86
I	0.74	0.96
C	0.86	0.98
M4	0.93	0.95
M5	0.87	0.95
M6	0.92	0.95
Total ASPECTS	0.40	**0.57**

V. DISCUSSIONS

The consideration of time plays a pivotal role in the development of medical applications [28], and this principle has been carefully integrated into our approach for detecting ischemia. In this regard, we meticulously selected algorithms that minimize computation time, emphasizing efficiency and rapidity [29]. The effectiveness of the first part of our study is underscored by its capacity to deliver results for multiple patients concurrently. When it comes to stroke diagnosis, every passing minute is of paramount importance, as delays can directly impact brain function. Therefore, our proposed approach has the potential to significantly enhance the quality of stroke care. Our study enables the achievement of our diagnostic goal in just 2 min, a stark contrast to the waiting time associated with manual assessment, which can span between 8 min and 14 min. These results have the potential to save patients' lives and preserve more neurons. Furthermore, our program contributes to the advancement of automatic e-ASPECTS software by automating the segmentation of the seven ASPECTS regions at the ganglionic level and three ASPECTS regions at the supra ganglionic level.

Since its inception in 2000, the Alberta Stroke Program Early Computed Tomography Score (ASPECTS) has played a crucial role in clinical applications, serving to evaluate the extent of early ischemic changes, identify eligible patients, assess treatment efficacy, and predict prognosis [5]. ASPECTS surpasses the 1/3 MCA method, which was previously the standard for quantifying early ischemic changes on NCCT scans [30]. Specifically, patients with low ASPECTS scores (0–5) are less likely to receive mechanical thrombectomy as it is not the recommended treatment [31]. Conversely, higher ASPECTS scores are linked to successful recanalization and improved prognosis [32, 33].

The automated ASPECTS scoring system we have developed applies the clinically validated Alberta Stroke Program Early CT score (ASPECTS) method, thereby enabling the automated assessment and quantification of early ischemic brain damage on CT scans of acute stroke patients. The second part of our framework introduced an automated system capable of estimating the ASPECT Score, which holds the potential to reduce scoring variability and assist physicians in identifying and quantifying early ischemic brain damage.

This study has effectively automated the manual approach used by physicians to detect abnormalities by assessing the dissimilarities between the left and right brain hemispheres. Furthermore, our automated tool can discern specificities in CT stroke images that may not be readily apparent to the human eye, thereby serving as a valuable resource for alerting neuro-physicians to the presence of early ischemic changes and the presence of disease. This innovative approach has the potential to revolutionize stroke diagnosis and treatment.

Moreover, the effectiveness and accuracy of the current system can be significantly enhanced through several key factors. One of these critical factors is the availability of a sufficiently large volume of CT image datasets. Having access to a vast and diverse dataset of CT images is essential for training and validating machine learning models. A rich dataset allows the algorithms to learn and adapt to a wide range of real-world scenarios and variations, ultimately improving their performance in detecting ASPECTS regions.

Another crucial factor is the reliability of ground-truth data. Ground-truth data refers to the manually annotated or expert-verified information that serves as the reference for machine learning models. In the case of ASPECTS scoring, having accurate and reliable ground-truth data for each image in the dataset is vital. These ground-truth annotations ensure that the machine learning models are trained on accurate examples, leading to more precise and reliable results.

Additionally, the clarity of the features in the CT images plays a significant role in the system's performance. Clear and well-defined features in the images make it easier for the algorithms to identify and segment ASPECTS regions accurately. This underscores the importance of high-quality imaging equipment and techniques in medical imaging.

Furthermore, the system's performance can be continuously improved by exploring and evaluating new machine learning methods, particularly deep learning techniques. Deep learning has shown remarkable promise in various medical image analysis tasks, including the segmentation of anatomical structures and the detection of abnormalities. By staying updated with the latest advancements in machine learning and adopting new methods, the system can benefit from state-of-the-art algorithms that may offer improved accuracy and efficiency in estimating ASPECTS ROIs.

To recapitulate, the current system's accuracy and reliability can be significantly enhanced through access to extensive CT image datasets, reliable ground-truth data, clear features in the CT images, and a willingness to explore and adopt cutting-edge machine learning methods. These factors collectively contribute to the system's effectiveness in automating the estimation of ASPECTS regions and improving stroke diagnosis and treatment.

VI. CONCLUSIONS

This paper presents a groundbreaking approach for the segmentation and extraction of ASPECTS ROIs from CT Brain stroke images. This novel method is compared with the standard clinical approach that relies on DICOM viewers and visual assessment by experts. Additionally, the paper introduces an objective and automated ASPECT Score estimation system, which is built upon the segmentation of ASPECTS ROIs and a bilateral comparison of Gray-Level Co-Occurrence Matrix (GLCM) features extracted from the ten ROIs.

In the context of exploring acute ischemic stroke imaged through CT scans, the study emphasizes the importance of a critical preprocessing step. This step involves skull bone stripping in CT stroke images, followed by the extraction and segmentation of ASPECTS regions using edge detection and thresholding techniques. The segmentation process of ASPECTs ROIs yields promising results with clinical implications.

The study introduces a novel automated method based on Non-Contrast Computed Tomography (NCCT) to assist neuro-physicians in diagnosing and evaluating acute ischemic stroke. This approach is semi-quantitative in nature and serves as a valuable reference for neuro-physicians in clinical practice, aiding in ischemic score judgment and ultimately improving treatment selection.

Looking ahead to future studies, the authors plan to develop a user-friendly and graphical interface for the automated ASPECTS score system. Such an interface would be a significant advancement, as it could enhance the accessibility and usability of the system, further benefiting the diagnosis and treatment of ischemic stroke. This user-friendly interface has the potential to streamline the process for healthcare professionals, making it a valuable tool in the clinical setting.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, HT; Data curation, KBM, AA; Formal analysis, AA; Methodology, HT; Project administration, ABH, LS; Software, HT; Supervision LS; Validation, AA-J., LS, ABH; Visualization, AA-J.; Investigation, YBH; Writing – original draft, HT, AA, AA-J. and YBH; Writing – review & editing, HT, ABH, LS and KBM. All authors had approved the final version.

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