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# Difussion-Weighted Images Analysis using Regional Convolutional Neural Network for Stroke Lesion Classification

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***Abstract*—Stroke is a major type of brain disorder, and the MRI sequence known as diffusion-weighted imaging (DWI) is often used to evaluate early changes related to strokes. Typically, stroke diagnosis requires manual assessment by neuroradiologists, which is subjective and time-consuming. Therefore, developing an automated stroke diagnosis system is crucial to streamline this process. This study presents a method for automatically detecting and categorizing stroke lesions using deep learning techniques applied to DWI. The dataset comprises 61 samples from Hospital Kuala Lumpur (HKL) and 69 samples from the public ISLES database, including acute hemorrhage, acute ischemic, chronic ischemic, and sub-acute ischemic strokes. The method employs a Regional Convolutional Neural Network (R-CNN) on DWI images, involving four stages: input image, region proposal network (RPN), computation of CNN features, and classification. Performance is evaluated using metrics such as accuracy, sensitivity, and specificity. The technique achieves a classification accuracy of 64.62% with an average training time of 16.3 seconds. Overall, this stroke classification method shows promise for enhancing the diagnosis and categorization of brain stroke lesions using deep learning.***

***Keywords*—diffusion-weighted imaging, stroke, Regional convolutional neural network**

## I. Introduction

Stroke is a significant health issue in Malaysia and globally. It ranks among the top five causes of death in Malaysia [1]. Annually, around 40,000 Malaysians experience strokes [2]. According to the National Stroke Association of Malaysia (NASAM), one in six people globally will experience a stroke, making it the third leading cause of disability in adults [3]. Often referred to as a brain attack, a stroke occurs when the blood supply to part of the brain is blocked or when a brain blood vessel bursts. This disruption in the supply of oxygen and nutrients leads to brain damage due to a vascular cause [4].

Emergency stroke treatment depends on whether the patient has an ischemic (blood clot) or hemorrhagic stroke (burst blood vessel), and three main stages of stroke: acute, sub-acute and chronic. Both types of stroke need different treatments to dissolve or remove the blood clots, or to prevent more excessive bleeding. It is difficult to differentiate the types and stages of strokes because of the overlapping of their features [5]. Accurate diagnosis of brain strokes is crucial and can only be performed by experienced neuroradiologists [6]. Consequently, early stroke detection and diagnosis play a pivotal role in formulating effective treatment strategies.

Diffusion-Weighted Imaging (DWI) is among the first magnetic resonance image (MRI) sequences to respond to the early detection of stroke and thus suitable for the detection of hyper acute and acute stroke [7]. This imaging method provides notable contrast for lesions, setting it apart from other MRI sequences [8]. However, while DWI imagery effectively visualizes stroke lesions, the diagnostic process is notably time-consuming compared to computer-aided diagnostic techniques [9].

Reference [6] proposed an automated stroke lesion segmentation and classification technique using DWI images. Fuzzy C-Means (FCM) was proposed for segmenting both acute and chronic ischemic stroke lesions [10]. In Reference [11], a method was introduced that utilizes infarction incidence features to classify ischemic stroke types (embolic, thrombotic, and hemorrhagic) among ischemic stroke patients, employing a decision tree technique. The classification approach yielded an overall sensitivity of 0.99. Meanwhile, Reference [12] introduced a method that utilizes texture content information extracted from Gray Level Co-occurrence Matrix (GLCM) to classify three distinct types of DWI ischemic stroke images using an Artificial Neural Network (ANN) classifier. The ANN technique proposed was able to separate the region between the normal and abnormal brain with the accuracy performance of 98%.

Reference [13] proposed a segmentation technique and classification technique for the ischemic stroke lesion. Darwinian Particle Swarm Optimization (DPSO) was proposed. Support Vector Machine (SVM) was involved after the DPSO to classify the types of stroke. According to the proposed technique, the percentage accuracy obtained was 90.1% with the percentage sensitivity was 87.37%. Reference [14] introduced an automated model-based segmentation technique for identifying ischemic stroke lesions [15].

Reference [16] presented a voxel-wise cascade classification method for segmenting stroke lesions utilizing T1, T2, and DWI images. Initially, the dataset underwent preprocessing with Random Forest inhomogeneity correction, followed by normalization using a histogram to enhance pathology robustness. The classification process operated voxel-wise, determining whether each voxel contained a lesion or not based on its set of features. Employing a cascade classifier, the system prioritized confidently deciding whether a voxel didn't contain a lesion. However, limitations of this approach included feature constraints and lengthy computation times. The researchers obtained an average Dice index score of 0.57. Conversely, Reference [17] proposed a new framework for segmenting ischemic stroke lesions in T1, T2, FLAIR, and DWI images using Random Forest (RF), achieving an overall result of 0.55.

In image analysis, one algorithm utilized in CNNs is the region-based convolutional neural network (R-CNN) detector. Reference [18] introduced the first R-CNN for object detection and semantic segmentation. This approach utilizes a selective search technique, where the image is processed through the CNN's input layer. Initially, selective search generates sub-segmentations to create different regions within the image. These regions are then merged based on similarities in color, texture, size, and shape, determining the final object locations (ROIs). This paper proposes using the regional convolutional neural network (R-CNN) detector to detect and classify stroke regions. The Region Proposal Network (RPN) is applied to extract the regions of interest (ROIs), and the classification is trained using a Convolutional Neural Network (CNN) to detect stroke lesions in brain DWI images.

## II. METHODOLOGY

In this section, techniques for stroke disease classification are discussed in detail. The diffusion weighted imaging (DWI) image analysis using the regional convolutional neural network (R-CNN) detector is implemented to extract the region of interest (ROI) using the region proposal network (RPN) and then is trained using convolutional neural network (CNN) to detect the stroke lesion. The accuracy of the deep learning technique is then verified.

R-CNN detector is implemented by only using the DWI images without going through the image pre-processing and segmentation. The R-CNN detector only involves the RPN, CNN features computation for classification. The R-CNN detector classification is evaluated based on the accuracy of the ROI obtained from the R-CNN detector with the example assigned according to the manual reference (ground-truth image) provided by the neuroradiologists. Finally, the performance of the deep learning techniques is verified.

### *A. Data Collection*

The dataset centered on four stroke types as below. Dataset 1 consists of 61 samples of acute ischemic, chronic ischemic, and acute hemorrhage images from Hospital Kuala Lumpur (HKL). Dataset 2 contains 69 samples of sub-acute ischemic stroke images from the public ISLES challenge 2015 online database [19].

TABLE I. STROKE DATASET

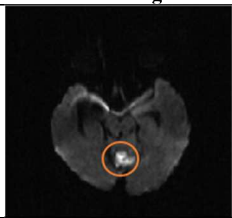
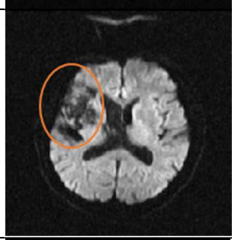
| Dataset | Type of Stroke | Number of DWI images |
|---|---|---|
| Dataset 1 (Clinical) | Acute Hemorrhage | 8 |
| | Acute Ischemic | 20 |
| | Chronic Ischemic | 33 |
| Dataset 2 (ISLES) | Sub-Acute Ischemic | 69 |

The DWI acquisition parameters used for dataset 1 are time echo (TE), 94 millisecond (ms); time repetition (TR), 3200 ms; pixels dimensions, 256 × 256; slice thickness, 6 millimeters (mm); gap between each slice, 6.5 mm; the intensity of diffusion weighting known as *b* value, 1000 s/mm2. All the images are extracted in DICOM format.

The ISLES database used DWI images in an uncompressed NIfTI format. The database collection is conducted according to the rules set out in the code of ethics of the WMA Helsinki, for experiments related to human [19]. The DWI images are extracted using (X)MedCon software and then converted into 12-bit DICOM format. The images consist of 69 samples with the sequences are skull-stripped, re-sampled to an isotropic spacing of $1^3$mm respectively. Each sample of dataset 2 has images with 230 x 230 dimensions.

Each sample of image is provided with a manual reference conducted by the neuroradiologist. For the samples that are collected from the clinical database, the manual segmentation images are saved in bitmap and then are converted and stored into the workspace variables in binary as a Mat-files using Matlab. The online database is gained from the public online ISLES challenge 2015 has been prepared by an expert of the ROI segmentation image. TABLE II shows the DWI image with each the stroke lesion which is indicated by the neuroradiologist [20].

TABLE II. STROKE IMAGES OF BRAIN AND LESIONS INDICATED BY NEUROLOGIST

| DWI Image | Type of Stroke |
|---|---|
|  | Acute Hemorrhage Stroke |
|  | Acute Ischemic Stroke |
|  | Chronic Ischemic Stroke |
|  | Sub-acute Ischemic Stroke |

## B. *Analysis*

In this research, the region with a convolutional neural network (R-CNN) detector is suggested for analyzing DWI images using deep learning techniques to identify the location of stroke lesions. The R-CNN method comprises four stages as shown below. Figure 1 illustrates the R-CNN detector framework analysis, while Figure 2 depicts the layers involved in the R-CNN network training process.

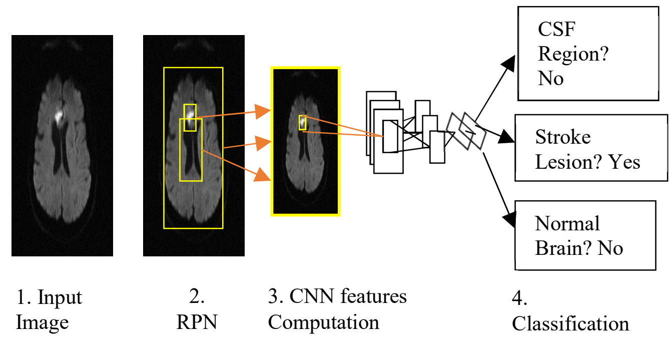



Fig. 1. The R-CNN detector framework analysis

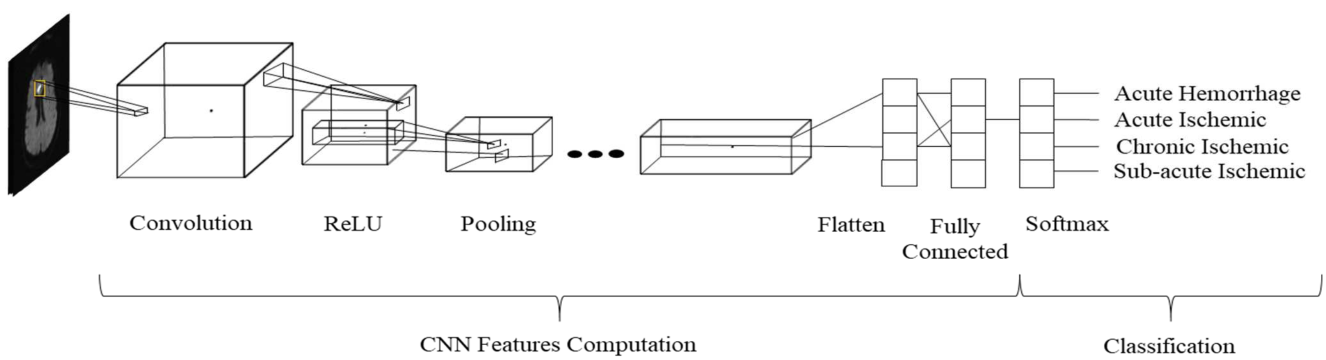



Fig. 2. The R-CNN features computation network layer

Region Proposal Network (RPN) is applied in the first stage of the DWI image analysis using deep learning technique. Several DWI images is chosen as a reference for this technique to detect the stroke lesion image. The RPN is proposed by applying ROI extraction where the stroke lesion is extracted using the Training Labeler app. Training Labeler app is used to draw each stroke lesion using a rectangular shape.

The format specifies the upper-left corner location and size of the stroke lesion in the DWI image. After the image is extracted, the value of the extract ROI is saved in a file directory where the file directory consists of the location of ROI that is determined by the bounding box. Fig. 3 shows the bounding box of the ROI in the DWI image.

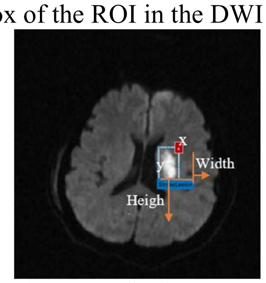



Fig. 3. Bounding box

The classification output layer trains the final results from learning the previous network layer. This layer operates by training two types of network layers which are the softmax layer and classification layer.

The softmax layer is a generalization of the logistic function after the fully connected layer. It represents a categorical distribution over the type of stroke labels and obtaining the probabilities of each stroke features element belonging to a label. The softmax function is defined as Equation (1):

$$\sigma(z)_{t_s} = \frac{e^{z_{t_s}}}{\sum_{t_s = 1}^{t_s} e^{z_{t_s}}} \tag{1}$$

where $t_s = 1 \dots t_s$. The softmax function normalizes the type of stroke, $t_s$ dimensional vector, $z$ of arbitrary real values into the type of stroke, $t_s$ dimensional vector $\sigma(z)$, which the component is sum to 1. The softmax function provides a weighted average of each $z_{t_s}$ relative to the aggregate of $z_{t_s}$'s in a way that exaggerates differences if the $z_{t_s}$'s are very different from each other in terms of scale, but returns a moderate value if $z_{t_s}$'s are relatively the same scale.

The softmax layer is a generalization of the logistic function after the fully connected layer. It represents a categorical distribution over the type of stroke labels and obtaining the probabilities of each stroke features element belonging to a label. The softmax function is defined as Equation (2):

$$\sigma(z)_{t_s} = \frac{e^{z_{t_s}}}{\sum_{t_s = 1}^{t_s} e^{z_{t_s}}} \tag{2}$$

where $t_s = 1 \dots t_s$. The softmax function normalizes the type of stroke, $t_s$ dimensional vector, $z$ of arbitrary real values into the type of stroke, $t_s$ dimensional vector $\sigma(z)$, which the component is sum to 1. The softmax function provides a weighted average of each $z_{t_s}$ relative to the aggregate of $z_{t_s}$'s in a way that exaggerates differences if the $z_{t_s}$'s are very different from each other in terms of scale, but returns a moderate value if $z_{t_s}$'s are relatively the same scale.

In the classification layer, the classification layer takes the values from the softmax function and assigns each input to one of the type of stroke, $t_s$ mutually exclusive classes using the cross entropy for a $1 - of - t_s$ coding scheme as written in Equation (3).

$$E(\theta) = -\sum_{f_s=1}^{f_s} \sum_{t_s=1}^{t_s} t_{f_s} \ln t_s(f_s, \theta) \tag{3}$$

where $t_{f_s}$ is the indicator that the features of stroke, $f_s$ belongs to the type of stroke, $t_s$, $\theta$ is the parameter vector. $t_s(f_s, \theta)$ is the output for the type of stroke sample $t_s$, which in this case, is the value from the softmax function. That is, it is the probability that the network associates the features of stroke, $f_s$ input with the type of stroke, $t_s$, $P(t_s = 1|f_s)$. Fig. 4 shows all the layers involved in this analysis.

```
layers=strokeLesionLayer

layers =

  15x1 Layer array with layers:

     1   'imageInput'    Image Input             32x32x1 images with 'zerocenter' normalization
     2   'conv'          Convolution             32 5x5 convolutions with stride [1  1] and padding [2  2]
     3   'maxpool'       Max Pooling             3x3 max pooling with stride [2  2] and padding [0  0]
     4   'relu'          ReLU                    ReLU
     5   'conv_1'        Convolution             32 5x5 convolutions with stride [1  1] and padding [2  2]
     6   'relu_1'        ReLU                    ReLU
     7   'avgpool'       Average Pooling         3x3 average pooling with stride [2  2] and padding [0  0]
     8   'conv_2'        Convolution             64 5x5 convolutions with stride [1  1] and padding [2  2]
     9   'relu_2'        ReLU                    ReLU
    10   'avgpool_1'     Average Pooling         3x3 average pooling with stride [2  2] and padding [0  0]
    11   'fc_rcnn'       Fully Connected         64 fully connected layer
    12   'relu_3'        ReLU                    ReLU
    13   'fc'            Fully Connected         2 fully connected layer
    14   'softmax'       Softmax                 softmax
    15   'classoutput'   Classification Output   crossentropyex
```

Fig. 4. The CNN features computation network layer for stroke lesion detection

## C. *Performance Analysis*

The performance evaluation technique is the last stage of the stroke analysis. Performance classifier from the DWI image analysis using deep learning technique is verified using accuracy shown in Equation (4), sensitivity shown in Equation (5) and specificity shown in Equation (6) [20].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The sensitivity and specificity of a classification are defined as follows:

Sensitivity: The likelihood that a positive result indicates the patient has a brain stroke lesion.

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

Specificity: The probability that a patient who does not have a brain stroke lesion is correctly identified as negative:

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

True positives (TP) are patients with a brain stroke lesion who are correctly identified as having one. True negatives (TN) are patients without a brain stroke lesion who are accurately identified as not having one. False positives (FP) happen when patients without a brain stroke lesion are incorrectly classified as having one, while false negatives (FN) occur when patients with a brain stroke lesion are mistakenly classified as not having one.

Overall, this research methodology section concludes the technique used for the brain stroke lesion classification. The sample data of brain stroke lesions includes four types of DWI images. The database of the brain stroke lesion is obtained from the clinical database and online database. The brain stroke lesion is separated into two types which are hyperintense lesion for acute hemorrhage, acute ischemic and sub-acute ischemic and hypointense lesion for chronic ischemic stroke.

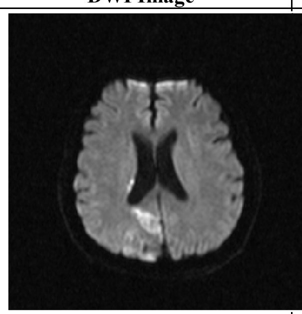
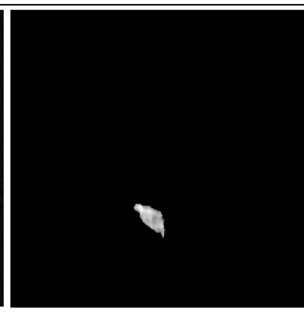
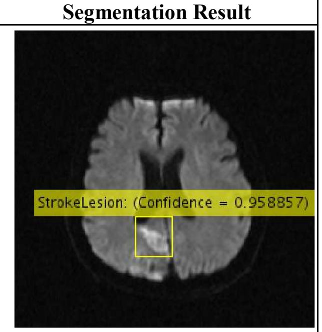
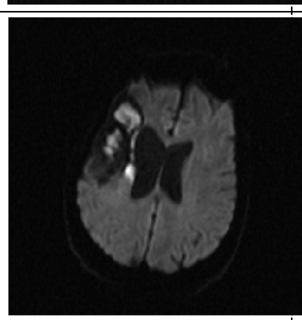
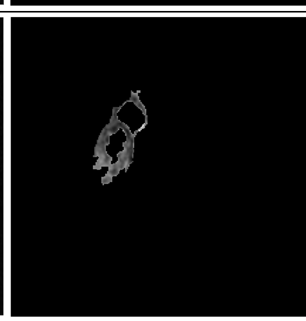
The DWI image analysis in this research employs a deep learning technique. This method proposes an R-CNN detector, which includes three stages. The RPN extracts the Region of Interest (ROI) from the DWI image using the MATLAB R2017a app. Based on the ROI's position, the CNN features are trained using several layers, including the convolution 2D layer, max and average pooling layers, ReLU layer, and the fully connected layer. The training process of the CNN features is then classified by the softmax layer and classification layer to determine the ROI. Finally, the obtained ROI is verified against manual segmentation to assess the R-CNN detector's performance. All classification techniques are validated using accuracy, sensitivity, and specificity metrics.

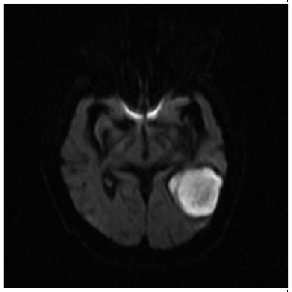
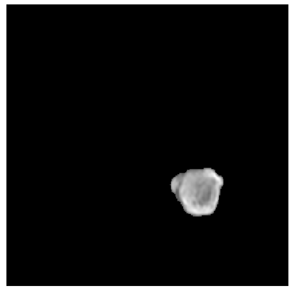
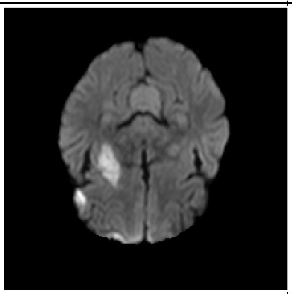
## III. Results

This section presents the results and discussion of the proposed technique. It includes an analysis using a deep learning technique with the proposed regional convolutional neural network (R-CNN) detector and a discussion of the findings. The performance of all classification methods is evaluated based on accuracy, sensitivity, and specificity. Additionally, the execution time for segmentation and classification results is discussed. All experiments are conducted on an Intel(R) Core(TM) i7-4790 CPU at 3.60 GHz with 16 GB of memory under the Windows 10 operating system.

In the DWI image analysis using deep learning technique, the R-CNN detector has been developed using MATLAB R2017a and all the experiments have been performed and presented here. The R-CNN detector is proposed for detecting and classifying the hyperintense and hypointense lesion in the DWI images. The detection of the ROI for the stroke lesion is presented in TABLE III.

TABLE III. DWI Stroke Lesion Classification Using the R-CNN Detector Technique

| Type of Stroke | DWI Image | Manual Reference | Segmentation Result |
|---|---|---|---|
| Acute Ischemic Stroke |  |  |   |
| Chronic Ischemic Stroke |  |  |   |

| | | | |
|---|---|---|---|
| Acute Hemorrhage Stroke |  |  |   |
| Sub-acute Ischemic Stroke |  |  |   |

Based on TABLE III, the R-CNN detector was able to detect the stroke lesion from the DWI image. The R-CNN detector were able to detect the ROI within its position in the DWI image of acute ischemic and acute hemorrhage stroke. For the chronic ischemic stroke, the ROI was detected but detection of the position of the ROI is not accurate. The R-CNN detects the ROI including the region of CSF. For the sub-acute ischemic, the R-CNN detector were able to detect on position of the ROI. The other position of the ROI in the DWI image of the sub-acute is not detected.

Fig. 5 represents the percentage performance evaluation of the R-CNN detector towards four type of stroke lesion. The range percentage of specificity is above 30%, with sub-acute ischemic stroke was the least 31% and acute hemorrhage were the most at 62%. The range percentage of sensitivity is above 50%, with chronic ischemic stroke being the least 55% and the acute hemorrhage and acute ischemic were the most at 75%. The R-CNN obtained 64.62% for overall accuracy, specificity and sensitivity stroke lesion classification.

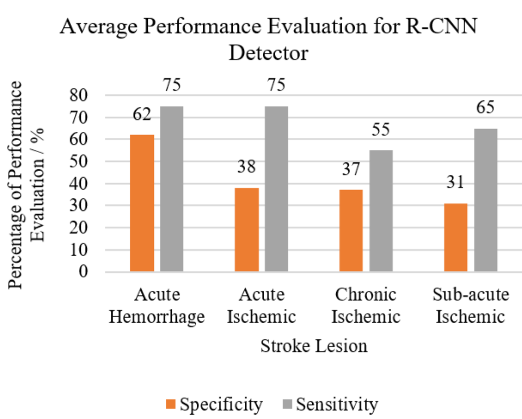



Fig. 5. R-CNN detector percentage of performance evaluation.

## A. *Performance Evaluation for Classification Technique*

In this section, the performance of the accuracy, sensitivity and specificity of each machine learning classification technique and R-CNN detector is represented. TABLE IV displays the accuracy, sensitivity, and specificity of the proposed classification techniques.

TABLE IV. Percentage of Accuracy, Sensitivity and Specify

| | R-CNN Detector (%) |
|---|---|
| Accuracy | 64.62 |
| Sensitivity | 64.62 |
| Specify | 64.62 |

The range percentage accuracy, sensitivity and specify for R-CNN detector are 64.62%.

## B. *Execution Time Performance*

The training time taken is evaluated to verify the computational time taken for deep learning technique. The training time taken for the R-CNN detector is at 16.30.

# IV. Conclusion

This research presented a deep learning method for classifying brain stroke lesions using Diffusion-weighted Imaging (DWI) images. The dataset consisted of four stroke types: acute hemorrhage, acute ischemic, chronic ischemic, and sub-acute ischemic strokes. It included 61 samples of acute ischemic, chronic ischemic, and acute hemorrhage images from Hospital Kuala Lumpur (HKL), along with 69 samples of sub-acute ischemic stroke images from the public ISLES database. The technique utilized the Region-Convolutional Neural Network (R-CNN) detector, achieving 64.62% accuracy, specificity, and sensitivity. The study concluded that this method could be improved for better classification performance through further analysis of the applied database.

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## References


[1] K. W. Loo and S. H. Gan, "Burden of Stroke in Malaysia," *International Journal of Stroke*, vol. 7, no. 2, pp. 165–167, Jan. 2012, doi: https://doi.org/10.1111/j.1747-4949.2011.00767.x.

[2] M. H. Jali, T. A. Izzuddin, Z. H. Bohari, H. Sarkawi, M. F. Sulaima, M. F. Baharom, and W. M. Bukhari, "Joint Torque Estimation Model of sEMG Signal for Arm Rehabilitation Device Using Artificial Neural Network Techniques," Lecture notes in electrical engineering, pp. 671–682, Nov. 2014, doi: https://doi.org/10.1007/978-3-319-07674-4_63.

[3] D. Smajlović, "Strokes in young adults: epidemiology and prevention," Vascular health and risk management, vol. 11, pp. 157–64, 2015, doi: https://doi.org/10.2147/VHRM.S53203.

[4] J.Peter, and A. H. Justus, "Knowledge and Practices of Stroke Survivors Regarding Secondary Stroke Prevention, Khomas Region, Namibia," *Journal of Medical Biomedical and Applied Sciences*, pp. 1-13, Feb 2016.

[5] V. Velayudhan, and P. Pawha, "Stroke Imaging," 2018 [online] Available at: https://emedicine.medscape.com/article/338385-overview [Accessed on 17 February 2024]

[6] N. M. Saad, N. S. M. Noor, A. R. Abdullah, S. Muda, A. F. Muda, and H. Musa, "Segmentation and Classification Analysis Techniques for Stroke based on Diffusion-Weighted Images," *IAENG International Journal of Computer Science*, 44(3), 2017.

[7] O. Maier, M. Wilms, J. von der Gablentz, U. Krämer and H. Handels "Ischemic Stroke Lesion Segmentation in Multi-Spectral MR Images with Support Vector Machine Classifiers," *In Medical Imaging 2014: Computer-Aided Diagnosis (9035)*, p. 903504.

[8] A. Shyna, and J. Deepa, "Automatic Detection and Segmentation of Ischemic Stroke Lesion from Diffusion Weighted MRI using Contourlet Transform Technique," *International Journal of Engineering Research & Technology (IJERT)*, 3(4), pp. 2335-2341, 2014.

[9] K. Nagenthiraja, K. Mouridsen, and L. R. Ribe, "Method for Delineation of Tissue Lesions," United States. Pat. 9,036,878, 2015.

[10] A. R. Mathew, and P. B. Anto, "Tumor Detection and Classification Of MRI Brain Image Using Wavelet Transform And SVM," *International Conference on Signal Processing and Communication (ICSPC'17)*, pp. 75-78, 2017.

[11] S. Y. Adam, A. Yousif, and M. B. Bashir, "Classification of Ischemic Stroke using Machine Learning Algorithms," *International Journal of Computer Applications*, 149(10), 2016.

[12] S. Gupta, A. Mishra, and R. Menaka, "Ischemic Stroke Detection Using Image Processing and ANN," *In Advanced Communication Control and Computing Technologies (ICACCCT), 2014 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)*, pp. 1416-1420, 2014.

[13] A. Subudhi, S. Sahoo, P. Biswal, and S. Sabut, "Segmentation and Classification of Ischemic Stroke Using Optimized Features in Brain MRI," *Biomedical Engineering: Applications, Basis and Communications*, 30(03), p. 1850011, 2018.

[14] T. Haeck, F. Maes, and P. Suetens, "ISLES Challenge 2015: Automated Model-Based Segmentation of Ischemic Stroke in MR Images," *In International Workshop on Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, pp. 246-253, 2015.

[15] S. M. Reza, L. Pei, and K. M. Iftekharuddin, "Ischemic Stroke Lesion Segmentation Using Local Gradient and Texture Features," *Ischemic Stroke Lesion Segmentation*, 2015.

[16] D. Robben, D. Christiaens, J. R. Rangarajan, J. Gelderblom, P. Joris, F. Maes, and P. Suetens, "ISLES Challenge 2015: A Voxel-Wise, Cascaded Classification Approach to Stroke Lesion Segmentation," *Ischemic Stroke Lesion Segmentation*, p. 27, 2015.

[17] L. Chen, P. Bentley, and D. Rueckert, "A Novel Framework for Sub-Acute Stroke Lesion Segmentation Based On Random Forest," *Ischemic Stroke Lesion Segmentation*, p. 9, 2015.

[18] R. Girshick, "Fast r-cnn". In *Proceedings of the IEEE international conference on computer vision*, pp. 1440-1448, 2015.

[19] O. Maier, B. Menze, J. von der Gablentz, L. Häni, M. Heinrich, M. Liebrand, S. Winzeck, A. Basit, P. Bentley, L. Chen, D. Christiaens, F. Dutil, K. Egger, C. Feng, B. Glocker, M. Götz, T. Haeck, H. Halme, M. Havaei, K. Iftekharuddin, P. Jodoin, K. Kamnitsas, E. Kellner, A. Korvenoja, H. Larochelle, C. Ledig, J. Lee, F. Maes, Q. Mahmood, K. Maier-Hein, R. McKinley, J. Muschelli, C. Pal, L. Pei, J. Rangarajan, S. Reza, D. Robben, D. Rueckert, E. Salli, P. Suetens, C. Wang, M. Wilms, J. Kirschke, U. Krämer, T. Münte, P. Schramm, R. Wiest, H. Handels, and M. Reyes, "A public evaluation benchmark for ischemic stroke lesion segmentation from multispectral MRI," *ISLES 2015*, 2015 [online]. Available at: https://www.virtualskeleton.ch/ISLES/Start2015 [Accessed on 30 January 2024]

[20] A. Rodtook, K. Kirimasthong, W. Lohitvisate, and S. S.Makhanov, "Automatic initialization of active contours and level set method in ultrasound images of breast abnormalities," *Pattern Recognition*, 79, pp. 172-182, 2018.