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Analysis of Early Stroke Diagnosis Based on Brain Magnetic Resonance Imaging using Machine Learning

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ABSTRACT

Stroke causes paralysis resulting from a hemorrhage in the brain or blockage of blood flow to the brain. It is third leading cause of death in Malaysia, with at least 32 deaths per day, and poses a major challenge to Malaysia's health services. A recent study showed that he could save a patient's life if he received treatment within six hours of a stroke. Unfortunately, Malaysia is facing a shortage of neuroradiologists, hampering efforts to treat its growing number of stroke patients. In this research, used Magnetic Resonance Imaging which is better compare to CT scan and CBCT because MRI will produce more detailed images of soft tissues, ligaments and organs. So that, advanced imaging using magnetic resonance imaging (MRI) has gained more attention than conventional angiography in the diagnosis of acute stroke due to its high spatial resolution and fast scan times. Traditionally, diagnosis was made manually by neuroradiologists during a highly subjective and time-consuming task. Detecting collaterals from MRI images is a challenging task due to the presence of noise and artifacts, small size, and heterogeneous structure of vessels. By the way, this paper is mainly about the early diagnosis of stroke based on brain magnetic resonance imaging using machine learning. Based on the results, can see that the Fuzzy c-means (FCM) and Watershed Transformation (WT) segmentation of brain infarcts which are original image, output of guided filter, gradient magnitude image, output of watershed transform and final detected infarct with morphological operation.

1. Introduction

In this new era, advanced imaging with magnetic resonance imaging (MRI) has gained more attention than conventional angiography in acute stroke diagnosis due to its high spatial resolution. So, the purpose of this paper is to detect early stroke diagnosis based on brain magnetic resonance imaging using machine learning. Traditionally, diagnosis was made manually by neuroradiologists during a highly subjective and time-consuming task. Detecting collaterals from MRI images is a

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challenging task due to the presence of noise and artifacts, small size, and heterogeneous structure of vessels.

1.1 Early Stroke Diagnosis

Cerebrovascular accident (CVA) or stroke is the third leading cause of death in Malaysia [1]. Stroke is a major challenge for the Malaysian healthcare system, with more than 50,000 new cases a year and the account for at least 32 deaths per day. It is also a leading cause of long-term disability worldwide. According to the Malaysian National Stroke Association (NASAM), stroke requires immediate medical attention and can be curable if treated quickly. Recent studies have shown that treatment within six hours of a stroke can save a patient's life. Unfortunately, there are only 107 neuroradiologists treating stroke patients in this era, and every state hospital has at least one neuroradiologist. This hampers efforts to treat stroke patients.

The collateral circulation is a network of small blood vessels that allow blood to flow through a stroke or blocked artery. Rapid and accurate diagnosis of collateral circulation enables prompt treatment. Advanced medical imaging with magnetic resonance imaging (MRI) has received more attention than conventional angiography in diagnosing acute stroke. However, current practice is to manually interpret the images by visual inspection [2]. This makes the process time consuming. Without timely diagnosis and treatment of stroke, the patient becomes disabled due to lack of blood, and oxygen causes the death of nerve cells. A number of factors, including infarct volume, penumbra size, and collateral circulation, are diagnostic features to consider. One of the most important indicators for successful treatment of stroke is the presence of adequate collateral circulation [3]. Therefore, neuroradiologists need tools to quickly and accurately diagnose acute stroke.

From the previous paper, can see that the collateral circulation detection from MRI images is a challenging task due to the presence of noise and artifacts, small size, and heterogeneous structure of vessels. New methods for segmenting and classifying medical images are regularly proposed [4]. Common machine learning techniques for vessel segmentation are region growing, clustering, active contours, and watersheds, while random forests, neural networks, and support vector machines are used for classification [5]. A disadvantage of the region growing method is that it is sensitive to noise and intensity non-uniformity, and the extracted regions can be punctured or separated [6]. A drawback of clustering is its inability to segment images corrupted by noise, contours, and other image artifacts [7]. Edge-based segmentation fails when applied to images with blurred boundaries [8]. Segmentation can be performed manually by a neuroradiologist, but it is time-consuming and can lead to irreproducible results. Therefore, processing time speed and accuracy are key requirements for computer-aided diagnostic systems.

Traditional machine learning methods require the complex task of denoising and extracting features before performing classification to achieve high-accuracy performance. Recent studies have shown that deep learning techniques such as convolutional neural networks (CNNs) are robust in processing noisy images, such as medical images, to solve complex pattern recognition problems. However, it has the problem of long computation time and complicated processing [9]. Additionally, the limited number of datasets on which to train the CNN can lead to poor classification performance. Due to these limitations, hybrid frameworks involving deep learning and machine learning techniques are considered promising approaches to achieve optimal accuracy in collateral circuit classification.

This part presents a review of this study. Learn about the human brain, stroke, collateral circulation concepts, and MRI. Stroke or cerebral infarction, is the sudden onset of neurological brain damage. According to the Institute for Health Metrics and Evaluation (2017), it is her third leading cause of death and the leading cause of permanent disability in Malaysia [10]. It has a major public health impact and is associated with high costs of initial treatment, rehabilitation and chronic care. In the United States, it occurs every 45 seconds and affects 795,000 people annually. 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 breast. Additionally, research on CAD systems and techniques has shown that the use of CAD can improve diagnostic accuracy for radiologists [11].

1.2 Recanalization

Recanalization is known as restoration of blood flow and is the most important modifiable prognostic factor of favorable outcome in ischemic stroke [12]. Timely restoration of local blood flow helps to rescue the threatened tissue, reduce cell death, and ultimately reduce patient disability with a 4-fold increase in the likelihood of a favorable outcome. In addition, mortality in patients with successful recanalization is reduced by a factor of four. Strategies for recanalization include the use of thrombolytic agents such as IV drugs, for example tissue plasminogen activator (tPA)) and/or mechanical interventions such as distal or proximal thrombectomy or stenting. 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 should be considered and only patients with specific indications such as large circumference, small infarct, and good collateral circulation should undergo such a procedure. This mechanical intervention can quickly restore blood flow. However, not all stroke patients are suitable for thrombectomy treatment because of the risks involved. One of the most important indicators of successful thrombectomy therapy is the presence of adequate collateral circulation [13].

2. Methodology

Depending on analysis, two types of strokes are distinguished, divided into hemorrhagic and ischemic [14]. Roughly 70% of all stroke cases are ischemic, and this situation is monitor with neurological deficits that persist for more than his 24 hours or are interrupted by death within 24 hours [15]. Roughly 12% of all strokes are hemorrhagic, 9% of which are intracerebral hemorrhages and 3% are subarachnoid hemorrhages. Hemorrhagic stroke is affected by rupture of a cerebral blood vessel or vascular abnormality that bleeds into adjacent brain tissue, impairing its consequences and leading to death rather than permanent disability. Compared with ischemic stroke, caused by blockage of the blood vessels that supply the brain, predominates. Ischemic stroke can be categorized according to its clinical manifestations. In the Oxfordshire Community Stroke Project [16], parts of stroke are divided into four groups according to initial symptoms and their severity to predict stroke extent and brain regions affected, underlying causes, and prognosis. Increase total anterior circulation stroke syndrome (TACS); stroke syndrome with partial anterior circulation (PACS); lacunar stroke syndrome (LACS); and posterior circulation stroke syndrome (POCS).

2.1 Acute Stroke Imaging

In stroke, dysfunction consistent to the location and extent of ischemic or hemorrhagic brain lesions. As you can see, early detection of stroke and its nature is critical for clinicians to determine the optimal course of treatment. Computed tomography (CT) and MR imaging are standard examination tools for ruling out cerebral hemorrhage, characterizing ischemic lesions, and quantifying potentially usable risk tissue [17]. CT is highly sensitive to the presence of hemorrhage, whereas MRI is the most sensitive technique for early detection of ischemic stroke. MRI, which uses various pulse sequences to improve signal contrast between normal and infarcted tissue, is the most sensitive technique for early detection of stroke [18]. Diffusion-weighted imaging sequences (DWI) of MRI are commonly used to identify areas of hypoperfusion, areas at risk, or irreversibly damaged infarct cores [19]. In the DWI sequence, the signal intensity decreases exponentially with the diffusion rate within the voxel. Acute cerebral ischemia induces transient changes in the intracellular sodium content of injured brain tissue, resulting in restricted intracellular water movement. DWI is highly sensitive to impaired water diffusion and manifests as a perceptible bright signal within minutes after acute ischemic stroke [20]. The discrepancy between the area of hypoperfusion and the area of acute infarction assessed on DWI appears as a dark environment the infarct core, suggesting potential salvage potential [21]. Increasing the b value attenuates the intensity of the signal and improves the lesion contrast [22]. Figure 1 shows examples of CT and MRI images collected from different patients with acute ischemic stroke.

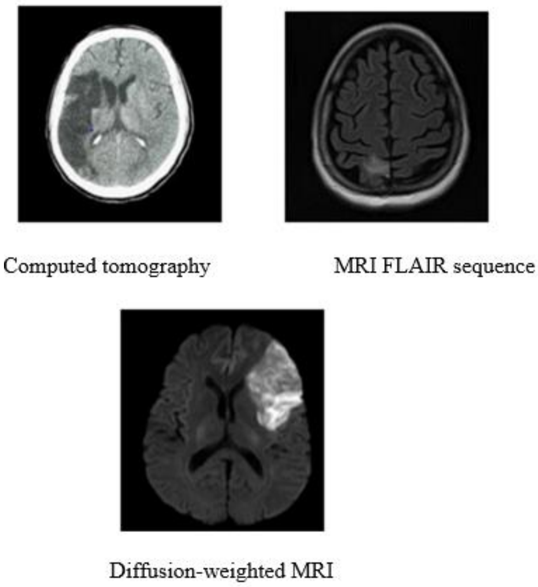

Fig. 1. Neuroimaging in acute ischemic stroke of different patients

The infarct can be seen as a hyperintense area on computed tomography (left). In MRI, different pulse sequences can enhance signal contrast between different tissues. Using FLAIR (Fluid Attenuated Inversion Recovery), the infarct appears as a bright signal relative to the surrounding brain tissue and a dark signal in the suppressed cerebrospinal fluid (middle). In DWI, the infarcted tissue shows less signal attenuation and appears as an area of hyperintensity due to limited water diffusion (right).

2.2 Image Segmentation

Image segmentation aims to present images in a more relevant way for investigation. Images can be manually or automatically segmented into different regions showing similarities in signal intensity and characteristics, and used to localize lesions in the brain [23]. Automated image segmentation is a key step in brain imaging that facilitates lesion detection and extent quantification. This information is essential for accurate disease prognosis and optimal clinical management.

2.3 Computer Aided Diagnosis (CAD) for Detection of Stroke

CAD methods are used in medical imaging for sick detection, prognosis, treatment management decision support, and treatment monitoring [24]. Manual segmentation is time consuming because MRI requires an expert to examine multiple images of the brain taken from different directions and with different pulse sequences. In addition, there is the potential for inter- and intra-observer bias [25]. Semi-automated and automated machine learning-based CAD systems for determining and segmenting ischemic stroke lesions have overcome these limitations and enabled high-flow screening of images for faster and more reproducible screening of ischemic stroke lesions allowing more sensitive detection [26]. Automated delineation of accurate topologies of stroke lesions facilitates quantitative analysis of infarct size and/or eligibility to aid in prognostic and therapeutic decision-making.

i. Image acquisition and preprocessing: The DWI sequence of MRI is the modality of choice for detecting acute ischemic stroke. In the preprocessing stage, images were first normalized by linear scaling, followed by background removal by simple thresholding. Contrast-Limited Adaptive Histogram Equalization (CLAHE) further improves image quality.
ii. Image segmentation: Lesions are segmented using different methods such as clustering, watershed and optimization and classified with different classifiers.
iii. Feature extraction: The extracted statistical or morphological features are used as input to a classifier for classifying strokes and their subtypes.
iv. Classification: Implement rule-based classifiers such as neural networks, support vector machines (SVMs), decision trees, and random forest classifiers to classify ischemic brain lesions according to established criteria.

2.4 Machine Learning

Machine learning techniques were assessed for both segmentation and classification of stroke lesions using measurement parameters such as sensitivity, accuracy and coefficient [27]. Classification is a technique that defines a group within its similarity. In MRI brain image classification, classification technique is applied to differentiate the normal and abnormal region in a brain image which include GM, WM, CSF and brain lesion. Nowadays, machine learning and deep learning is applied in brain image classification based on the implementation of the artificial intelligence. Figure 2 shows the relation of artificial intelligence, machine learning and deep learning [28].

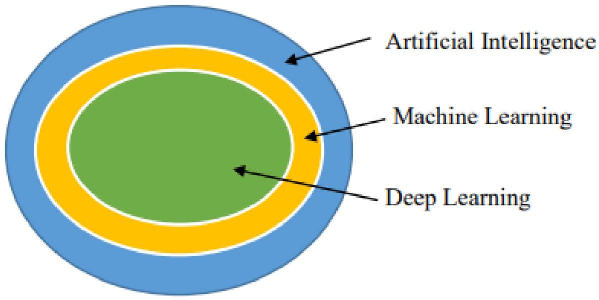

Fig. 2. Comparison between artificial Intelligence, machine learning and deep learning

Artificial intelligence has a capability to imitate intelligent human behaviour. Machine learning is a subset of artificial intelligent where it uses computerize algorithm to act in specific ways without asking the programming to clearly understand. Deep leaning is a subset of machine learning which is inspired by the human brain structure and is primarily effective in feature detection. Machine learning is normally computed based on supervised learning while deep learning is normally computed based on unsupervised learning [29].

2.5 Stroke Detection Technique

There are three types of stroke techniques those are Magnetic Resonance Imaging (MRI), Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT). In this research, mainly chosen that Magnetic Resonance Imaging (MRI) compare to CT scan and CBCT because it is easier to produce more detailed images of soft tissues, ligaments and organs.

2.5.1 Magnetic resonance imaging (MRI)

Magnetic resonance imaging (MRI) plays a significant role in the diagnosis of lumbar disc disease. However, the use of MRI is limited because of Magnetic resonance imaging (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. This article focuses on techniques used for early detection of stroke using magnetic imaging of the brain. More importantly, MRI is contraindicated in some patients who are claustrophobic or have pacemakers due to the potential for damage. In contrast, computed tomography (CT) scans are much cheaper and faster and don't have the same limitations. 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. Figure 3 shows the example of MRI machine.

Fig. 3. MRI machine

2.5.2 Cone beam computed tomography (CBCT)

Neuroimaging techniques for stroke detection are widely accepted by neuroradiologists to visualize anatomical images of the body for diagnosis, treatment planning, prognosis, and evaluation of treatment outcomes. Surgery and implant placement require a radiograph of her with accurate anatomical dimensions [30]. Recently, cone-beam computed tomography (CBCT) has become one of the most popular imaging modalities for diagnosing and determining treatment planning for diseases of the mouth, jaw, and face. CBCT machines are X-ray machines that have played a key role in revealing brain problems, producing informative images and delineating craniofacial structures, including the patient's anatomy. Previous studies have shown that average measurements of CBCT images do not differ significantly from real objects. One of the characteristics of an ideal radiograph is that it provides information in the same shape and size as the object being imaged. Figure 4 shows the CBCT device used for scanning.

Fig. 4. CBCT machine

CBCT technology consists of using a circular or rectangular conical X-ray beam covering a single 360° scan. To stabilize the head holder, the X-ray source and reciprocating detector array move simultaneously around the patient's head. The individual projection images, the base images, are slightly offset from each other and are recorded at a certain interval, similar to the lateral cephalometric X-ray images. This series of basic projection images is called holder projection data. There are software programs that contain advanced algorithms that are applied to create 3D volume data sets. This dataset can be used to provide primary reconstructed images in all three orthogonal planes (axial, sagittal, and coronal). Figure 5 shows a CBCT image visualized with the CBCT device.

Fig. 5. CBCT image

2.5.3 Computed tomography (CT)

Computed tomography (CT) is a medical imaging technique that is widely used for diagnostic and therapeutic purposes in a variety of clinical applications. Magnetic resonance imaging (MRI) is another imaging procedure that visualizes anatomical details and is used in radiology and nuclear medicine. Unlike CT scans, MRIs can detect subtle differences in soft tissues, ligaments, and organs, which aids in diagnosis. However, MRI is not only much more expensive, but it also takes longer to obtain results. That is, patients often prefer her CT scan to her MRI. Lumbar disc herniation is common in older people and those who sit for long periods of time. Using MRI to monitor spinal and disc signals in the lumbar spine is critical in the management of this condition. However, some patients who are claustrophobic or have a pacemaker cannot have an MRI due to possible injuries. Therefore, the ability to generate reliable magnetic resonance (MR) images from CT scans is critical for these patients. This not only increases the diagnostic value of CT scans, but also provides additional reference information for diagnosis. Therefore, in this study, we propose a synthesis method based on convolutional neural networks (CNN) [31,32] and adversarial training [33] to construct MR images of the lumbar spine from CT scan data. Figure 6 shows the CT machine used for scanning.

Fig. 6. CT machine

2.5.4 Comparison between CT, CBCT and MRI

Table 1 shows a comparison of three stroke diagnostic techniques: CT scan, CBCT, and MRI.

Table 1
Comparison between CT scan, CBCT and MRI

	CT scans	CBCT	MRI
Principle	Uses multiple x-rays and taken at various angles to produce cross-sectional images	Capable to collimate the primary X-ray beam to the area of interest, reducing the size of irradiation	Uses powerful magnetic fields and radiofrequency pulses to produce detailed images
Radiation	Minimal	Lower radiation dose	None
Uses	Good for observing bone and very good for soft tissues, with the use of intravenous contrast dye	Poor soft tissue contrast	Good for detecting which is slight differences in soft tissue
Cost	Normally less expensive than MRI	Quiet expensive compare to CT and CBCT	More expensive than CT scans
Time taken	Very fast process and taking only about 5 minutes depends on the area being scanned	Longer scanning time	Depends on the part of the body being examined and can range from 15 minutes to 2 hours
Application	Produces general image of an area like internal organs, fractures or head trauma	Produces general image of an area like internal organs, fractures or head trauma	Produces more detailed images of soft tissue, ligaments and organs
Benefits	Quick and provide images of tissue, organs and skeletal structure	Noise and provides better image degradation	Produces more detailed images
Risks	Harmful for unborn babies, small dose of radiation and potential reaction to the use of dyes	Poor resolution and difficulty in interpretation	Loud noises from the machine can cause hearing issues and increase body temperature during long MRIs

3. Results

There are two sections in this part which are Fuzzy C-means Clustering (FCM) and Watershed Transformation (WT). The results that obtained from this research have been shown below:

3.1 Clustering

The Fuzzy C-means Clustering (FCM) approach has been strongly appealed in medical image analysis [34] because it obtains valuable information from the original image. Therefore, standard FCM fails to provide accurate results when there is excessive non-uniformity or noise in the image intensity [35]. The FCM algorithm divides the image into meaningful regions [36], and constraints for performing brain tissue segmentation in diffusion variable MRI can also be improved by including in the FCM algorithm [37]. Adaptive FCM algorithms gradually improve the objective function to improve segmentation [38,39]. A hybrid approach integrating K-means and FCM algorithms is shown in Figure 7. This improved the accuracy of cerebral infarction detection with a small amount of computation [40].

Fig. 7. Original DWI image, morphological binary image and detected infarct marked as red

3.2 Watershed Transformation (WT)

The WT algorithm is commonly used in image segmentation to clarify object boundaries in low-contrast images [41]. Shortcomings of WT such as over-segmentation can be removed by using proper filters. Challenging regions including gray and white circumstance in the brain were splitted using the directed WT algorithm on noise 3D brain MRI images [42,43]. A classification accuracy of 0.90 was achieved with morphological manipulation of the WT model [44,45]. An interactive multiscale WT algorithm was able to accurately segment brain tumors on MRI compared to manual segmentation. A segmentation approaches combining WT which is a random forest algorithm supplies better detection of infarcts with 95% accuracy in the brain DWI in Figure 8 [46].

For image segmentation using various probabilistic models, expectation maximization also has been used [47,48]. Then, used EM to estimate Gaussian parameters and classify colour images [49] and segmented images using a Bayesian algorithm-based finite mixture model in which the EM algorithm was used to estimate the parameters of the Gaussian mixture model and applied the EM algorithm for efficient automatic segmentation of the brain from non-brain tissue to 3D MRI data. Development of a hybrid genetic algorithm variational EM model (GA-VEM) with improved performance for brain segmentation in MRI images. In Ref. [50], spatial information and bias correction of EM and FCM algorithms mitigated the effects of noise, improving the accuracy of gray and white matter segmentation in brain MRI [51], and combined WT and EM algorithms improved the accuracy of brain MRI. Lesions were segmented using a clustering approach [52]. We created a statistical model from the data and applied the EM algorithm to successfully detect brain lesions on MRI [53]. Until recently, understanding stroke defects in brain imaging required clear segmentation of lesion boundaries [54]. Using a new methodology, a system based on Delaunay triangulation and optimization was developed to detect cerebral infarction with 95% accuracy in Figure 9 [55].

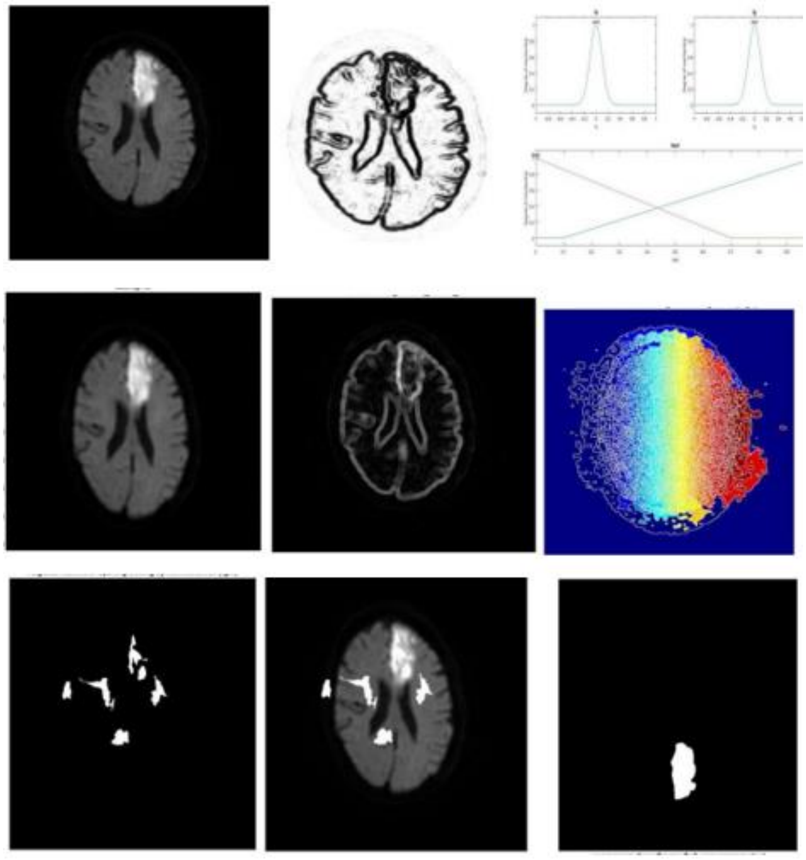

Fig. 8. Watershed segmentation of brain infarcts which are original image, edge detection with fuzziness, membership function, output of guided filter, gradient magnitude image, output of watershed transform, reconstruction of image, superimposed image on original image and final detected infarct with morphological operation

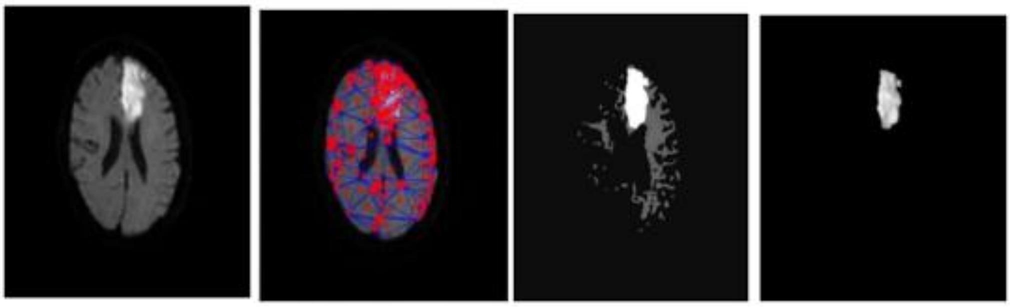

Fig. 9. Ischemic stroke lesion is seen on the original DWI, Voronoi cells are generated, and Delaunay triangulation applied and the extracted lesion detected using Delaunay triangulation FODPSO

4. Conclusions

In the nutshell, the purpose of this paper is to analyses early stroke diagnosis based on brain magnetic resonance imaging by using machine learning. In this research, can determined that the growth of automated CAD tools for systematic stroke detection and quantification of stroke extent is required, which has important therapeutic and prognostic implications. Ultimately, this will lead to timely and improved stroke management, reducing patient morbidity and mortality. Apart from that, advances in neuro-imaging acquisition techniques and the application of machine learning will play an important role. In this paper, extensively searched different image analysis techniques applied to detect stroke lesions using MRI scans. This study focused on machine learning approaches to review some of the methods for segmenting and classifying stroke in MRI images. Moreover, in this investigation it is chosen that Magnetic Resonance Imaging (MRI) compare to CT scan and CBCT because it is easier to produce more detailed images of soft tissues, ligaments and organs. Based on the results, can see that the Fuzzy c-means (FCM) and Watershed Transformation (WT) segmentation of brain infarcts which are original image, output of guided filter, gradient magnitude image, output of watershed transform and final detected infarct with morphological operation. It concluded that the integration of machine learning models and intelligent technology could enable faster and more accurate MRI detection of stroke in all over clinical scenarios, helping clinical decision management. Additionally, limitations of various techniques and possible solutions are discussed. As concluded, this study will be a valuable source of knowledge, source of ideas and inspiration for researchers in this field.

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