Segmentation and classification techniques used to detect early stroke diagnosis using brain magnetic resonance imaging: a review

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ABSTRACT

Stroke is a leading cause of disability and death worldwide. Early diagnosis and treatment are crucial in reducing the risk of stroke-related complications. Brain magnetic resonance imaging (MRI) is a common diagnostic tool used for stroke evaluation. However, manual interpretation of MRI images can be time-consuming and subjective. Machine learning (ML) algorithms have shown promise in automating and improving stroke diagnosis accuracy. This article focuses on classification and segmentation techniques used to detect early stroke diagnosis using brain magnetic imaging. The diagnosis, treatment, and prognosis of complications and patient outcomes in a number of neurological diseases are currently made possible by ML through pattern recognition algorithms. However, the use of MRI is limited because of MRI plays an important role in diagnosing lumbar disc disease. However, the use of MRI is limited due to its high cost and significant operational and processing time. More importantly, MRI is contraindicated in some patients who are claustrophobic or have pacemakers due to the potential for damage. Recent studies have shown that treatment within six hours of a stroke can save a patient's life. Unfortunately, Malaysia is facing a shortage of neuroradiologists, hampering efforts to treat its growing number of stroke patients.

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1. INTRODUCTION

Stroke is the second leading cause of death worldwide and requires immediate treatment to avoid serious long-term disability and death. It occurs when a blood clot blocks a blood vessel or ruptures, blocking blood flow to an area of the brain. As shown in Figure 1, stroke can be classified as ischemic stroke (as shown in Figure 1(a)) and hemorrhagic stroke (as shown in Figure 1(b)). Ischemic stroke, in which a blood vessel suddenly blocks an artery in the brain [1], and hemorrhagic stroke (cerebral hemorrhage), in which a blood vessel ruptures [2].

Stroke has a major impact on public health, resulting in significant costs for primary care, rehabilitation, and treatment of chronic diseases. In 2015, 6.3 million of his deaths worldwide were due to stroke, making it her second leading cause of death after ischemic heart disease. In June 2019, the Institute for Health Metrics and Evaluation reported that stroke was still her third leading cause of death in Malaysia (Institute for Health Metrics and Evaluation, 2017) [3]. It is estimated that approximately 1.9 million neurons and 14 billion synapses die every minute during a stroke, and the ischemic brain ages by approximately 3.6 years every hour. This difficulty reinforces the notion that "time is the brain". Despite the dire need, there are no computer-aided diagnosis (CAD) systems for stroke, but there are numerous CAD systems for other fields such as mammography and thorax. In addition, research on CAD systems and techniques shows that the use of CAD can improve the diagnostic accuracy of radiologists.

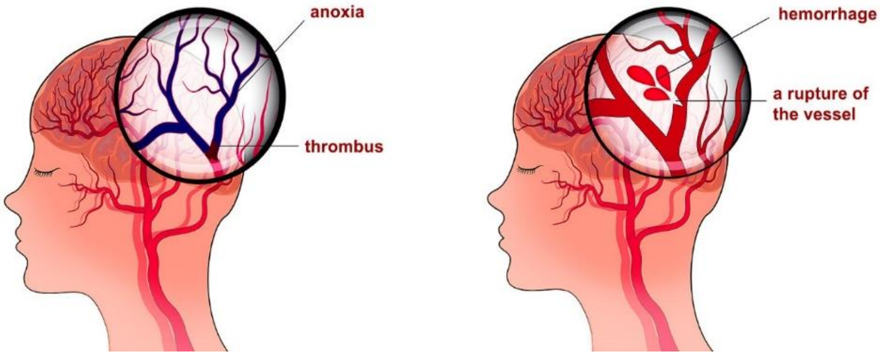

Figure 1. Types of strokes: (a) ischemic stroke and (b) hemorrhagic stroke [1]

Reperfusion injury plays an important role in the outcome of ischemic stroke patients when blood flow is restored [4]. For this reason, much attention has been paid to cardio protection by ischemic preconditioning, perconditioning, and postconditioning, with differing results regarding possible treatments [5]. Timely restoration of local blood flow helps to rescue the threatened tissue, reduce cell death, and ultimately reduce patient disability. Successful recanalization increases the likelihood of a favorable outcome by a factor of 4 compared to patients without recanalization. In addition, mortality in patients with successful recanalization is reduced by a factor of four [6]. Strategies for recanalization include the use of thrombolytic drugs, such as IV drugs (eg, tissue plasminogen activator (tPA)), and/or mechanical interventions, such as distal or proximal thrombectomy or stent retrievers method. Thrombectomy is the removal of blood clots using a long catheter with a mechanical device attached to the tip. The short intervention time, high recanalization rate, and potential for rapid and efficient restoration of blood flow make the use of thrombectomy attractive. However, the risks associated with thrombectomy must be considered, and only patients with specific indications, such as large circumference, small infarct, and good collateral circulation, should undergo such a procedure. I have. In other words, advanced patient selection based on pretreatment imaging is critical to achieving high rates of good outcomes with mechanical recanalization [7].

The brain is one of the most complex organs in the human body. This organ consists of billions of nerve cells interconnected with a series of supporting networks. The brain is characterized by complex spatiotemporal patterns. For this reason, the brain is considered to be the most complex system in which the degree of correspondence between structural and functional connections depends on spatial resolution and temporal scale [8]. The brain has the ability to control intelligence, creativity, emotions and memory. The brain, protected by the skull, consists of the cerebrum, cerebellum, and brainstem. Figure 2 shows the structure of the human brain. The brain is also divided into several lobes:

- The frontal lobe is responsible for problem-solving, decision-making, and motor skills.
- The parietal lobe controls sensation, handwriting, and posture.
- The temporal lobe is involved in memory and hearing.
- The occipital lobe contains the brain's visual processing system.

The brain communicates with the body through 12 pairs of cerebrovascular vessels through the spinal cord and blood flow. Ten of the 12 pairs of cerebral vessels that control hearing, eye movements, facial sensations, taste, swallowing, and movements of the muscles of the face, neck, shoulders, and tongue originate in the brainstem. The cerebral blood vessels responsible for smell and vision originate in the cerebrum. Therefore, good blood circulation in blood vessels is very important to avoid neuropathy leading to nerve cell damage and subsequent cell death [9].

The collateral circulation is an auxiliary vascular network that is dynamically recruited upon arterial occlusion. In recent years, many studies have emphasized the importance of preoperative evaluation. Peripheries and infarct areas are readily discernible on clinical maps generated from angiographic scans, including measurements of cerebral blood flow and volume. A collateral circulation is defined as an auxiliary vascular network that is dynamically recruited when a region loses its regular blood supply due to occlusion of a major arterial trunk [10]. Parallel blood vessels in the human brain that carry blood to the same target tissue or cell. Cerebral blood flow follows the cerebral perfusion gradient. A "pressure boundary zone" develops between two vessel regions when there is an upstream flow obstruction [11]. The collateral circulation can be divided into lateral cranial collateral circulation and medial cranial collateral circulation. As shown in Figure 3, the lateral cranial collateral circulation is supplied by external carotid artery anastomoses leading to many branches of the neck that are potential sources of collateral blood flow [12]. The cranial collaterals can be further divided into primary and secondary collaterals as shown in Figure 4. The primary pathway involves the arterial segments of the circle of Willis and the secondary pathway involves the leptomeningeal anastomosis connecting the distal portions of the cerebral arteries.

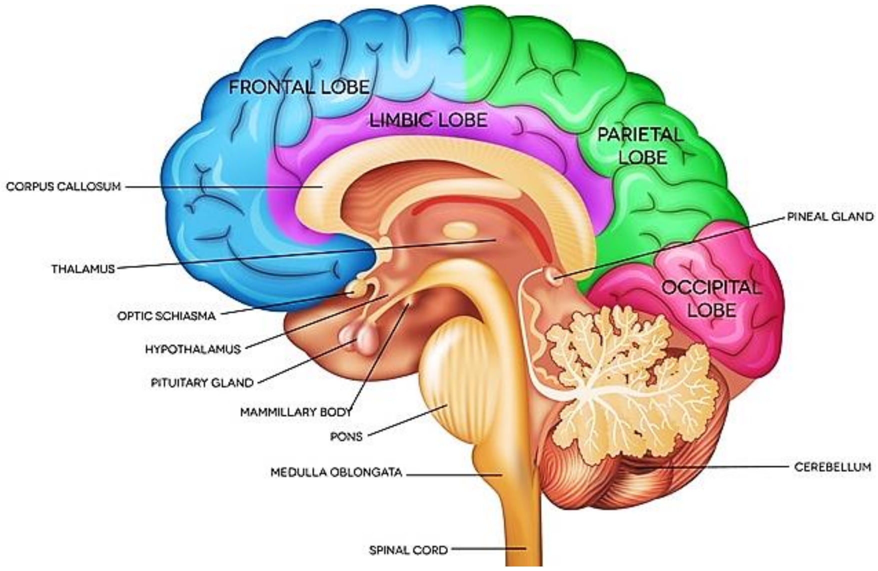

Figure 2. Anatomy of human brain

Figure 3. Extracranial collateral circulation

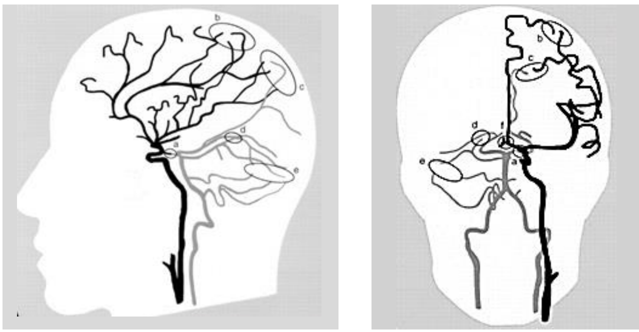

Figure 4. Intracranial collateral circulation

The Willis circuit, shown in Figure 5, is a critical connection of arteries at the base of the brain that allows adequate blood flow from the arteries to both the anterior and hemispheres. A structure located in the central part of the brain that contains the pituitary stalk and other important structures. There are two arteries called carotid arteries. The carotid arteries supply blood to the brain and flow down both sides of the neck and connect directly to the circle of Willis. Each carotid artery branches into an internal carotid artery and an external carotid artery. The internal carotid artery then branches into the cerebral arteries. This structure allows all blood from the two internal carotid arteries to flow through the circle of Willis.

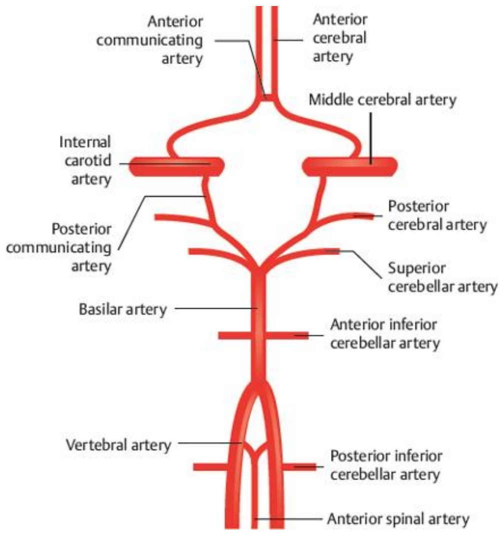

Figure 5. Circle of Willis

2. COMPARISON BETWEEN ARTIFICIAL INTELLIGENCE, MACHINE LEARNING AND DEEP LEARNING

A process known classification uses a group's similarities to define it. The classification technique is used in magnetic resonance imaging (MRI) brain image classification to distinguish between normal and abnormal regions in a brain images that comprises the gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) and brain lesion. Currently days, artificial intelligence-based brain imaging classification techniques like machine learning and deep learning are used. The relationship between deep learning, machine learning, and artificial intelligence is illustrated in Figure 6.

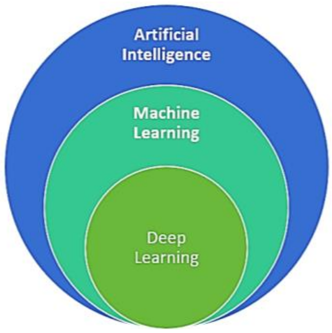

Figure 6. Circles of artificial intelligence, machine learning and deep learning [13]

Intelligent human behaviour can be imitated by artificial intelligence. A subset of artificial intelligence called machine learning use computerised algorithms to operate in certain ways without explicitly requesting the programming to execute them. Deep learning is a branch of machine learning that was inspired by the structure of the human brain and excels at feature detection. Deep learning is typically computed using unsupervised learning, as opposed to machine learning, which is typically calculated using supervised learning [14]. Supervised learning starts with the goal of predicting a known outcome or goal. Remarkably, trained people are capable of performing all of these activities successfully, hence computers frequently attempt to mimic human performance.

Classification, which chooses subgroups that best describe brand-new instances of data, and prediction, which calculates unknown parameters, are the main objectives of supervised learning. Unsupervised learning, however, has unpredictable results. Unsupervised learning, on the other hand, involves spotting naturally occurring groups or patterns in data. As a result of the intrinsic difficulty of this job, it is frequently determined by how well these groups do on future supervised learning tasks how valuable their unsupervised learning has been. All of these techniques produced worthwhile outcomes, although supervised classification performs better in terms of classification accuracy than unsupervised classification

(classification success rate). Due to the simplicity of obtaining data from brain analyses, discriminant analysis, support vector machines (SVMs), k-nearest neighbours (k-NN), and decision trees are well known as classification methods of MRI brain pictures in machine learning. [15].

3. EARLY STROKE SEGMENTATION TECHNIQUES

Image segmentation is very important because radiologists need to know the exact location, size, intensity, and other details of lesions to make conclusions and diagnoses. Segmentation involves recognizing and marking meaningful regions within specific image data. Five different image segmentation methods are analyzed: adaptive threshold, fuzzy C-means, region-growing, marker-controlled watershed, and k-means.

3.1. Adaptive threshold

The segmentation technique of adaptive thresholding converts a grayscale image with a fixed value into a binary image. Thresholding is the process of converting a grayscale image to a black-and-white image by precisely setting pixels whose values are above a certain threshold to white and those below it to black [16]. Adaptive thresholding assigns an image threshold for each pixel with reference to the gray-level intensities of neighboring pixels, given by (1).

$$G(x,y) = \begin{cases} 1 & if\ \ I(x,y) \geq \tau \\ 0 & otherwise \end{cases} \tag{1}$$

3.2. Region growing

Region growing is a basic and common image segmentation method used to segment homogeneous regions with the same intensity value. It requires no prior knowledge of the shape, so it can be implemented on objects of various shapes [17]. The main working principles include that each pixel must be in a specific region, that pixels within a region must be connected and satisfy certain similarity conditions, that regions are disjoint, and that there are two different It includes that regions must not have the same properties [18]. It is initialized with the starting point of each region of interest, which can be selected manually or automatically. Neighboring pixels or regions are then connected to seed points according to some predefined similarity criteria. This process continues until all pixels in some regions have been classified, preserving the connectivity of all pixels grown from the seed point. Contains local relationships between pixels. Its computational simplicity improves the use of this method. However, it is sensitive to seed initialization and noise. It does not work well with images that have adjacent regions that share similar intensities and regions that do not vary smoothly, such as textured images. It can be applied to images subject to lighting changes, but requires proper preprocessing.

The partial volume effect is also an important factor limiting the accuracy of segmentation as it obscures the difference in intensity at the boundary of two tissue types, thereby leading to voxels representing multiple tissue types [19]. This has been overcome with the introduction of modified region growing method (MRGM) by using gradient information to identify borders, and MRGM has been proven to provide better tumor segmentation results in 3D T1-MRI images [20]. Effective choice of threshold for selecting similarity conditions between two regions is important in efficient segmentation by minimizing the variance between uniform regions and maximizing the gradient along the boundary [21]. The seed region growth method for tumor segmentation uses a fixed threshold along with some pretreatments and yields satisfactory results. However, adaptive thresholds may prove more reliable. Only strength constraints were considered, but the inclusion of a directional constraint [22] improved the results. An extended version of traditional regional cultivation was developed [23]. Brain MRIs are processed from the generation of brain MRI T2 thresholds and PD images using a seed region growth algorithm, which are further processed by a Markov logic algorithm and classified based on the presence of tumors.

3.3. Marker-controlled watershed

Watershed segmentation is a gradient-based segmentation technique. In this study, watershed segmentation locates watersheds and watershed ridges by assigning intensity levels as surfaces, high intensity to bright pixels and low intensity to dark pixels [24]. Based on the edge detection method, the magnitude of the gradient is calculated from the foreground and background markings of the image. Morphological operations and watershed edges are then applied. A watershed transformation is formed based on the represented edges of the watershed [25]. The input image I(x,y) and the gradients along the x and y axes are computed based on (2) and (3).

$$I_x = \frac{\delta f}{\delta x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \tag{2}$$

$$I_y = \frac{\delta f}{\delta y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

Then the gradient of the image is defined as (3):

$$\nabla I(x,y) = \frac{\delta f}{\delta x} i + \frac{\delta f}{\delta y} j = I_x i + I_y j \tag{3}$$

where i and j are unit vectors along x and y axis respectively. The magnitude of gradient is given by (4).

$$g(x,y) = |\nabla f(x,y)| = \sqrt{{g_x}^2 + {g_y}^2} \tag{4}$$

In order to address issues such as noise and irregularities that can lead to over-segmentation in the image, morphological surgical techniques can be employed. These techniques involve applying morphological operations, such as erosion or dilation, to modify the image and reduce the impact of gradients. By selectively removing or expanding certain image components, the surgical techniques aim to achieve a more accurate segmentation result and overcome the challenges posed by noise and irregularities.

4. EARLY STROKE CLASSIFICATION TECHNIQUES

4.1. Discriminant analysis model

The model of discriminant analysis as shown in Figure 7. This model uses a Gaussian distribution to classify the dataset within its categories. Gaussian generates data from each category, finds a linear combination of features, and computes the boundaries of the data between each category. Determine categories of new data by collecting linear combinations of features that can be formed from linear or quadratic functions.

4.2. SVM analysis model

The SVM analytical model shown in Figure 8 allocate facts with the classification beside finding a linear decision boundary (hyperplane). If the data can be linearly separable, the hyperplane best suited for SVM has the widest margin between the two categories [26]. If the data cannot be linearly separable, use function loss to penalize points on opposite sides of the hyperplane. Transformation kernels can be utilized by SVM to alter nonlinearly separable data into higher dimensions, where linear decision boundaries can be identified.

4.3. k-NN analysis model

The k-NN analysis model is illustrated in Figure 9, and it classifies data into its respective category by examining the nearest neighbors. Data points that are close to each other are deemed to have similar characteristics and are classified as belonging to the same category [27]. To identify class parameters, k-NN calculates distance metrics, such as Euclidean, city block, cosine, and Chebyshev.

4.4. Decision tree analysis model

A decision tree analyzes data with its categories by constructing predictions. It determines the tree diagram concept. To make a prediction, the process starts from the root of the tree and moves towards the node leaf as shown in Figure 10 [28]. The routes produce branches, and a split is made by selecting predictor values that can be differentiated using trained weights. The number of branches and weight values are determined during the training phase. Additional modifications or simplifications can be made to the model.

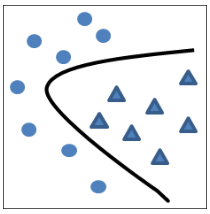

Figure 7. Discriminant analysis model

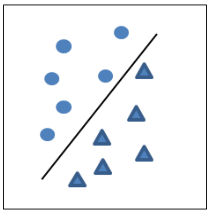

Figure 8. SVM analysis model

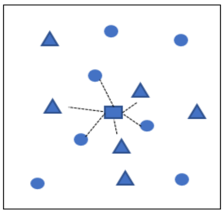

Figure 9. k-NN analysis model

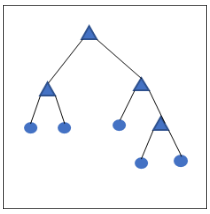

Figure 10. Decision tree analysis model

5. RESULTS AND DISCUSSIONS

Different methods are employed to segment and classify brain strokes using MRI scans, despite the limited amount of research available for assessment in databases. Tables 1 and 2 summarize the comparative analysis of these segmentation and classification techniques. In addition, based on this review, MRI is a more common imaging modality for segmentation research than CT. The primary objective of all these segmentation techniques is to create a system that is both efficient and accurate. In this part, using machine learning various techniques demonstrated for segmentation and classification, those are adaptive thresholding, marker-controlled watershed using correlation template, FCM, region growing, k-means, discriminant analysis model, SVM analysis model, k-NN analysis model and decision tree analysis model. Segmentation results describes k-means using the fast marching technique (FMM). Table 1 presents a summarized comparison of the segmentation techniques discussed above. Additionally, according to the review, the use of magnetic resonance imaging (MRI) for segmentation research is more commonplace than that of CT imaging [29]. Overall, the aim of all these segmentation techniques is to develop an accurate and effective system.

Table 1. Comparison between segmentation techniques

Techniques	Characteristics	Advantage	Disadvantage
Threshold	Threshold Method based on analyzing the histogram [30]	Simplest technique, does not require prior information [36]	Not effective when the Region of Interest (ROI) and the unwanted area have similar intensity [40]
FCM	FCM Method based on partitioning data into homogeneous clusters [31]	Fuzzy logic allows for partial membership, better for real-world problems [37]	Determining the membership function is difficult [41]
Region Growing	Region Growing is the selection of an initial seed point and examination of neighboring pixels [32]	Effective at noise resistance, applicable when it is easy to identify similarity criteria [38]	Manual selection of the homogeneity criterion [42], [43]
Watershed	Watershed Method based on topological surfaces [33]	Results are computationally efficient, detects continuous edges [33]	Can lead to over-segmentation [33]
K-means	K-means Method that divides data into k clusters to define k-centroid values of each cluster [34], [35]	Simple and suitable for large datasets [39].	Challenges with clustering data of varying sizes and densities [44]

Table 2. Comparison between classification techniques

Techniques	Characteristics	Advantage	Disadvantage
Discriminant Analysis Model	Discriminant Method has an efficient method for feature extraction and dimension reduction [45]	Assigns exact values to outcomes of various actions [45]	It is restricted to one output attribute [45]
SVM Analysis Model	SVM Method is a best classifier for categorising two or more categories [46]	Provides better accuracy compare to other classifier easily handle complex nonlinear data points and easily handle complex nonlinear data points [47]	It is expensive [47]
k-NN Analysis Model	k-NN Method is a nonparametric learning set of a classification algorithm that categorises objects based on the closest pixel [48]	It is easy to implement [48]	Sensitive to noise and requires large storage space [48]
Decision Tree Analysis Model	Decision tree Method minimizes the ambiguity of complicated decisions [49]	It handles both numerical and categorical data [49]	It is an unstable classifier, for example performance of classifier is depend upon the type of dataset [49]

The clustering technique is commonly used during the segmentation process. K-means is computationally faster than fuzzy c-means [50]. K-means employs several clusters to distinguish different tissue types, whereas fuzzy c-means uses a smaller number of clusters [37]. Fuzzy c-means is better at detecting anomalies with greater accuracy by preserving more information from the original image compared to k-means. Although computer-aided detection/diagnosis (CAD) has a substantial impact on automating image processing and analysis, it will never fully substitute medical professionals such as radiologists and doctors. Apart from that, the SVM is normally used during the classification process because it provides better accuracy compare to other classifier easily handle complex nonlinear data points and easily handle complex nonlinear data points.

6. CONCLUSION

In the nutshell, the researchers focused at MRI brain segmentation and brain stroke classification systems. Based on the research, DWI evaluates the capacity of molecular diffusion movements in a tissue structure, including the boundaries between white matter and gray matter brain tissues, cerebrospinal fluid, and brain lesions. These regions have distinct diffusion criteria that may be affected by illnesses. These boundaries can also be found in WM and GM brain tissues. Diffusivity affects picture contrast; a chronic stroke with high diffusion (watery tissues) appears dark (hypopointense), but a recent stroke with less diffusion seems dazzling (hyperintense). At last, different diagnosis of brain lesions is traditionally execute manually by skilled neuroradiologists, which is a very internal and time-consuming method.

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REFERENCES

[1] H. C. B. R. Alves, F. T. Pacheco, and A. J. Rocha, "Collateral blood vessels in acute ischemic stroke: a physiological window to predict future outcomes," *Arquivos de Neuro-Psiquiatria*, vol. 74, no. 8, pp. 662–670, May 2016, doi: 10.1590/0004-282x20160050.

[2] P. Parmar, "Stroke: classification and diagnosis," *Clinical Pharmacist*, 2018, doi: 10.1211/CP.2018.20204150.

[3] Institute for Health Metrics and Evaluation, "Findings from the Global Burden of Disease Study 2017", https://www.healthdata.org/, 2018. Available at: https://www.healthdata.org/sites/default/files/files/policy_report/2019/GBD_2017_Booklet.pdf.

[4] M. Gauberti *et al.*, "Ischemia-Reperfusion Injury After Endovascular Thrombectomy for Ischemic Stroke," *Stroke*, vol. 49, no. 12, pp. 3071–3074, Dec. 2018, doi: 10.1161/strokeaha.118.022015.

[5] A. Jamaiyar *et al.*, "Cardioprotection during ischemia by coronary collateral growth," *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 316, no. 1, pp. H1–H9, Jan. 2019, doi: 10.1152/ajpheart.00145.2018.

[6] K. Sharma *et al.*, "Automatic Segmentation of Kidneys using Deep Learning for Total Kidney Volume Quantification in Autosomal Dominant Polycystic Kidney Disease," *Scientific Reports*, vol. 7, no. 1, May 2017, doi: 10.1038/s41598-017-01779-0.

[7] J. S. Balami *et al.*, "A Systematic Review and Meta-Analysis of Randomized Controlled Trials of Endovascular Thrombectomy Compared with Best Medical Treatment for Acute Ischemic Stroke," *International Journal of Stroke*, vol. 10, no. 8, pp. 1168–1178, Aug. 2015, doi: 10.1111/ijs.12618.

[8] K. Batista-García-Ramó and C. Fernández-Verdecia, "What We Know About the Brain Structure–Function Relationship," *Behavioral Sciences*, vol. 8, no. 4, p. 39, Apr. 2018, doi: 10.3390/bs8040039.

[9] D. Kuriakose and Z. Xiao, "Pathophysiology and Treatment of Stroke: Present Status and Future Perspectives," *International Journal of Molecular Sciences*, vol. 21, no. 20, p. 7609, Oct. 2020, doi: 10.3390/ijms21207609.

[10] S. Jung, R. Wiest, J. Gralla, R. McKinley, H. Mattle, and D. Liebeskind, "Relevance of the cerebral collateral circulation in ischaemic stroke: time is brain, but collaterals set the pace," *Swiss Medical Weekly*, Dec. 2017, doi: 10.4414/smw.2017.14538.

[11] M. Kaps, "Extracranial and intracranial collateral pathways," in *Manual of Neurosonology*, Cambridge University Press, 2016, pp. 165–168. doi: 10.1017/cbo9781107447905.017.

[12] A. Krishnaswamy, J. P. Klein, and S. R. Kapadia, "Clinical cerebrovascular anatomy," *Catheterization and Cardiovascular Interventions*, vol. 75, no. 4, pp. 530–539, Jan. 2010, doi: 10.1002/ccd.22299.

[13] S. M. S. Reza, L. Pei, and K. M. Iftekharuddin, "Ischemic Stroke Lesion Segmentation Using Local Gradient and Texture Features," *in Proc. MICCAI-ISLES*, pp. 23–26, 2015.

[14] L. Chen, P. Bentley, and D. Rueckert, "A novel framework for sub-acute stroke lesion segmentation based on random forest," *Proc. MICCAI-ISLES*, pp. 13–16, 2015

[15] S. R. Telrandhe, "Implementation of Brain Tumor Detection using Segmentation Algorithm & SVM," *International Journal Computer Science Engineering*, vol. 8, no. 7, pp. 278–284, 2016.

[16] P. Guruprasad, "Overview Of Different Thresholding Methods In Image Processing," *TEQIP Sponsored 3rd National Conference on ETACC*, no. June, 2020.

[17] Kumar Mohan, Shanavas Muhammad, Sidappa Ashwin, and et al, "Cone beam computed tomography - know its secrets.," *Journal of international oral health: JIOH*, vol. 7, no. 2, pp. 64–8, 2015.

[18] M. Merzougui and A. El Allaoui, "Region growing segmentation optimized by evolutionary approach and Maximum Entropy," *Procedia Computer Science*, vol. 151, pp. 1046–1051, 2019, doi: 10.1016/j.procs.2019.04.148.

[19] Z. Cheng and J. Wang, "Improved region growing method for image segmentation of three-phase materials," *Powder Technology*, vol. 368, pp. 80–89, May 2020, doi: 10.1016/j.powtec.2020.04.032.

[20] Y. M. Salman, "Modified technique for volumetric brain tumor measurements," *Journal of Biomedical Science and Engineering*, vol. 02, no. 01, pp. 16–19, 2009, doi: 10.4236/jbise.2009.21003.

[21] W. Deng, W. Xiao, H. Deng, and J. Liu, "MRI brain tumor segmentation with region growing method based on the gradients and variances along and inside of the boundary curve," Oct. 2010. doi: 10.1109/bmei.2010.5639536.

[22] A. R. Kavitha, C. Chellamuthu, and K. Rupa, "An efficient approach for brain tumour detection based on modified region growing and neural network in MRI images," Mar. 2012. doi: 10.1109/icceet.2012.6203809.

[23] I. S. Bajwa, M. N. Asghar, and M. A. Naeem, "Learning-based improved seeded region growing algorithm for brain tumor identification," *Proceedings of the Pakistan Academy of Sciences: Part A*, vol. 54, no. 2, pp. 127–133, 2017.

[24] A. K. Nugroho, T. A. Putranto, I. K. E. Purnama, and M. H. Purnomo, "Multi Segmentation Method for Hemorraghic Detection," Mar. 2018. doi: 10.1109/icoias.2018.8494039.

[25] M. M and S. P, "MRI Brain Tumour Segmentation Using Hybrid Clustering and Classification by Back Propagation Algorithm," *Asian Pacific Journal of Cancer Prevention*, vol. 19, no. 11, pp. 3257–3263, Nov. 2018, doi: 10.31557/apjcp.2018.19.11.3257.

[26] D. Robben *et al.*, "A voxel-wise, cascaded classification approach to ischemic stroke lesion segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9556, pp. 254–265, 2016, doi: 10.1007/978-3-319-30858-6_22.

[27] S. Yahiya, A. Yousif, and M. Bakri, "Classification of Ischemic Stroke using Machine Learning Algorithms," *International Journal of Computer Applications*, vol. 149, no. 10, pp. 26–31, Sep. 2016, doi: 10.5120/ijca2016911607.

[28] B. V Kiranmayee, "EFFECTIVE ANALYSIS OF BRAIN TUMOR USING HYBRID DATA MINING TECHNIQUES," *International Journal of Advanced Research in Computer Science*, vol. 8, no. 7, pp. 286–293, Aug. 2017, doi: 10.26483/ijarcs.v8i7.4237.

[29] A. Irimia, A. S. Maher, K. A. Rostowsky, N. F. Chowdhury, D. H. Hwang, and E. M. Law, "Brain Segmentation From Computed Tomography of Healthy Aging and Geriatric Concussion at Variable Spatial Resolutions," *Frontiers in Neuroinformatics*, vol. 13, Mar. 2019, doi: 10.3389/fninf.2019.00009.

[30] L. Cui and H. Zhang, "Study on threshold segmentation of multi-resolution 3D human brain CT image," *Journal of Innovative Optical Health Sciences*, vol. 11, no. 06, Nov. 2018, doi: 10.1142/s1793545818500372.

[31] P. Kaur, P. Sharma, and A. Palmia, "Fuzzy clustering-based image segmentation techniques used to segment <scp>magnetic resonance imaging/computed tomographyscan brain: Comparative analysis," *International Journal of Imaging Systems and Technology*, vol. 30, no. 4, pp. 1294–1323, May 2020, doi: 10.1002/ima.22439.

[32] B. Suneetha and A. Jhansi Rani, "Brain Tumor Detection in MR Imaging Using DW-MTM Filter and Region-Growing Segmentation Approach," in *First International Conference on Artificial Intelligence and Cognitive Computing*, Springer Singapore, 2018, pp. 549–560. doi: 10.1007/978-981-13-1580-0_53.

[33] G. M. Tarhini and R. Shbib, "Detection of Brain Tumor in MRI Images Using Watershed and Threshold-Based Segmentation," *International Journal of Signal Processing Systems*, vol. 8, no. 1, pp. 19–25, Mar. 2020, doi: 10.18178/ijsps.8.1.19-25.

[34] R. Vankayalapati, K. B. Ghutugade, R. Vannapuram, and B. P. S. Prasanna, "K-Means Algorithm for Clustering of Learners Performance Levels Using Machine Learning Techniques," *Revue d'Intelligence Artificielle*, vol. 35, no. 1, pp. 99–104, Feb. 2021, doi: 10.18280/ria.350112.

[35] J. Sami Ur Rahman and S. Kumar Selvaperumal, "Integrated approach of brain segmentation using neuro fuzzy k-means," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 1, p. 270, Jan. 2022, doi: 10.11591/ijeecs.v29.i1.pp270-276.

[36] T. Badriyah, N. Sakinah, I. Syarif, and D. R. Syarif, "Segmentation Stroke Objects based on CT Scan Image using Thresholding Method," Dec. 2019. doi: 10.1109/stud49732.2019.9018825.

[37] I. Kumar, C. Bhatt, and K. U. Singh, "Entropy based automatic unsupervised brain intracranial hemorrhage segmentation using CT images," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 2589–2600, Jun. 2022, doi: 10.1016/j.jksuci.2020.01.003.

[38] W. Zhu and Y. Shen, "A Region Growing Segmentation Approach for MRI Brain Image Processing," Oct. 2019. doi: 10.1109/icasid.2019.8925066.

[39] X. Qian, Y. Lin, Y. Zhao, X. Yue, B. Lu, and J. Wang, "Objective Ventricle Segmentation in Brain CT with Ischemic Stroke Based on Anatomical Knowledge," *BioMed Research International*, vol. 2017, pp. 1–11, 2017, doi: 10.1155/2017/8690892.

[40] P. Singh, V. Khanna, and M. Kamal, "Hemorrhage segmentation by fuzzy c-mean with Modified Level Set on CT imaging," Feb. 2018. doi: 10.1109/spin.2018.8474166.

[41] B. Hachemi *et al.*, "Fully automatic multisegmentation approach for magnetic resonance imaging brain tumor detection using improved region-growing and quasi-Monte Carlo-expectation maximization algorithm," *International Journal of Imaging Systems and Technology*, vol. 30, no. 1, pp. 104–111, Nov. 2019, doi: 10.1002/ima.22376.

[42] A. M. A. A. Abang Isa *et al.*, "Pseudo-colour with K-means Clustering Algorithm for Acute Ischemic Stroke Lesion Segmentation in Brain MRI," *Pertanika Journal of Science and Technology*, vol. 29, no. 2, Apr. 2021, doi: 10.47836/pjst.29.2.03.

[43] S. Abbas and A. M. Mahmoud, "DiaMe: IoMT deep predictive model based on threshold aware region growing technique," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 5, p. 4250, Oct. 2021, doi: 10.11591/ijece.v11i5.pp4250-4262.

[44] T. C. Hakyemez, A. Bozanta, and M. Coşkun, "K-Means vs . Fuzzy C-Means : A Comparative Analysis of Two Popular Clustering Techniques on the Featured Mobile Applications Benchmark," *5th International Management Information Systems Conference*, 2018.

[45] T.-K. Kim, B. Stenger, J. Kittler, and R. Cipolla, "Incremental Linear Discriminant Analysis Using Sufficient Spanning Sets and Its Applications," *International Journal of Computer Vision*, vol. 91, no. 2, pp. 216–232, Sep. 2010, doi: 10.1007/s11263-010-0381-3.

[46] A. Sage and P. Badura, "Intracranial Hemorrhage Detection in Head CT Using Double-Branch Convolutional Neural Network, Support Vector Machine, and Random Forest," *Applied Sciences*, vol. 10, no. 21, p. 7577, Oct. 2020, doi: 10.3390/app10217577.

[47] S. A. Taie and W. Ghonaim, "A new model for early diagnosis of alzheimer's disease based on BAT-SVM classifier," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 2, pp. 759–766, Apr. 2021, doi: 10.11591/eei.v10i2.2714.

[48] A. H. Ali, S. A. Al-hadi, M. R. Naeemah, and A. N. Mazher, "Classification of Brain Lesion using K- Nearest Neighbor technique and Texture Analysis," *Journal of Physics: Conference Series*, vol. 1178, p. 12018, Feb. 2019, doi: 10.1088/1742-6596/1178/1/012018.

[49] N. M. Saad, A. R. Abdullah, A. R. Syafeeza, N. S. M. Noor, N. H. Ali, and A. S. Muda, "Automated Classification of Stroke Lesion Using Bagged Tree Classifier," *IOP Conference Series: Materials Science and Engineering*, vol. 884, no. 1, p. 12078, Jul. 2020, doi: 10.1088/1757-899x/884/1/012078.

[50] M. S. Alam *et al.*, "Automatic Human Brain Tumor Detection in MRI Image Using Template-Based K Means and Improved Fuzzy C Means Clustering Algorithm," *Big Data and Cognitive Computing*, vol. 3, no. 2, p. 27, May 2019, doi: 10.3390/bdcc3020027.

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