UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Electronics and Computer Engineering

STROKE LESION SEGMENTATION AND CLASSIFICATION FOR DIFFUSION-WEIGHTED IMAGING

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A thesis submitted
in fulfilment of the requirements for the degree of Master of Science
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DECLARATION

I declare that this thesis entitled "Stroke Lesion Segmentation and Classification for Diffusion-Weighted Imaging" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature	:	....
Name	:	Nor Shahirah binti Mohd Noor
Date	:	....

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronic Engineering.

Signature	:	....
Supervisor Name	:	Dr. Norhashimah binti Mohd Saad
Date	:	....

DEDICATION

Specially dedicated to:

My husband, parents, parents-in-law, siblings and family for their priceless supports and generous prayers.

ABSTRACT

Magnetic Resonance Imaging (MRI) plays an important role in the diagnosis of brain disorders. Stroke is one of the major categories of brain disorders. Recent studies support the notion of stroke as the "time is brain" due to the fact that if the treatment is done within six hours of suffering a stroke, the patient's life can be saved and the outcome can be improved. Conventionally, the diagnosis of brain stroke is performed manually by professional neuroradiologists during a highly subjective and time- consuming process. Therefore, this study proposes a technique for automatic detection, segmentation and classification of brain stroke lesion from MRI images. The types of stroke lesion are acute hemorrhage stroke, acute ischemic stroke, chronic ischemic stroke and sub-acute ischemic stroke. Diffusion weighted imaging (DWI) sequences from the MRI is chosen for the analysis using machine learning and deep learning techniques. The machine learning technique consists of four stages which are pre-processing, segmentation, features extraction and classification. For segmentation, adaptive thresholding, gray level co-occurrence matrix (GLCM), marker-controlled watershed, fuzzy c-Means (FCM) and k-Means are proposed to segment the stroke region. Statistical features are calculated and fed into several classification techniques, which are the linear discriminant analysis (LDA), support vector machine (SVM), weighted k- Nearest Neighbor (k-NN) and bagged tree classifier. Deep learning using regional convolutional neural network (R-CNN) technique is also proposed in the analysis. The technique consists of four stages which are input image, Region Proposal Network (RPN), Convolutional Neural Network (CNN) features computation and classification. The segmentation performances are evaluated using Jaccard indices, Dice Coefficient, false positive and false negative rates. For classification, the performances are evaluated using accuracy, sensitivity and specificity. Segmentation results demonstrated that k-Means offered the best performance for stroke lesion segmentation while sub-acute ischemic stroke gave the highest rate with 0.85 Dice index. Results demonstrated that support vector machine (SVM) offered the best performance for stroke lesion classification with accuracy 98.5% and average training time is 1.8 second. In conclusion, the proposed stroke classification technique has the potential to diagnose and classify brain stroke lesions.

SEGMENTASI DAN KLASIFIKASI LESI STROK UNTUK PENGIMEJAN PEMBERAT-RESAPAN

ABSTRAK

Pengimejan resonan magnet (MRI) memainkan peranan penting dalam diagnosis gangguan otak. Strok adalah salah satu daripada kategori utama gangguan otak. Kajian terkini menyokong tanggapan strok sebagai "masa adalah otak" kerana hakikat bahawa jika rawatan itu dilakukan dalam masa enam jam mengalami strok, kehidupan pesakit dapat diselamatkan dan hasilnya dapat ditingkatkan. Secara konvensional, diagnosis strok otak dilakukan secara manual oleh pakar neuroradiologi semasa proses yang sangat subjektif dan memakan masa. Oleh itu, kajian ini mencadangkan teknik pengesanan automatik, segmentasi dan klasifikasi lesi strok otak dari imej MRI. Jenis lesi strok adalah strok pendarahan akut, strok iskemia akut, strok iskemia kronik dan strok iskemia sub-akut. Imej berwajar difusi (DWI) dari MRI dipilih untuk analisis menggunakan teknik pembelajaran mesin dan teknik pembelajaran dalam. Teknik pembelajaran mesin terdiri daripada empat peringkat iaitu pra-pemprosesan, pengsegmenan, ciri-ciri pengekstrakan dan pengkelasan. Untuk pengsegmenan, teknik ambang adaptif, matrik gray level co-occurrence (GLCM), fuzzy c-Means (FCM) dan k-Means dicadangkan untuk pengsegmenan rantau lesi. Ciri-ciri statistik diekstrak daripada rantau tarikan dan diinputkan kepada pengelas dari prestasi pengsegmenan lesi terbaik. Ciri-ciri statistik dikira dan dimasukkan ke dalam beberapa teknik klasifikasi, iaitu analisis diskriminasi linier (LDA), mesin vektor sokongan (SVM), berwajaran k- Nearest Neighbor (k-NN) dan bagged tree. Pembelajaran dalam menggunakan teknik pengesan serantau jaringan saraf konvolusi (R-CNN) juga dicadangkan dalam analisis. Teknik ini terdiri daripada empat peringkat iaitu imej input, jaringan cadangan rantau (RPN), ciri-ciri pengiraan jaringan saraf konvolusi (CNN) dan pengkelasan. Keputusan segmentasi dinilai menggunakan indeks Jaccard, koefficient Dice, dan kadar positif palsu dan negatif palsu. Untuk klasifikasi, keputusan dinilai dengan menggunakan ketepatan, kepekaan dan kekhususan. Keputusan menunjukkan bahawa k-Means memberikan prestasi terbaik untuk pengsegmenan lesi strok sementara strok iskemia sub-akut memberikan kadar pekali Dice tertinggi dengan 0.85. Keputusan menunjukkan bahawa mesin vektor sokongan (SVM) menawarkan prestasi terbaik untuk pengkelasan lesi strok dengan ketepatan 98.5% dan purata masa pelaksanaan ialah 1.8 saat. Sebagai kesimpulannya, teknik pengkelasan strok yang dicadangkan mempunyai potensi untuk mendiagnosis dan mengklasifikasikan lesi strok otak.

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LIST OF ABBREVIATIONS

2D	-	Two-dimensional
AO	-	Area overlap
app	-	Application
AUC	-	Area under curve
AVM	-	Arteriovenous Malformation
BFTree	-	Best-First decision tree
CAD	-	Computer-aided diagnosis
CNN	-	Convolutional neural network
CSF	-	Cerebrospinal fluid
CSM	-	Cohesion based Self Merging Algorithm
CT	-	Computer tomography
DC	-	Dice coefficient
DICOM	-	Digital Imaging and Communications in Medicine
DNNs	-	Deep neural networks
DWI	-	Diffusion-weighted imaging
FCM	-	Fuzzy c-Mean
FLAIR	-	Fluid-attenuated inversion recovery
FMM	-	Fast marching method
FN	-	False negative

FNR	-	False negative rate
FP	-	False positive
FPR	-	False positive rate
GLCM	-	Gray Level Co-Occurrence Method
GM	-	Gray matter
GMI	-	Gradient Magnitude Intensity
GPU	-	Graphics processing unit
HCS	-	Harmony Crow Search
HKL	-	Hospital Kuala Lumpur
HOG	-	Histogram Oriented Gradient
ISLES	-	Ischemic Stroke Lesion Segmentation
k-NN	-	k- Nearest Neighbor
LDA	-	Linear discriminant analysis
LSM	-	Level-set method
MATLAB	-	Matrix Laboratory
Max	-	Maximum
mm	-	Millimeter
ms	-	Milliseconds
MRI	-	Magnetic resonance imaging
NASAM	-	National Stroke Association of Malaysia
NIfTI	-	Neuroimaging Informatics Technology Initiative
NNge	-	Nearest Neighbor With Generalization
ReLU	-	Rectifier linear unit
R-CNN	-	Regional convolutional neural network

RF	-	Resonance frequency
ROC	-	Receiver operating characteristic
ROI	-	Region of Interest
RPN	-	Region proposal network
s	-	Second
SGD	-	Stochastic gradient descent
SVM	-	Support vector machine
SVNN	-	Support vector neural network
TE	-	Time echo
TN	-	True negative
TP	-	True positive
TPR	-	True positive rate
TR	-	Time repetition
UKMMC	-	Universiti Kebangsaan Malaysia Medical Centre
UPM	-	Universiti Putra Malaysia
UTeM	-	Universiti Teknikal Malaysia Melaka
WM	-	White matter
WMA	-	World Medical Association

LIST OF SYMBOLS

b	-	Intensity of diffusion weight
G_d	-	Diffusion gradient
Δ	-	Time spacing between gradient
δ	-	Duration of the gradient
$S_{(b)}$	-	Signal received for gradient
$S_{(0)}$	-	Signal strength of non- diffusion weighting
D	-	Diffusion
γ,a	-	Constant
G	-	Gradient magnitude
$g(x,y)$	-	DWI image
$f(x,y)$	-	Segmented image
τ	-	Threshold
N_b	-	Number of bit in input image
$I(x,y)$	-	Image Normalization
s	-	Output of image enhancement
r	-	Input of image enhancement
c	-	Amplitude of intensity image
$P(i)$	-	Intensity level