PATCHMATCH BASED TREE-SEED FUZZY CLUSTERING FOR ISCHEMIC STROKE LESION SEGMENTATION IN BRAIN MR IMAGES

[1]Mr. Tushar R. Sangole, [2]Dr. Amit K. Gaikwad, [3]Dr. Vinod M. Vaze

Research Scholar, JJTU, Rajasthan, India[1], Associate Professor, SIT Kolhapur[2], Department of Computer Science JJTU, Rajasthan, India[3]

tusharrsangole@gmail.com

ABSTRACT

Ischemic Stroke Lesion (ISL) arises when the artery of the brain gets blocked. The blood provisions nutrients and oxygen to the brain and take out carbon dioxide and other waste cells. In case an artery gets congested, the brain cells will not be able to function and will ultimately stop functioning (Khoshnam SE et al 2017). Nerve symptoms and symptoms of IS usually occur abruptly but can also be sometimes progressive in nature. Signs and symptoms vary based on the position of the occlusion and the flow (Sommer CJ 2017). Atherosclerotic stroke is generally found in elders, and arises without symptoms in 80% of the cases. IS can be initiated by a variety of ailments, like contraction of the arteries head or neck region (Jiang X et al 2018).This is usually produced by atherosclerosis, deposition of cholesterol, or generation blood clots which arise as a consequence of rapid heartbeat, heart attack, damages in heart valve, or some other underlying origins, including drug overdose, severe blood vessel injury in the neck, or abnormal blood flow (Renna R et al 2014). MRI is extensively utilized to identify cerebral ischemia.

Medical imaging procedures are used to obtain images of various regions of the human body for analyzing the condition and for further treatment. MRI is a scheme for getting comprehensive images of the interior organs, as well as the muscles of the brain &spinal cord. It is first utilized to picture body image and bodily functions (Liu J et al 2014).

Since the brain manages whole functions of the human body, the brain is considered to be one of the significant organs of the body. Several illnesses like infections, tumors, and strokes affect the brain. In addition, tumor brain may be a noncancerous or cancerous group or abnormal cell growth in the brain. Methods like MRI can be employed for detecting brain tumors. Lately, MRI scans have gained attention due to the requirement for a better evaluation of huge amounts of information (El-Dahshan et al 2014). Obtaining brain samples and automated classification of brain cells from MRI scans is important both in medicine and in experimental studies of common and diseased brain tumors. The most significant step in the fabrication of medical imaging is segmentation, which separates the matters in the image for processing.

Keywords: Patch match, Tree seed, Ischemic Stroke lesion, lesion segmentation

INTRODUCTION

Annually, approximately sixteen thousand new cases of brain tumours are discovered in people all over the world, According to the NHS, the global incidence of brain tumours has greater than before, and it is now a major concern (brain Tumour studies 2019). Gliomas of the brain and critical fearful device account for up to 30% of all gliomas; roughly 80% of these are spiteful gliomas (Goodenberger and Jenkins 2012). This discovery demonstrates the high cost of a well-planned tumour treatment. Given the wide variety of brain tumours that exist around the world, primary brain tumours are extremely rare. Tumors typically begin in the brain or a primary anxious device and only hardly, such as the liver or lungs, are extremely uncommon. The vast majority of these tumours have spread (Paolillo and Schinelli 2015). As a result, depending on the histological appearance of the tumour, most initial brain tumours are classified as the two types of grades that are named as LGG and HGG.

Surgery, radiation therapy, and chemotherapy are all used in the treatment of gliomas by clinicians. Tumor treatment outcomes are influenced by the location, kind, and severity of the tumour. Because of this, tumour segmentation plays a essential part in the development of surgical procedures and conduct plans. Clinical imaging modalities identify and assess tumours. To assist with surgery and radiotherapy planning, selecting the optimal treatment for a certain clinical diagnosis is necessary (Fink et al. 2015). While looking for the target volumes' contour on C-MRI (conventional magnetic resonance imaging), it can be useful for radiotherapy planning for high-grade gliomas (a type of brain cancer) (Niyazi et al. 2016). Through spatial information integrated throughout several go-sectional images, the MRI 3-d slice illustration decreases mistakes in medical practise while also assisting radiologist in seeing 3-dimensional anatomy from go-sectional photographs (Wu et al. 2010). Tumor assessment necessitates manually drawing a circle around the target area to capture the full 3-D quantity of the tumour. Although manual tumour margin segmentation Time-consuming when applied appropriately, semi-automatic processes can reduce the time required each slice to less than 2 minutes. minutes per tumour and can take up to sixteen minutes per tumour (Odland et al., 2015) Visible detection by humans elements in a photograph capabilities is also limited, increasing the likelihood of human error during guide segmentation. Furthermore this means that, for large MRI datasets, computerized segmentation will always be useful. An ischemic stroke is a chronic condition that often results in mortality. After the start of symptoms, many medical imaging modalities are available to aid in the diagnosis of stroke. When it comes to stroke analysis, time is of the key since the window of opportunity for treatment is quite narrow (about 3 hours following the beginning of similar concerns). The study and investigation related to this topic in current time with objective to get the early medication on in the early stages of the disease using Visual evaluation of DWI scans is challenging because taking different types of scan of brain in various stages of various sections at different time periods and locations is quite difficult and in concern to that it will be challenging task to get over its results in order to do the early medication that will effect to stroke, which further complicates the situation. As a result, an automated system that can reliably detect stroke lesions in DWI data will aid doctors in making more accurate diagnoses. This is the main point of the thesis.

A change in one of the acquisition parameters (the b-value) produces a new DWI scan with a different contrast. SNR is lowered while using DWI with higher b-values since they give superior sensitivity, more conspicuity of stroke lesions, and fewer artefacts. In addition to the diffusion weighted images or scans that we are performing with the human brain in various coefficients might also be made out. These scan images will provide different types of conclusions as well to take into various results of the maps generated with considering all these facts we will get to a particular solution of values that needs to be taken out from the various scans we have performed and that was difficult to start with the medication thus we suggested this new technique that will accurately show the location of brain tumor so that early medication will be started on the basis of new technologies and the events of machine learning technologies that can be used.

In most cases, the symptoms of a stroke reveal themselves immediately, albeit they may sometimes exhibit themselves gradually. During the initial stages of a stroke, some people may have mild symptoms such as forgetfulness, hearing loss, or vision degradation, as well as dementia or strange behaviour, among other things. Stroke may have disastrous consequences if not treated properly and promptly. Perhaps it will result in irreparable damage to the person's brain and spinal cord if improper treatment is not provided promptly and appropriately. It is possible for doctors to design treatment recommendations that are tailored to the specific needs of each patient if they can identify where a stroke has occurred at an early stage of the disease process. Stroke in brain tissue can be detected with the help of minimal methods that are used in conjunction with techniques such as automated stereoscopic scanning, which are illustrations of imaging techniques in which the damaged tissue exhibits properties that are distinct from those of normal cerebral matter. MRI is one of the most often used techniques to establish the presence of a stroke lesion, the age of the lesion, and the location of the lesion since it is particularly sensitive and accurate in detecting bone areas, soft tissues, and aberrant lesions. CT, in contrast to MRI, is incapable of detecting tiny lesions. The limitations of human delineation have spurred the development of semi-automatic and automated systems for identifying lesions in magnetic resonance imaging (MRI) data. Stroke is a leading cause of mortality and disability around the world. Known as an ischemic stroke, this kind of A obstruction of the extracellular fluid arteries is what causes a stroke to occur, which results in the brain tissue being harmed by the stroke. Due to the fact that the size of the lesion is a key result for the purposes of clinical investigations, high-quality and reproducible segmentation is desirable. Despite the fact that this is a challenging job owing to important factors, It is a required friction, in the same way that general friction affects the appearance, location, and appearance of lesions.

METHODOLOGY

A computer-aided detection and classification method for MRI brain tumour images that distinguish between benign and malignant tumours. The image sharpening is performed on the T1-w image, while the anisotropic diffusion filtering is performed on the T2-w picture. The rationale for employing an unsharp mask to generate a sharp picture is because the clarity of the T1-w is explained by its sharpness, which is why it is necessary to use an unsharp mask. In a similar vein, the anisotropic diffusion filter reduces information loss by efficiently maintaining precise structures and object boundaries. For both axial T1-w and T2-w pictures, the alpha blending method is employed in the compositing process. This is accomplished by the use of the Enhanced Watershed Segmentation (EWATS) algorithm to segment the tumour region. Because, as previously said, whereas past research has utilised several MRI modalities as input, we were able to obtain the findings that we achieved while just training each MRI modality individually. This is because, as previously stated, previous research has used multiple MRI modalities as input. In contrast to previous research that has used all four MRI modalities as input, we were able to accomplish the findings that we achieved while just training each MRI modality independently. This is in contrast to other research that has utilised all four MRI modalities as input. Following our investigation, we determined that when our 3D model is confronted with a brain tumour, it is capable of accurately identifying it as such. Due to the network architecture's ability to gather exact 3D information on tumorous areas received from surrounding MRI slices (j 1, j + 1) recorded using the same modality; the system achieves exceptionally high accuracy. This is made feasible by the network architecture's capacity to collect large amounts of three-dimensional information and store it in a centralised location, as previously stated. It is necessary that the MRI slices (j 1, j + 1) from the surrounding areas be of the same mode as the tumorous regions for the proposed method to be capable of retrieving reliable 3D information about tumorous sections from the surrounding areas when obtaining information about sections having tumors from MRI portions (j 1, j

+ 1) from the tumorous regions The convolutional layers can extract even more information as a result of this, which is particularly important when it comes to boosting the accuracy of brain tumour segmentation, as previously said. In addition to categorisation, there is also For the purpose of determining the precise position of a tumour in the brain, it was decided that the four highest feature maps from initial MRI scans would be utilised in combination with one another to establish the exact location of the tumour. It is possible to establish the location of the tumour in addition to the pixel intensity values obtained from those photographs. It is important to take into consideration the following factors: Because the hierarchical features contained finer information (at a higher resolution), they were utilised to produce the score maps for each SegNet model's final deconvolution layer. These score maps were then used to generate the score maps for each SegNet model's final deconvolution layer. Several hierarchical features of this layer enable the reliable identification of tumours at the cellular level, making it an excellent candidate for cancer detection. A breakdown of the layers that make up this structure is shown below: It is required to employ greater resolutions in order to be effective (in this case). BRATS 2017 training dataset was used to generate the evaluation findings reported in this chapter, which are shown in Table 5-4 for each of the four distinct types of magnetic resonance imaging procedures (MRI). Table 5-4 illustrates that SegNet _Max_ DT outperforms the other two networks in terms of performance. Every one of the SegNet models evaluated in this study was an unique SegNet model. As described in Section 6.2.4, it was decided to categorise the sub-tumour regions based on their greatest qualities (highest scores) rather of their weakest traits (lowest scores) in order to avoid duplicating results (lowest scores). Because of this, SegNet Max _DT may be able to provide the most accurate results.

In order to resolve this issue, the maximum feature maps of all SegNet models were pooled. Therefore, the classifier was only given with the strongest and most useful characteristics from all SegNet models, which resulted in enhanced performance for the classifier. Due to the fact that each imaging modality has its own set of features, it is necessary to understand how the features of each modality interact with one another, let alone which factors are most likely to improve segmentation results. In addition, when using a single complex model, it is more efficient to train several simple models rather than a single scalar model, as shown in the following example: For the second advantage, the recovery of attributes important to a SegNet model's unique modality may be achieved, allowing clinicians to get thorough information about the modality on which they would be executing their job. Additionally, extended scan periods are required to collect all of the numerous MRI modalities presently accessible in the field, which adds to the MRI restriction. The evaluation between open CV and current techniques revealed that the accuracy of this approach was the greatest and the execution time the shortest for the method under consideration. Open CV is a freeware library for machine learning and computer vision that may be downloaded from the internet

The data set [1] for ischemic stroke segmentation comprises data sets from five distinct hospitals in Singapore, the United States of America, Germany, and France. The data sets were collected from a total of 57 hospitals in Singapore, the United States of America, Germany, and France. Machines ranging from 1.5 T to 3 T, as well as GE, Siemens, and Philips, were used to collect the data sets. This data collection includes instances of lacunar stroke, ischemic stroke with hemorrhagic transition, and non-lacunar stroke, among other types of neurological disorders. In order to identify Acute or Sub-Acute Ischemic Stroke lesions in the human brain using magnetic resonance imaging (MRI) or computed tomography (CT) images, a variety of classification methods can be used. The approach presented in this research deals with a variety of classification methods that can be used to identify Acute/Sub-Acute Ischemic Stroke lesions in the human brain using magnetic resonance imaging (MRI) or computed tomography (CT) images. As a result, it is effective in both visual and mathematical execution since it takes into account several factors such as the age at which the stroke happened, systemic blood pressure, collateral flow, as well as the type of therapy that was delivered. The strategy we utilised for picture segmentation made advantage of the knowledge gained during the training phase of Random forest classifiers, which helped us to segment photos more successfully.

In the year 2019, Sunil Babu and colleagues did research. Researchers have proved that they can identify and segment brain tumour stroke lesions, and that this has a significant influence on the medical profession by proving their findings. [1] The clinical diagnosis, prognosis prediction, and therapy of various illnesses are all affected as a result of this. Additionally, this tool may be used for general brain modelling, such as the production of brain atlases, as well as for anatomical modelling, such as the construction of brain atlases. Both of these tasks can be accomplished with reasonable simplicity using this tool. To evaluate functional impairments in stroke patients and to investigate sleep disturbances in stroke patients, it is necessary to have comprehensive information on the location and quantity of brain lesions detected. The strokes, hemorrhages with TIS are types of attacks that occur in general human beings.(TIAs-also called to as ministries). Ischemic However, whereas hemorrhagic stroke results from a significant increase in blood leakage, ischemic stroke results from a significant decrease in blood flow. Stroke will result in stoppage of blood supply to the brain thought to occur as the it results in the stoppage of blood flow the particular region, resulting in the end of brain tissue in that section of the brain. In the repercussion of an hamorrhage, other types of strokes are the most common types of stroke, and they are also the most dangerous types of stroke. Stroke caused by the gathering of some size of blood in the brain is known as thrombotic stroke, and it is recognised by the medical community as such. An embolic stroke [4] is a type of stroke that occurs when a blood clot forms in an artery. It is the nearly everyone frequent type of stroke and affects around one in every 100 people. When it comes to identifying the site of a stroke, CT scanning and MRI scanning are the multiple scanning modalities that are most commonly utilised in the medical sector. CT scanning is a type of scan that uses x-rays to determine the location of the stroke. There are two types of techniques that are used for scanning the brain of human that ara CT and MRI that are now available to the public (MRI). Because CT-dependent methods are having very minimum chances of correctness along with chances of repetations this population [5], it is particularly advantageous to employ MRI scanners for early diagnosis of brain infarction in older adults. When it comes to early identification of brain infarction, MRI scanners are particularly useful since they detect infarcts before symptoms appear on the brain. The development of a reliable technique for segmenting subacute ischemic stroke lesions is a crucial component of our current work, which is being carried out in tandem with other research projects at this time.

MACHINE LEARNING AND FEATURE EXTRACTION

When techniques were first developed, they comprised of three steps: pre-processing of magnetic resonance images (MR pictures), feature development, and withdrawal and organization. When pre-processing images, the intermediate filter was employed for the purpose of improving the image quality while also maintaining the edges [37]. Image segmentation using clustering algorithms such as different types of clustering methods that are used for algorithms, others results in the generation of helpful features from images. When it comes to understanding and interpreting photographs, image segmentation is critical. Postoperative planning and matching, tissue categorization, tumour recognition, tumour volume calculation, blood cell segmentation, and blood cell delineation are all included are just a few of the many uses in brain imaging that it has to offer. In [17], a brain tumour segmentation technique is applied to 3D MR images by means of a CNN. [33] Proposes the application of a deep learning model with the purpose of automatically identifying anatomical structure of the brain. Using a combination of discrete Gaussian and higher-order patterns such as Markov-Gibbs patterns, random field classification is utilised in a voting technique for an ensemble of visual appearances such as intensity and adaptive form modes, as well as in other applications. [32] Describes the development of a cross shallow auto-encoder combined with a Bayesian fuzzy clustering-based segmentation technique. Following denoising with a non-local mean filter, a Bayesian fuzzy clustering strategy is a method that was applied in this research for the purpose of classifying brain tumours. The approach is described in detail below. In [11], the 2D MRI images are partitioned into the left and right hemispheres, and statistical parameters such as mean, homogeneity, absolute value, and inertia are generated for the Support Vector Machine (SVM) classifier before being fed into the classifier. Because of the large amount of features in step two, most studies include an additional step to extract features that contain more significant information using methods such as principal component analysis (PCA), SIFT detectors, and SURF descriptors [18], which are described below. In [10], after performing a hybrid feature extraction using a covariance matrix, a regularised extreme learning approach is utilised to categorise brain abnormalities and determine its severity. Using evolutionary styles similar as flyspeck mass optimization (PSO) to pick from a pool of features is known as evolutionary optimization is also discussed in [30]. On image analysis, classification methods such as k-nearest neighbours, decision trees, Support Vector Machine (SVM), the Naive Bayes, expectation-maximization, and the random forest are the most commonly used machine learning techniques [38]. Features are extracted for a hybrid Functional Near-Infrared Spectroscopy (fNIRS) and Electro Encephalo Graphy (EEG) brain-computer interface in [14] and categorised using SVM and Linear Discriminant Analysis (LDA) (LDA). Convolutional Neural Networks (CNN) are becoming increasingly used in various fields, including medical imaging, video analysis, and natural language processing, for feature extraction in a variety of applications. Having the ability to recognise the most relevant patterns and information from the training images are called recognition ability is the most important feature of CNN's performance. For example, VGGNet [31], GoogleNet [36], and AlexNet [19] are successful image classification architectures that have been widely employed in medical pictures, such as brain abnormality detection. It is discussed in [4] how to perform pre-processing and data preparation using 3D filters and CNNs with multi-path and cascade designs. In order to create a range of new portraits of a person with diverse expressions and poses, pixel CNN architecture is used. In [39], a cascade of CNNs is used to iteratively generate a room decoration from the ground up. Because CNN has a significant computational cost, researchers are attempting to develop new, computationally simple models that are accurate in tumour classification while maintaining low computational costs. The use of an ensemble of tiny collaborative learners rather than a complicated network is a common strategy for meeting the needs of quick training execution and convergence, among other things. These peer networks' learning processes can be completely independent of one another or they can be completely dependent on one another. A common machine learning objective is to estimate the distribution of data, which is one of the most challenging problems to solve. For example, there are hard-coded relationships between image pixels and their neighbours, which are impossible to identify without prior knowledge of the relationship. In this case, the auto-regressive models are data-driven estimators that discover such connections in a large amount of data. The better images created by these models are conditioned on noisy or incomplete data, and this is the output of the models. An acceptable density estimator is probable to be used to tackle a broad range of classification, regression, missing data, and other problems of this nature.

CONCLUSION

For the segmentation of ISL, we propose PatchMatch based Tree-Seed Fuzzy Clustering (PM-TSFC). Fuzzy C-means (FCM) clustering is a typical clustering procedure in machine learning and pattern recognition. For proper segmentation of ISL, each pixel should be allotted to the nearest cluster. To do this, we employ FCM to minimize the weighted distance between pixels & cluster centers. Moreover, the inclusion of Tree Seed Optimization algorithm helps to find the nearest optimal cluster center. This makes the proposed PM-TSFC to segment ISL with greater accuracy.
Below are the techniques that will be used while detecting the brain tumor from the images.

- Lesion Detection
- Data Pre-processing
- Lesion Segmentation

In experiments, it was discovered that 3D joint slices make use of additional 3D data information, which was supported by the findings. The strategy used by the SegNet Max DT model for picking the maximum number of features also appears to be promising, as it has the potential to enhance the configuration of our model over time. While the use of the BRATS 2017 dataset by SegNet Max DT produced better segmentation results.

Every image is subjected to histogram equalisation in order to improve the image quality and increase contrast. It is this algorithm that is used in the local area. The Radon Transform is applied to the image after it has been corrected for equalisation. This programme generates a 2-dimensional graph at a specific angle, and the image develops a pixel value beside a radial line in the same direction as the graph. They extracted features throughout the feature extraction procedure as a result of the presence of higher order spectra and numerous entropies. In feature ranking, a major feature can be listed first based on a metric that is used to determine its importance. Each type of linear discriminant analysis is classified into one of three categories.

REFERENCES

1. Abulnaga SM, Rubin J. Ischemic stroke lesion segmentation in CT perfusion scans using pyramid pooling and focal loss. InInternational MICCAI Brainlesion Workshop 2018 Sep 16 (pp. 352-363). Springer, Cham.
2. Acharya UR, Meiburger KM, Faust O, Koh JE, Oh SL, Ciaccio EJ, Subudhi A, Jahmunah V, Sabut S. Automatic detection of ischemic stroke using higher order spectra features in brain MRI images. Cognitive systems research. 2019 Dec 1;58:134-42.
3. Babu MS, Vijayalakshmi V. A review on acute/sub-acute ischemic stroke lesion segmentation and registration challenges. Multimedia Tools and Applications. 2019 Jan 1;78(2):2481-506.
4. Babu MS, Vijayalakshmi V. An Effective Approach for Sub-acute Ischemic Stroke Lesion Segmentation by Adopting Meta-Heuristics Feature Selection Technique Along with Hybrid Naive Bayes and Sample-Weighted Random Forest Classification. Sensing and Imaging. 2019 Dec 1;20(1):7.

5. Bertels J, Robben D, Vandermeulen D, Suetens P. Contra-lateral information CNN for core lesion segmentation based on native CTP in acute stroke. InInternational MICCAI Brainlesion Workshop 2018 Sep 16 (pp. 263-270). Springer, Cham.
6. Bharathi PG, Agrawal A, Sundaram P, Sardesai S. Combination of hand-crafted and unsupervised learned features for ischemic stroke lesion detection from Magnetic Resonance Images. Biocybernetics and Biomedical Engineering. 2019 Apr 1;39(2):410-25.
7. Binaghi E, Omodei M, Pedoia V, Balbi S, Lattanzi D, Monti E. Automatic Segmentation of MR Brain Tumor Images using Support Vector Machine in Combination with Graph Cut. InIJCCI (NCTA) 2014 Oct 22 (pp. 152-157).
8. Chen W, Liu B, Peng S, Sun J, Qiao X. S3D-UNet: separable 3D U-Net for brain tumor segmentation. InInternational MICCAI Brainlesion Workshop 2018 Sep 16 (pp. 358-368). Springer, Cham.
9. Chen, X., & Pan, L. (2018). A survey of graph cuts/graph search based medical image segmentation. IEEE reviews in biomedical engineering, 11, 112-124.
10. Chin CL, Lin BJ, Wu GR, Weng TC, Yang CS, Su RC, Pan YJ. An automated early ischemic stroke detection system using CNN deep learning algorithm. In2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST) 2017 Nov 8 (pp. 368-372). IEEE.
11. Dong H, Yang G, Liu F, Mo Y, Guo Y. Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks. Inannual conference on medical image understanding and analysis 2017 Jul 11 (pp. 506-517). Springer, Cham.
12. El-Dahshan ES, Mohsen HM, Revett K, Salem AB. Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. Expert systems with Applications. 2014 Sep 1;41(11):5526-45.
13. Feng X, Ye G, Cao R, Qi P, Lu J, Chen J, Wang D. Identification of Predictors for Hemorrhagic Transformation in Patients with Acute Ischemic Stroke After Endovascular Therapy Using the Decision Tree Model. Clinical Interventions in Aging. 2020;15:1611.
14. Gautam, A., & Raman, B. (2019). Segmentation of ischemic stroke lesion from 3d mr images using random forest. Multimedia Tools and Applications, 78(6), 6559-6579.
15. Griffis, J. C., Allendorfer, J. B., & Szaflarski, J. P. (2016). Voxel-based Gaussian naïve Bayes classification of ischemic stroke lesions in individual T1-weighted MRI scans. Journal of neuroscience methods, 257, 97-108.
16. Gupta, A., Vupputuri, A., & Ghosh, N. (2019, July). Delineation of Ischemic Core and Penumbra Volumes from MRI using MSNet Architecture. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 6730-6733). IEEE.
17. Huber T, Alber G, Bette S, Boeckh-Behrens T, Gempt J, Ringel F, Alberts E, Zimmer C, Bauer JS. Reliability of semi-automated segmentations in glioblastoma. Clinical neuroradiology. 2017 Jun 1;27(2):153-61.
18. Jiang X, Andjelkovic AV, Zhu L, Yang T, Bennett MV, Chen J, Keep RF, Shi Y. Blood-brain barrier dysfunction and recovery after ischemic stroke. Progress in neurobiology. 2018 Apr 1;163:144-71.
19. Kamnitsas K, Baumgartner C, Ledig C, Newcombe V, Simpson J, Kane A, Menon D, Nori A, Criminisi A, Rueckert D, Glocker B. Unsupervised domain adaptation in brain lesion segmentation

with adversarial networks. InInternational conference on information processing in medical imaging 2017 Jun 25 (pp. 597-609). Springer, Cham.

20. Kamnitsas K, Ferrante E, Parisot S, Ledig C, Nori AV, Criminisi A, Rueckert D, Glocker B. DeepMedic for brain tumor segmentation. InInternational workshop on Brainlesion: Glioma, multiple sclerosis, stroke and traumatic brain injuries 2016 Oct 17 (pp. 138-149). Springer, Cham.