Evaluation of Window Parameters of Noncontrast Cranial CT Brain Images for Hyperacute and Acute Ischemic Stroke Classification with Deep Learning

Supatta Viriyavisuthisakul
School of Management Technology,
Sirindhorn International Institute of Technology (SIIT), Thammasat University
Pathum Thani, Thailand
supattavir@dome.tu.ac.th
School of Information Science, Japan Advanced Institute of Information Technology (JAIST),
Nomi city, Japan

Natsuda Kaothanthong
School of Management Technology,
Sirindhorn International Institute of Technology (SIIT), Thammasat University
Pathum Thani, Thailand
natsuda@siit.tu.ac.th

Parinya Sanguansat
Panyapiwat Institute of Management,
Nonthaburi, Thailand
parinyasan@pim.ac.th

Choochart Haruechaiyasak
National Electronics and Computer Technology Center,
Pathum Thani, Thailand
choochart.haruechaiyasak@nectec.or.th

Minh Le Nguyen
School of Information Science, Japan Advanced Institute of Information Technology (JAIST),
Nomi city, Japan
nguyenml@jaist.ac.jp

Soawapot Sarampakhul, Tanapon Chansumpao and Dittapong Songsaeng
Department of Radiology, Siriraj Hospital, Faculty of Medicine, Mahidol University,
Bangkok, Thailand
soawapotsaram@gmail.com, bahpaw@hotmail.com, and dsongsaeng@gmail.com

Abstract

Most of the recent study about deep learning in medical images have revolved the ability of deep learning models to interpretation of diagnostic result and anatomical recognition. However, deep learning can also be used to enhance a wide range of non-interpretive issues such as image enhancement that relevant to radiologists and patients. For ischemic stroke, a noncontrast cranial computer tomography (NCCT) is imaging technique used for diagnosis. The cerebral infarction in early stage on NCCT is difficult to notice because of limitation of image. Normally, the patients need to do a computer tomography perfusion (CTp) for identification the damage, but it takes time while the patients should be received the treatment quickly. Another problem about NCCT image, the range of intensity is very wide and sparse. It is needed to rescale in the suitable range for the classifier. In this paper, we aim to find the suitable window setting for classifying the Hyperacute and Acute phase of ischemic stroke in NCCT image without CTp by using Inception V3. The dataset is prepared in axial slices. Each slide is classified to either normal or lesion. Due to limitation of the training samples availability, transfer learning is applied for weight initialization of the model. The result indicates that the model can perform well with window level at 35 and window width at 95, 90.84% accuracy.

Keywords
Hyperacute ischemic stroke, Acute ischemic stroke, Noncontrast cranial computer tomography, Windowing CT, Image classification

1. Introduction

1.1 Background of the study

Stroke is the second leading causes of death worldwide. In Thailand, stroke becomes the first cause of death or functional disability. The ischemic stroke and hemorrhage stroke are major causes. The ischemic stroke is caused by clot which results in a low blood supply in brain the region (Musuka et al. 2015). It is classified into 4 stages: hyperacute, acute, subacute, and a chronic infarction (Pressman BD and Tourje EJ 1987), (Nakano S and Iseda T 2001). However, if the earlier stroke is detected, it can increase the chance of survival and recovery.

Neuroimaging is used by physician for diagnosis. There are many types of the neuroimaging such as a magnetic resonance imaging (MRI) and a computer tomography (CT). In Thailand, CT is widely used since the cost is cheaper than MRI. It becomes a diagnosis standard and widely available (Barber PA et al. 2005), (Kidwell CS et al. 1999). The image content is represented by a quantitative scale called a Hounsfield Unit (HU), which can be mapped to a color scale using a windowing process. There are two parameters that can be adjusted to show the different composition, window level (WL) and window width (WW) (Osborne et al. 2016), (Melisa Sia 2020), (Xue et al. 2012)

Although, CT is fast and cheap, it still has a limitation. The difficulty of visually identify the lesion and location of stroke in hyperacute and acute phase is problem because the lesion looks similar to normal tissue. In this way, a technique called a computer tomography perfusion (CTp) is used to indirectly show flow or status of flow toward brain parenchyma (Mortimer et al. 2013) by using the contrast agent. Unfortunately, a limitation of this technique is a specialist, which may not be available in every hospital.

Therefore, most of the recent study in deep learning on medical images have revolved the ability of deep learning models to classify or segmentation the lesion for helping interpretation of diagnostic in many kind of disease such as brain stroke (Clèrigues et al. 2019), (Cheon et al. 2019), (Meier et al. 2019), (Mirtskhulava et al. 2015), brain tumor (Nadeem et al. 2020), lung cancer (Weng et al. 2017), retina (Christopher et al. 2018), and breast cancer (Chougrad et al. 2018). Although, the developing models for diagnosis interpretation are challenging task, noninterpretive problems such as image enhancement and developing workflow is also helping improve patient outcome (Richardson et al. 2020) that deep learning can also be applied in this task to achieve the ultimate goal of treatment.

The rest of the paper is organized as follows. The previous work on the CT windowing can be found in Section 1. Section 2 is clarified the objective of study. Section 3 describes about proposed method, the datasets, CT windowing process, classification that applied in this work. The detail of the experimental result is explained in Section 4 and the conclusion is in Section 5.

1.2 Literature Review

In Computer tomography (CT) is known as modalities to assess the infarct stroke. The value of window level (WL) and window width (WW) are important factors with diagnosis accuracy. It can reveal the subtle abnormalities in patient brain. Normally, the default brain windows setting on CT image are window level at 40, window width at 80 (Ee et al. 2017), but this window is hard to review the infarct, especially in early stage of stroke. Therefore, many works are discovering on the suitable value for selecting an appropriate window level and window width for detecting an ischemic stroke are proposed.

In 2004, Sim et al. (Sim et al. 2016) proposed four mathematical central moments, mean, variance, kurtosis, and skewness were applied and compared on different CT images. The range of window setting was window level at 40 and window width between 50 and 60 were studied. In this experiment, the best parameters were window level at 40 and window width at 55 when compared with different existing techniques including the expert evaluations from the hospital staff.

In 2005, Przelaskowski et al. (Artur Przelaskowski et al. 2005) introduced two methods for perception improvement, review window setting and local contrast enhancement in multi-scale domain. A test set had 11 set images, acute stroke image and later image with clearly visible (developmental stage). The results indicated that the approach of acute stroke detection was improved. The reliable clinical test had done by three radiologists. They found that two proposed stroke display were window level 40, window width 30 followed by enhanced multi-scale display with visible hypodense area.

In 2011, Hiroyuki Nagashima (Nagashima et al. 2011), studied effect of the window width on low contrast detectability by using CT images at the various milliampere-seconds (mAs) values. The brain CT images of 30 hyperacute ischemic cases and 30 normal cares were applied on various window width at 20, 40, 60, and 80. They found that interpretation accuracy was improved by displaying simultaneously when the CT image set on window widths at 20 and 80.

In 2018, Lailatul Mugniroq (Muqmiroh et al. 2018) studied on window level between 20 and 40, window width between 8 and 40, got 26 variations of the value. The result reported that best value of window level at 25 and window width at 35 for subacute ischemic stroke by 28 radiologists which the majority voted this window.

2. Objectives of the Study

In this paper, we aim to find the suitable windows parameters for early ischemic stroke in NCCT image without CTp. We focus only hyperacute and acute stage, because these stages require immediately treatment and the most able to recover to normal tissue.

Currently, the physician uses CT image for diagnosis but the infarct in hyperacute and acute does not show the clear size and location. Therefore, the patients need to do CTp by injection the contrast agent which this process makes time-consuming. However, NCCT without CTp is difficult to identify. Thus, it needs to do windowing which just small range of windows that can reveal the detail of disease. The window selecting process does not have a standard window of early ischemic stroke, the physicians have to scale and find the windows range by their own experience which just only expert can choose the right windows for interpretation.

Nowadays, CNN is the state-of-the-art in classification task. We do not focus on development the novel technique in this classifier, but we try to find the windows that suit to interpret in real task instead of manually adjustment. The Inception V3 is used in this work because there was only one pre-trained model available that was the most similar to our task to use in transfer learning.

3. Proposed method

An overview of the proposed method is depicted in Figure 1. There are two main parts: a CT windowing process and a classification model. In the CT windowing process, window level and window width, are adjusted for each slice using the pre-defined value, WL and WW that were studied in the preliminary. Then, each adjusted image is augmented to increase the size of the dataset and balance the number of images in the two classes (normal/lesion). The augmented images are grouped in patient level to perform a 5-fold cross validation for a model development. For a classification model, it is constructed for each CT window using a deep learning and a pre-trained network. In other word, 14 models from 14-selected pair of windows are constructed to find the suitable CT window for classifying an NCCT slice for hyperacute and acute ischemic stroke.

3.1 Data Collection

The noncontrast cranial computer tomography (NCCT) scan of 49 patients were collected from Siriraj Hospital, Thailand. All NCCT images taken within 2-3 hours of stroke onset without injecting the contrast agent. The brain images were acquired in axial slices continuously, with 5 mm spacing base using vary parameter of 80, 120, 140 kilovoltage peak (kVp), and 110-640 milliampere-seconds (mAs) that set on the scanning machine. Both ischemic stroke and normal brain were collected in half and half. Moreover, each slice was assigned the label to a corresponding slice of an NCCT by experienced radiologists, “lesion” label for ischemic stroke, and “normal” label for normal brain. In Figure 2 shown the example of NCCT slice without CTp between the lesion slice and normal slice. The texture of both images is similar and hard to interpret by naked eyes. Finally, the total number of slices is 735 images. The dataset is completely separated in patient-level into 5 folds, 147 images per fold, each fold consists of around 73 images of normal brain slice and around 74 images of lesion slices.

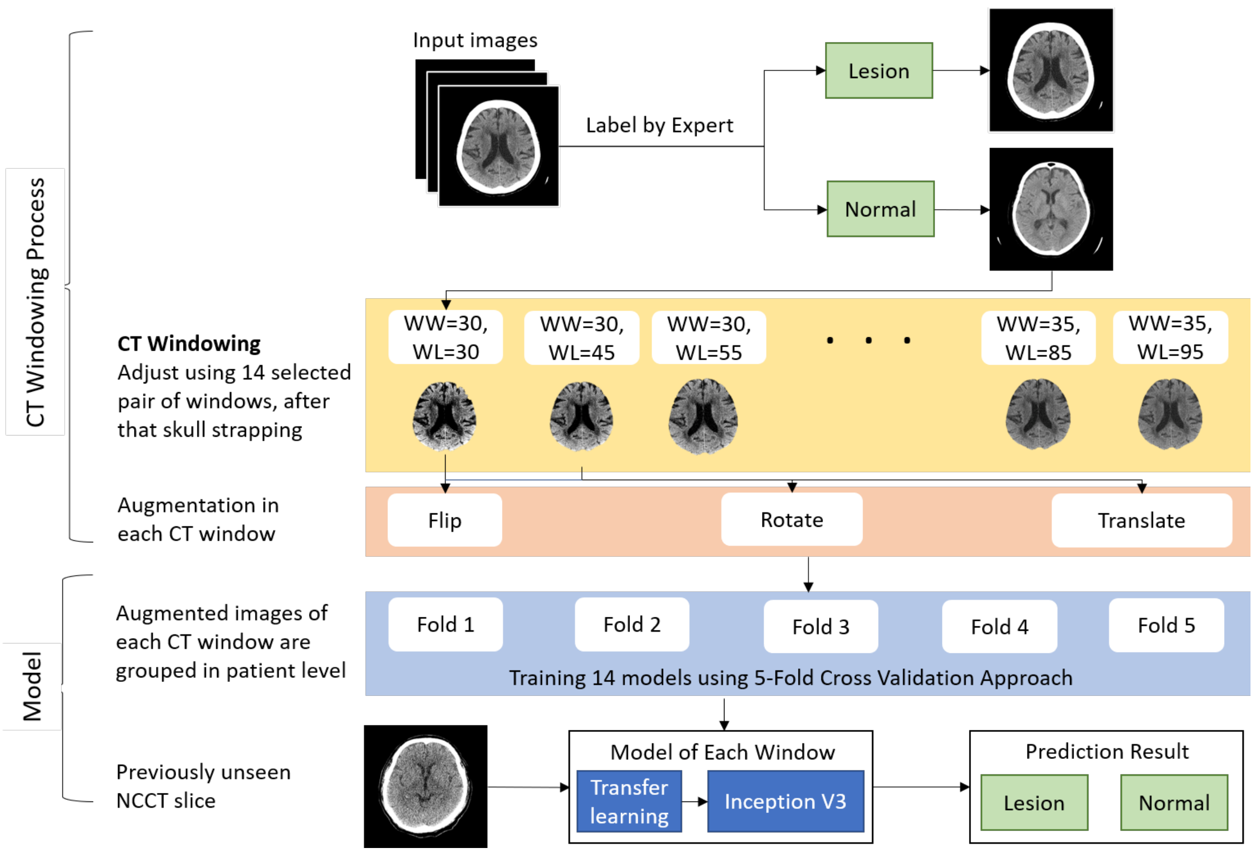

Figure 1: Overview of the proposed method. It composes of two main part: CT windowing process and classification model. There are two steps in the CT windowing process which are CT window adjustment (WL and WW), image augmentation. In the model, 14 models are independently constructed to measure the classification performance of each CT window.

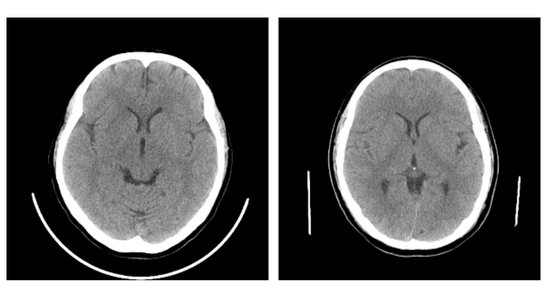

Figure 2: NCCT image without CTp of patients in axial slice, 5 mm thickness, window setting at window level 40 and window width 80, 200 mAs and 120 kVp (a) NCCT image of 49-year-old woman with an acute stroke (b) NCCT image of 31-year-old men with no stroke confirmed by radiologists

3.2 CT Windowing

An NCCT is represented using a Housfield Unit (HU), which is displayed in 4,096 levels and contained in Dicom format. The housefied values is mapped in the intensity range which it can be displayed each composition in image. To visualize the content in an NCCT, the physician can adjust the window level and window width, which window level refers to the middle value of HU and window width refers to the range of HU. For brain CT images, it is usually reviewed using the default setting of window level 40 and window width 80 (Ee et al. 2017).

To find a suitable value of window level and window width for the deep learning to classify the lesion slice, 14 pairs of values are selected based on the reported result in (Sim et al. 2016), (Artur Przelaskowski et al. 2005), (Nagashima et al. 2011), (Muqmiroh et al. 2018) and (Lee et al. 2019). See, Table 1 for the list of the 14 windows values that interested.

Table 1: Range of the window level and setting of our approach window width

Window Level (WL)	Window width (WW)
30	30, 45, 55, 60, 70, 80, 95, 100
35	30, 40, 45, 80, 85, 95

After adjusted the pair of the window parameters, the next step is skull strapping. We find the bone and undesired region by adjusting the windows that contained those information and mask as 0. On the other hand, the brain region is masked with value 1.

3.3 Image Augmentation

Since we have a limitation in dataset, image augmentation is applied. Each fold has 147 slices which consists of 74 slices in lesion label and 73 slices in normal label. The slice is resized to 256x256 and augmented by flip, rotate, and translate to increase training data.

Table 2: The number of images of each augmentation function that processed in each fold.

Class	Number of Images				
	Original	Flip	Rotate	Translate	Total
Normal	73	73	292	3,577	4,015
Lesion	74	74	296	3,626	4,070
Total	147	147	588	7,203	8,085

The number of images from each function of augmentation was determined with consideration of the quality of the original image and the necessity of the reconstruction. The number of images in each augmentation function are shown in Table 2.

3.4 Classification Model

A set of augmented images of each CT window, it is used by a training process to obtain a classification model for classifying an unseen NCCT slice. In this work, the augmented images are separated in patient-level into 5 folds. These folds are used to train the model using 5-fold cross validation approach.

In this work, transfer learning of hemorrhage classifier (The Neural Engineer 2020) is applied to define the initial weight. It was trained by using the Inception V3 with a transfer learning from ImageNet dataset (Russakovsky et al. 2015) as the weight initialization.

There are two main steps in the classification model. The first step is retraining the model of hemorrhage classifier by using a brain CT dataset from a Radiological Society of North America (RSNA). The second step is transfer learning the hemorrhage classifier to be pre-trained model and train this model by using the augmented images from our dataset. We modify the architecture of the Inception V3 by replacing the last layer by a new dense layer that corresponding to our targets and add a sigmoid activation function to classify weight into normal or ischemic lesion classes as depicted in Figure 3.

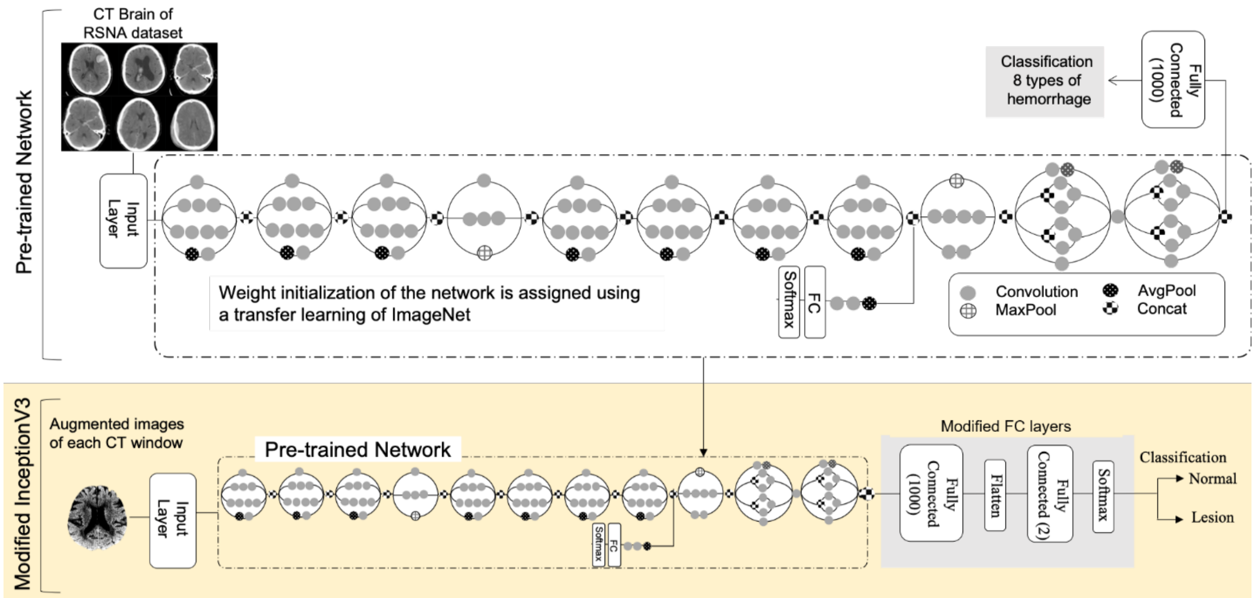

Figure 3: The classification model using pre-trained model from hemorrhage classifier, Inception V3.

4. Experiment

The proposed window parameters and the augmented images as described in the previous section are trained using 5-fold cross validation approach. The classification model is trained for five rounds. For each round, one fold is selected as a testing data and the rest are used for training the model.

The parameters of the Inception V3 for training the model are as follows. The size of the input image is 256 x 256. The batch size for training is 32 and the optimized is Adam. The number of training is 441 epochs per fold, one slice is trained three times in sub-epoch.

4.1 Windows Evaluation

In this work, ROC curve, sensitivity, specificity, and accuracy are used for evaluating the efficiency of the proposed window parameters together with inception V3 model. The ROC curve and an area under curve (AUC) shows how well the model can separate the NCCT slices in two classes, lesion and normal.

The highest average accuracy among the overall k-fold experiment is 84.60% from window level 35 and window width 40 as shown in Table 3. However, we concern about the performance of class prediction. The AUC is used to compare the efficiency. We found that the window level 35 and window width 95 has the highest value at 90.84%. ROC curve in Figure 4 can show the performance of this window in each fold. In additional, the most of misinterpretation of window level 35 and window width 95, is normal class as shown in Table 4. For the sensitivity and the specificity of this window, are 78.10% and 86.20%, respectively.

Table 3: Comparison of the performance in each window using the overall result computed from each k-fold experiment

No	WL	WW	Avg. Acc. (%)	Avg. Spec. (%)	Avg. Sen. (%)	AUC (%)
1	30	30	80	73	87.2	84.89
2	30	45	76	84.3	76	88.31
3	30	55	86.9	77.8	86.9	88.38
4	30	60	92.9	72.2	92.9	84.67
5	30	70	79.5	80	79.5	87.58
6	30	80	91	74.6	91	87.54
7	30	95	70.2	86.5	70.2	88.74
8	30	100	88.5	75.7	88.5	86.35
9	35	30	85.5	81.1	85.5	87.03
10	**35**	**40**	**84.6**	85.7	83.6	89.94
11	35	45	56.6	82.4	56.6	77.93
12	35	80	76	83.8	76	86.02
13	35	85	74.3	86.8	74.3	90.06
14	**35**	**95**	78.1	**86.2**	**78.10**	**90.84**

Table 4: Confusion Matrix of the window level 35 and window width 95

		Predicted	
		Normal	**Lesion**
Actual	**Normal**	286	80
	Lesion	51	319

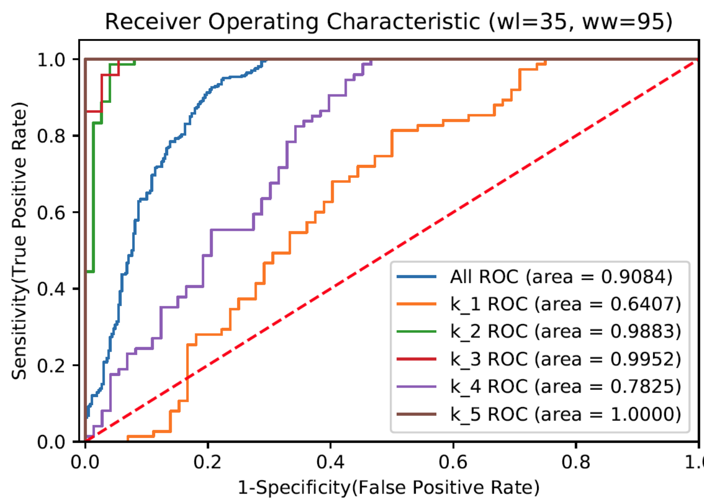

Figure 4: The ROC curves of the window level 35 and window width 95

5. Conclusion

In this work, we presented and evaluated the window parameters, window level and window width for hyperacute and acute ischemic stroke classification on NCCT images without CTp by using deep learning. The dataset contains two classes of brain that is normal or lesion (ischemic stroke). The NCCT image pixel is 12 bit or 4,096 level of the intensity which contain the different composition in image, thus we performed contrast enhancement by determining the suitable windowing parameters (WL, WW) from our 14 predefined windows via 5-fold cross validation. Every training data need to prepare by skull-strapping and image augmentation in 54 ways of affine transformations i.e. flipping, rotation, and translation. We applied transfer learning from brain hemorrhage stroke classification model that it used the Inception V3 engine and transferred that weights to initialize our model and adding some convolutional layers to meet our condition. The result of proposed window parameter and classification model achieved a good performance with NCCT images of hyperacute and acute stroke. We found that the model can well predict with window level at 35 and window width at 95, it gets the area of under curve at 90.84% and average accuracy of 82.20%

For the limitation of this approach, it needs to be adjusted the window level and window with by manual for finding the highest accuracy. However, we can take benefit of this image enhancement to support the image segmentation in the preprocessing part which can be extended in the future.

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Biographies

Supatta Viriyavisuthisakul received her B. Sc. degree in information technology from Thai-Nichi Institute of Management, and M.Sc. degree in information technology at Panyapiwat Institute of Management, Thailand in 2013 and 2016, respectively. She is currently studying in Ph.D degree in engineering technology at Sirindhorn International Institute of Technology (SIIT), Thailand and information science from School of Information Science, Japan Advanced Institute of Science and Technology (JAIST). Her research areas are information technology and machine learning.

Natsuda Kaothanthong received her B. Sc. degree in information technology from Sirindhorn International Institute of Technology (SIIT), Thailand in 2008. She received M.S and Ph.D. degree in information sciences from Graduate School of Information Sciences, Tohoku University, Japan in 2011 and 2014, respectively. Her research areas are data mining, business intelligence, computer vision, and computational geometry.

Parinya Sanguansat received the B.Eng., M.Eng. and Ph.D. degrees in Electrical Engineering from the Chulalongkorn University, Thailand, in 2001, 2004 and 2007, respectively. He is an assistant professor in the Faculty of Engineering and Technology, Panyapiwat Institute of Management, Thailand. His research areas are machine learning, image processing, digital signal processing in pattern recognition.

Choochart Haruechaiyasak received the B. Sc. degree in Electrical Engineering from University of Rochester, Rochester NY, U.S.A. in 1995. He graduated M.Sc. in Computer Engineering from University of Southern California, Los Angeles CA, U. S. A. in 1997. He graduated Ph. D. in Electrical and Computer Engineering from University of Miami, Miami FL, U.S.A. in 2003. His research areas are text mining, sentiment analysis, information retrieval (IR), natural language processing (NLP) and web intelligence.

Minh Le Nguyen received his B.Sc. degree in information technology from Hanoi University of Science, and M.Sc. degree in information technology from Vietnam National University, Hanoi in 1998 and 2001, respectively. He received his Ph.D degree in information science from School of Information Science, Japan Advanced Institute of Science and Technology (JAIST) in 2004. He is now an associate professor at School of Information Science, JAIST. His research interests include text summarization, machine translation, natural language processing, machine learning, and information retrieval.

Soawapot Sarampakhul is currently radiology resident at Siriraj Hospital, Mahidol University, Bangkok, Thailand. His skills and expertise are neuroimaging, and stroke imaging.

Tanapon Chansumpao is currently radiology resident at Siriraj Hospital, Mahidol University, Bangkok, Thailand. His skills and expertise are neuroimaging, and stroke imaging.

Dittapong Songsaeng received his M.D. degree in Medical from Chiang Mai University, Thailand in 1998. He is now an associate professor at Department of radiology at Faculty of Medicine Siriraj Hospital, Mahidol University, Thailand. His skills and expertise are neuroimaging, head and neck radiology, interventional neuroradiology, magnetic resonance, and stroke imaging.