Journal of Social Research

P-ISSN: 2827-9832
E-ISSN: 2828-335x
http://ijsr.internationaljournallabs.com/index.php/ijsr

COMPARISON OF HEMORRHAGIC STROKE MEASUREMENT RESULTS IN CT-SCAN MODALITY WITH SOFTWARE VOLUME EVALUATION METHOD AND OTSU THRESHOLDING SEGMENTATION METHOD

Ahmad Ali Bisri, Sidin Haryanto, Dwi Rochmayanti
Poltekkes Kemenkes Semarang, Indonesia
ahmadalibisri@gmail.com

ABSTRACT

Evaluation of CT-scan image results of hemorrhagic strokes was carried out using the volume evaluation software method manually; this method has several weaknesses in that the measurement takes a relatively long time. This researcher applies a digital image processing program with the help of Matlab software by utilizing the segmentation process of the Otsu thresholding method to measure hemorrhagic strokes. To determine differences in the results of hemorrhagic stroke measurements using the software volume evaluation method and the Otsu thresholding method. Quasi-experimental research with a post-test only control group design on CT-scan images. Create an otsu thresholding design using the Matlab R2021a program. Digital images were used as data for 32 CT-Scan images of the head. Processing and analysis of the results in this research used quantitative methods using the Mann-Whitney non-parametric statistical test. Measurement of hemorrhagic stroke using the software volume evaluation method with the Otsu thresholding method shows that there is a difference with a value of 0.04 with a p value < 0.05 and the software volume evaluation method has an average percentage difference of 59% from the Otsu thresholding method. Measurements using volume evaluation software take longer than the automatic Otsu thresholding method, but the results are not better than the volume evaluation software method. The software volume evaluation method is better in measuring hemorrhagic stroke volume compared to the Otsu thresholding method.

Keywords: head CT-Scan, stroke hemoragik, segmentation, software volume evaluation, otsu thresholding

INTRODUCTION

One of the leading causes of disease, death, and disability in the world is stroke (Musung et al., 2022). Most isemic and hemorrhagic strokes have risen to 85-94 per 100,000 people. In addition, 87% of stoke disability and 85% of these related deaths occurred in developing countries and low-income countries (Murphy & Werring, 2020). The absolute burden of the number of cases increased substantially (70%,0 increase in stroke incidence, 43% stroke death-related stroke, 102% general stroke and 143% DALYs. The absolute number of DALYs due to male stroke 77.0 million exceeds that of Women 66.0 million at the global level in 2019 (Feigin et al., 2022). The Riskesdas survey from 2007 to 2018 revealed an increase in the prevalence of stroke in Indonesia. Based on diagnoses made in the population under the age of 15 years, the prevalence of stroke in Indonesia has increased, with figures of 6.9% in 2007, 7.4% in 2013, and 10.9% in 2018 (Hidayati et al., 2021).

Stroke is a condition that affects the central nervous system of the body, specifically the brain. A stroke is a clinical syndrome caused by a global or widespread neurological disorder that lasts for 24 hours or more and can result in disability or death. A stroke can result from sudden bleeding or a weak blood supply in the brain. Strokes can be classified as hemorrhagic or non-hemmorrhagic, or ischemic, in two different ways. Hemorrhagic stroke is caused by rupture of blood vessels in the brain, while isemic stroke is caused by blood vessels that are blocked with plaque (Budianto et al., 2021). Stroke is not a single disease but can be caused by various risk factors, processes and disease mechanisms including hypertension, millitus diabetes, smokers, hyperlipidaemia, alcohol consumption, drug abuse, and obesity (Murphy & Werring, 2020). Abnormalities in stroke can be assessed using modalities such as MRI and CT-Scan to assess anatomical structure, physiological function and pathology.

CT scan is a modality using x-rays that are attenuated after passing through an object, then received by the detector and converted from an electrical signal into a digital signal then entered into a computer for the image reconstruction process (Seeram & Sil, 2013). CT-Scan modalities are the most commonly used emergency room diagnostic modalities for patients with head injuries or patients with stroke symptoms. The most critical and time-sensitive abnormalities that can be easily detected on CT scans include intracranial hemorrhage, intracranial suppressors and assisting in stroke diagnosis (Chilamkurthy et al., 2018) (Xu et al., 2020).

Abnormalities in stroke are important for rapid diagnosis and quantitative assessment of ischemic stroke in the acute stage to improve treatment success as it can result in permanent damage to brain regions (Zhao et al., 2019). According to Mouridsen et al, stroke imaging must be done quickly will provide better results, but stroke imaging requires the presence of radiologists and neurologists, and this is a time-limiting step so that automatic methods are needed in the evaluation of stroke imaging (Mouridsen et al., 2020). Sometimes for radiologists experienced in identifying bleeding on CT-scan of the head it may be difficult to find the location, due to extensive spatial and structural heterogeneity in each scan, there is noise and complexity in the low contrast between bleeding and normal (Li et al., 2020). The condition of the isemic stroke patient is important in control because intracranial hemorrhage after the stroke affects the outcome in an attempt to proceed with recanalization. Dangerous complications, namely parenchymal hematoma, intracerebral hemorrage (ICH) and the development of infarction with hemmorage can cause neurological decline (Hong et al., 2021). Damage to brain tissue increases with the size of the hematoma. In general, acute ICH should be treated with emergency measures such as intubation, ventilation, and nerve monitoring (Arab et al., 2020). The volume of the hematoma is considered an indicator of 30-day mortality and functional prognosis for ich patients. Patients with a hematoma volume of less than 30 ml have a 30-day mortality rate of less than 20%, but patients with a volume greater than 60 ml have a mortality rate of more than 90%. Patients who had more than 30 ml hematomas were more likely to remain functionally dependent at 30 days (Hillal et al., 2022).

The calculation of bleeding volume can be done 2 methods used, namely manual calculations and using software. Calculation using automatic volume software is a limitation of the segmentation area in the area of the object specified by volume. the number of voxels with a range of HU values from the lowest value to the highest value in the bleeding CT number on the image will be estimated for the restricted area. Scan, HU is the value of the tissue absorption coefficient (CT number) (Masrochah S et al., 2021). The advantage of the automatic volume software method is that it uses segmentation techniques with freehand ROI, the more precise the segmentation technique, the more accurate the volume calculation results. The drawback is that it has a longer time process when compared to Broderick's manual method because of the process of segmenting the bleeding area and determining the HU value according to the bleeding area (Kiswoto et al., 2010). Manual calculation of bleeding volume using the "Coniglobus Formula" is currently the main method used in clinical practice to determine the volume of ICH. The general idea is to imagine the ICH as having an ellipsoid shape and calculate its volume using the formula V=A B C 1/2, where V is the volume of ICH, A is the largest lesion diameter at the maximum ICH slice in the CT image, B is the largest width perpendicular to A at this slice, and C is the sum of the slices thickness of the ICH slice. To measure volume, the "Coniglobus formula" is an easy and fast method with good accuracy for ellipsoid-shaped ICH. However, the non-ellipsoid form of most ICH in clinical practice and the limited experience of radiologists resulted in large errors in ICH volume measurements (Peng et al., 2022). To improve ICH efficiency, various methods based on machine learning can be used for automatic segmentation. Machine learning is part of artificial intelligence that is widely used in various fields (Wang et al., 2021). Information and communication technology is developing rapidly, and this has a significant impact on society as well as industry (Fukuyama, 2018).

In the industrial era 4.0 is the transformation of industrial manufacturing through digitalization and the exploitation of the potential of new technologies in ensuring efficiency through automation to increase needs (Joyia et al., 2017). In the 5.0 era, all aspects of life become new knowledge that will be devoted to increasing human capacity in providing opportunities for mankind (Widiastuti, 2020). The Internet of Things (IoT), Artificial Intelligence (AI), and advances in robotics in industry have significantly changed people's way of life. With the help of technology, humans can find solutions to social problems more quickly and easily, as well as reduce the need for physical work (Sugiono, 2020). IoT offers several benefits to humans, society, the environment, customers, businesses and the medical field. IoT in Health system monitors Health remotely so as to reduce excess time used, Internet Of Medical Things (IoMT) plays an important role in the health industry to improve the accuracy, reliability, productivity of electronic devices (Joyia et al., 2017). IoMT must have the following capabilities: simple connectivity, easy device management, information enabtion, information analytics and risk reduction. By collecting data from multiple sources, normalizing that data into a consistent structure of data sets can be the basis for highly effective AI technology (Dimitrov, 2016). Deep Learning (DL) has been widely used in various applications as a powerful machine Learning (ML) method to deal with various complex problems that require very high accuracy and sensitivity, particularly in the medical industry (Alqudah et al., 2020). Deep Learning has also been trained to find and measure disease patterns or anatomical volume using the "segmentation" method, as well as to detect abnormalities in radiological images such as chest radiography, chest CT, and head CT (Chilamkurthy s et al., 2018). With decreased performance tied to the quality and consistency of radiological interpretation, Deep Learning algorithms can be effectively trained to be a useful complement to identify acute head CT abnormalities (Chilamkurthy s et al., 2018).

Advances in technology, particularly in the field of digital image processing, allow computers to identify traumatic brain damage or brain hemorrhage by looking for traits often found in the brain. In order for the system to further identify the type of damage based on its characteristics, complex calculations, and the volume of the brain hemorrhage area, the special features that have been collected can be used as training data for machine learning (Sumijan et al., 2021). Radiologists often divide ICH zones manually. It takes time, and a tiring workday can easily result in incorrect segmentation. Therefore, it is very important to create automated and precise computer-aided segmentation techniques (Hu et al., 2020). Image segmentation is the process of adding objects to an area of an image or separating them into sections, each of which has a comparable set of characteristics. If there is only one object in an image, the object stands out from both the background and other objects (Sumijan S et al., 2021). Immediate interpretation is essential in patients with suspected intracranial hemmorage (ICH) to assess the need for neurocare care, thereby reducing diagnosis time, speeding up treatment and possibly reducing morbidity and mortality due to stroke (Sumijan S et al., 2021). The advantages of the segmentation method are effective thresholding techniques, by selecting thresholds automatically, and carrying out region-based segmentation techniques fairly and the process involves comparing threshold values with pixel color values of digital images (Sumijan et al., 2019) (Makandar & Halalli, 2016). Researchers developed an automatic segmentation method using otsu theresholding so that this application helps radiologists in measuring volume precisely and accurately. In this study, a digital image processing program was developed in determining the value of hemorrhagic volume automatically using the otsu thresholding segmentation method.

METHOD

This type of research is quasi-experimental using posttest research design only without control group design. This study aims to determine the difference in the results of measuring hemorrhagic stroke volume using the volume evaluation software measurement method on CT-Scan aircraft and with the segmentation process using the otsu thresholding method. The target population in this study is CT-Scan images with cases of hemorrhagic stroke at the radiology installation of Koja Regional General Hospital,

Data analysis of hemorrhagic stroke volume measurement results using CT-Scan software Input the results of hemorrhagic stroke volume measurement using the otsu thresholding segmentation method process then carried out data normality tests using the Shapiro Wilk test, to determine the type of statistical analysis used Bivariate analysis, if the data is abnormally distributed (p value > 0.05), then an independent T-test is carried out and if the data is carried out Abnormally distributed (p value < 0.05) is done by Man-Whitney.

RESULTS AND DISCUSSION

Quasi-experimental research by treating the measurement and calculation of hemorrhagic stroke volume using the volume evaluation software method on CT-Scan aircraft and with the segmentation process of the otsu thresholding method. The samples used were 32 images of head CT-Scan patients with hemorrhagic stroke cases from March-June 2023 with 18 male patients and 14 female patients. The image used to measure the volume of hemorrhagic stroke on the axial cut CT-Scan, after measurement using volume evaluation software on the CT-Scan, the sample is automatically measured using matlab software with the otsu thresholding segmentation method.

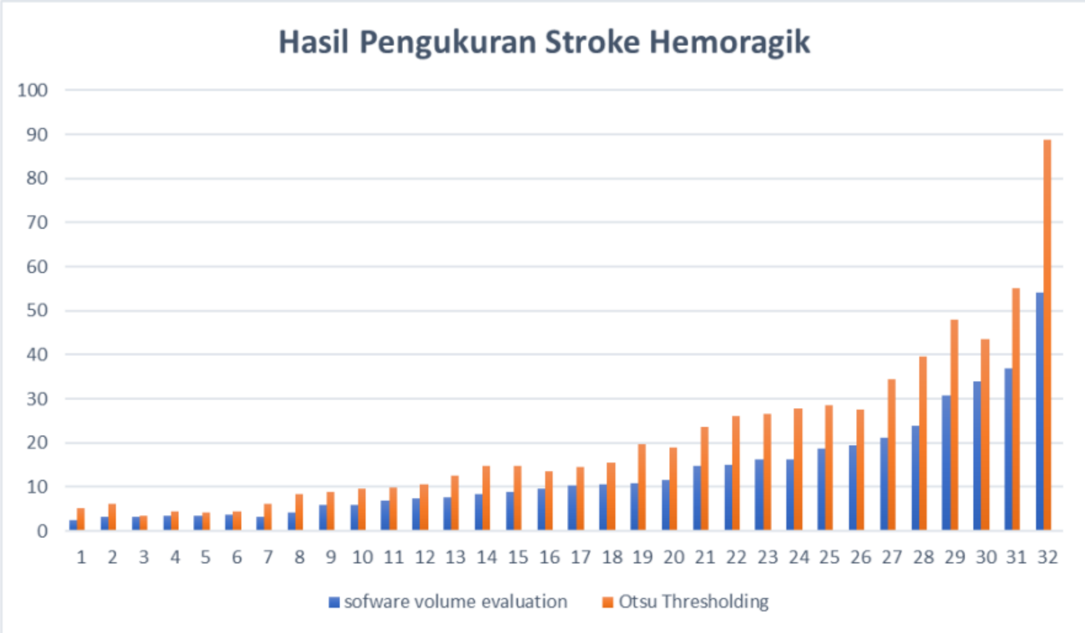

Figure 1. Graph of hemorrhagic stroke volume results using volume evaluation software method and otsu thresholding method

Based on the graph of the results of measuring hemorrhagic stroke volume, there are 32 CT-Scan images using the volume evaluation software method and the otsu thresholding method. Of the 32 CT-Scan images with hemorrhagic stroke cases, there were 24 images with higher volume measurement values in the otsu thresholding method compared to using the software volume evaluation method, 4 images that had values with an insignificant difference from both methods and 4 images with the otsu thresholding method had twice the value of measurements using the volume evaluation software method. Based on the graph, the average percentage value is 59%. These two methods are able to display the measurement of hemorrhagic stroke volume based on the area of hemorrhagic stroke.

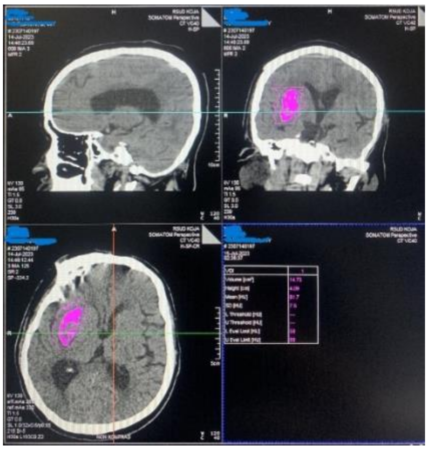

Figure 1. Results of Hemorrhagic Stroke Volume Measurement Using Software Volume Evaluation Method

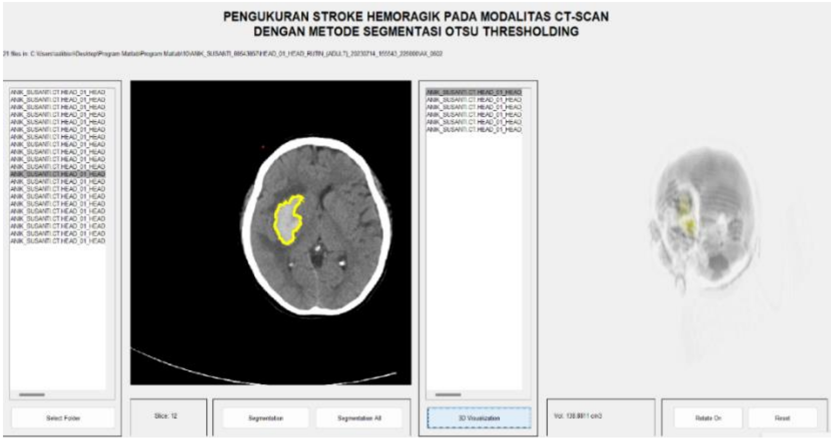

Figure 2. Results of measuring hemorrhagic stroke volume using the Otsu Thresholding segmentation method

1. Data Normality Test Results

Table 1. Normality Test Results of hemorrhagic stroke volume measurement data using volume evaluation software method and otsu thresholding method

No	Measurement Techniques	*Signifikansi (p-value)*
1	*Software Volume Evaluation*	0.000
2	Otsu *thresholding*	0.000

In this statistical test, researchers used data from measuring hemorrhagic stroke volume with the volume evaluation software method and the otsu thresholding segmentation method carried out for data normality and obtained results on Shapiro-Wilk p-value (<0.05) which means the data is abnormally distributed so that it can be continued with non-parametric statistics with man whitney.

Table 2. Univariate analysis results of hemorrhagic stroke volume measurement using volume evaluation software method and otsu thresholding method

	Software Volume Evaluation	*Otsu thresholding*
Mean	13.50	20.98
Median	10.00	14.68
Mode	3.78	3.38
Std.deviation	1.174	1.834
Range	51.64	85.33

2. Volume Difference Test Results

Table 3. Results of Mann-whitney Test Analysis of hemorrhagic stroke volume measurement using software volume evaluation method and otsu thresholding method

No	Measurement Techniques	*Signifikansi (P-Value)*	Makna
1	*Software Volume Evaluation*	0.000	There's a Difference
2	Otsu *thresholding*		

The results of the mann-whitney statistical test above the volume evaluation software method and the otsu thresholding method obtained an Asymp Sig confidence level of < 0.000. This states that there is a difference between the software volume evaluation method and the otsu thresholding method.

Discussion

This study produced quantitative data in the form of the results of measuring the volume of hemorrhagic stroke carried out using the CT-Scan modality with the volume evaluation software method at the Koja Regional General Hospital carried out by users (radiographers) who are accustomed to measuring the volume of hemorrhagic strokes and using the otsu thresholding method. Based on the results of non-parametric statistical tests, mann-whitney stated that there was a significant difference in the results of measuring the volume of hemorrhagic stroke between using CT-Scan modality with the volume evaluation software method and with the otsu thresholding segmentation method with the meaning value of Asym sig < 0.000. The difference in the results of measuring hemorrhagic stroke volume in these two methods is because the process of measuring hemorrhagic stoke volume in these two methods is different in both methods.

The difference in the results of measuring hemorrhagic stoke volume using CT-Scan modality with the volume evaluation software method and the otsu thresholding segmentation method was obtained due to differences in the way of measuring hemorrhagic stroke volume carried out in both methods. In measurement using CT-Scan modality with the volume evaluation software method, the obsever measures the slice by following the suspected area of hemorrhagic stoke manually from the initial slice to the suspected final area, so as to obtain the results of the measurement and accuracy is needed in measuring the suspected hemorrhagic stroke area covered by the area. The use of the volume evaluation software method based on the steps affects the segmentation time of hemorrhagic stroke volume so that it takes a longer time. In research according to Kiswoyo (2017) the volume evaluation software method for measuring hemorrhagic stroke volume is influenced by slice thickness, bleeding area segmentation techniques with freehand ROI and HU value range. The time needed is longer because of the process of segmenting the bleeding area and determining the value of HU according to the type of bleeding (Kiswoyo AS et al., 2010). Meanwhile, in the otsu thresholding segmentation method, measurements are carried out automatically, no manual measurement of the hemorrhagic stroke area is carried out, but the hemorrhagic stroke area has been covered automatically. Based on the many steps, the segmentation process using the otsu thresholding method does not require a long time in segmenting because the otsu thresholding method has automatically measured the volume of hemorrhagic stroke automatically.

In research according to Amelia (2017) the use of the otsu thresholding method for the image segmentation process can be implemented. The segmentation results can be used to determine the area so that the volume of bleeding can be calculated and the size of the volume of bleeding can be used by doctors for further medical treatment (Khamidah i., 2015). In graph 1, the results of hemorrhagic stroke volume in the otsu thresholding method have several higher volume results compared to the volume evaluation software method. Based on s husman's (2021) research, the weakness of the Otsu thresholding segmentation algorithm is the irregular boundaries generated from adjacent pixels. This results in the segmentation regions not being connected so that the similarity coefficient value is lower. The results of the Otsu thresholding algorithm are also not good when objects have significant grayish contrast compared to the background, considering only intensity and ignoring possible relationships between pixels. Based on the results of research using the otsu thresholding method can already produce measurements for volume in cases of hemorrhagic stroke and has the advantage of automatic measures. Better time efficiency, especially conditions are increasingly advantageous if it requires proper handling otherwise in non-urgent conditions using the volume evaluation software method can be used and it takes the accuracy of the user (radiographer) in segmenting his measurements to produce appropriate volume measurements.

CONCLUSION

The results of the mann-whitney non-parametric statistical test on the results of inter-hemorrhagic stroke volume measurement using CT-Scan modality with the software volume evaluation method and with the otsu thresholding segmentation method with a meaningful value of Asym sig < 0.04 $p < 0.05$ results have an average percentage of 59% measurement using the otsu thresholding method compared to the volume evaluation software method. This shows that there is a significant difference between the results of measuring the volume of hemorrhagic stroke between using CT-Scan modality with the volume evaluation software method and with the OTSU thresholding segmentation method.

The results of measuring the volume of hemorrhagic stroke using the software volume evaluation method with manual segmentation techniques so that it takes longer to measure but the results of measuring hemorrhagic stroke are better than the otsu thresholding method and measuring the volume of hemorrhagic stroke using the otsu thresholding method has been done automatically in image segmentation so it does not take a long time but the results of measuring hemorrhagic stroke are larger So it is not better than volume evaluation software.

REFERENCES

Alqudah, A. M., Alquraan, H., Qasmieh, I. A., Alqudah, A., & Al-Sharu, W. (2020). Brain tumor classification using deep learning technique--a comparison between cropped, uncropped, and segmented lesion images with different sizes. *ArXiv Preprint ArXiv:2001.08844*.

Arab, A., Chinda, B., Medvedev, G., Siu, W., Guo, H., Gu, T., Moreno, S., Hamarneh, G., Ester, M., & Song, X. (2020). A fast and fully-automated deep-learning approach for accurate hemorrhage segmentation and volume quantification in non-contrast whole-head CT. *Scientific Reports*, *10*(1), 19389.

Budianto, P., Prabaningtyas, H., Putra, S. E., Mirawati, D. K., Muhammad, F., & Hafizan, M. (2021). Stroke Iskemik Akut: Dasar dan Klinis. *Fakultas Kedokteran Sebelas Maret*.

Chilamkurthy, S., Ghosh, R., Tanamala, S., Biviji, M., Campeau, N. G., Venugopal, V. K., Mahajan, V., Rao, P., & Warier, P. (2018). Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. *The Lancet*, *392*(10162), 2388–2396.

Dimitrov, D. V. (2016). Medical internet of things and big data in healthcare. *Healthcare Informatics Research*, *22*(3), 156.

Feigin, V. L., Brainin, M., Norrving, B., Martins, S., Sacco, R. L., Hacke, W., Fisher, M., Pandian, J., & Lindsay, P. (2022). World Stroke Organization (WSO): global stroke fact sheet 2022. *International Journal of Stroke*, *17*(1), 18–29.

Fukuyama, M. (2018). Society 5.0: Aiming for a new human-centered society. *Japan Spotlight*, *27*(5), 47–50.

Hidayati, A., Martini, S., & Hendrati, L. Y. (2021). Determinan Kejadian Stroke pada Pasien Hipertensi (Analisis Data Sekunder IFLS 5). *Jurnal Kesehatan Global*, *4*(2), 54–65.

Hillal, A., Ullberg, T., Ramgren, B., & Wassélius, J. (2022). Computed tomography in acute intracerebral hemorrhage: neuroimaging predictors of hematoma expansion and outcome. *Insights into Imaging*, *13*(1), 180.

Hong, J. M., Kim, D. S., & Kim, M. (2021). Hemorrhagic transformation after ischemic stroke: mechanisms and management. *Frontiers in Neurology*, *12*, 703258.

Hu, K., Chen, K., He, X., Zhang, Y., Chen, Z., Li, X., & Gao, X. (2020). Automatic segmentation of intracerebral hemorrhage in CT images using encoder–decoder convolutional neural network. *Information Processing & Management*, *57*(6), 102352.

Joyia, G. J., Liaqat, R. M., Farooq, A., & Rehman, S. (2017). Internet of medical things (IoMT): Applications, benefits and future challenges in healthcare domain. *J. Commun.*, *12*(4), 240–247.

Li, L., Wei, M., Liu, B. O., Atchaneeyasakul, K., Zhou, F., Pan, Z., Kumar, S. A., Zhang, J. Y., Pu, Y., & Liebeskind, D. S. (2020). Deep learning for hemorrhagic lesion detection and segmentation on brain CT images. *IEEE Journal of Biomedical and Health Informatics*, *25*(5), 1646–1659.

Makandar, A., & Halalli, B. (2016). Threshold based segmentation technique for mass detection in mammography. *J Comput*, *11*(6), 472–478.

Mouridsen, K., Thurner, P., & Zaharchuk, G. (2020). Artificial intelligence applications in stroke. *Stroke*, *51*(8), 2573–2579.

Murphy, S. J. X., & Werring, D. J. (2020). Stroke: causes and clinical features. *Medicine*, *48*(9), 561–566.

Musung, J. M., Kakoma, P. K., Bugeme, M., Banze, J. P. M., Mukeng, C. K., Muyumba, O. N., Kamalo, B. M., Kapya, H. K., Ngongo, G. L., & Kitwa, L. (2022). Risk Factors for Hemorrhagic Stroke among Adults in the Democratic Republic of the Congo: A Hospital-Based Study in a Limited Resource Setting. *Stroke Research and Treatment*, *2022*(1), 7840921.

Peng, Q., Chen, X., Zhang, C., Li, W., Liu, J., Shi, T., Wu, Y., Feng, H., Nian, Y., & Hu, R. (2022). Deep learning-based computed tomography image segmentation and volume measurement of intracerebral hemorrhage. *Frontiers in Neuroscience*, *16*, 965680.

Seeram, E., & Sil, J. (2013). Computed tomography: Physical principles, instrumentation, and quality control. In *Practical SPECT/CT in Nuclear Medicine* (pp. 77–107). Springer.

Sugiono, S. (2020). Industri Konten Digital Dalam Perspektif Society 5.0 (Digital Content Industry in Society 5.0 Perspective). *JURNAL IPTEKKOM Jurnal Ilmu Pengetahuan & Teknologi Informasi*, *22*(2), 175–191.

Sumijan, S., Yuhandri, Y., & Boy, W. (2021). Hybrid thresholding method in detection and extraction of brain hemorrhage on the CT-scan image. *Journal of Computer Scine and Information Technology*, 7–14.

Wang, T., Song, N., Liu, L., Zhu, Z., Chen, B., Yang, W., & Chen, Z. (2021). Efficiency of a deep learning-based artificial intelligence diagnostic system in spontaneous intracerebral hemorrhage volume measurement. *BMC Medical Imaging*, *21*, 1–9.

Widiastuti, T. (2020). Ethnomethodology Study of Digitalized Social Communication Apprehension in Basmala Youth Community Members. *Jurnal Komunikasi Ikatan Sarjana Komunikasi Indonesia*, *5*(1), 42–51.

Xu, Y., Holanda, G., Souza, L. F. de F., Silva, H., Gomes, A., Silva, I., Ferreira, M., Jia, C., Han, T., & de Albuquerque, V. H. C. (2020). Deep learning-enhanced internet of medical things to analyze brain ct scans of hemorrhagic stroke patients: a new approach. *IEEE Sensors Journal*, *21*(22), 24941–24951.

Zhao, B., Ding, S., Wu, H., Liu, G., Cao, C., Jin, S., & Liu, Z. (2019). Automatic acute ischemic stroke lesion segmentation using semi-supervised learning. *ArXiv Preprint ArXiv:1908.03735*.