Study on CNN-based Stroke Diagnosis System

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***Abstract*—A stroke is the most common, very dangerous single-organ disease and aggravates social burden in the aging society. The stroke can be tested through a variety of imaging methods, among which a test method using CT imaging is known to deal promptly with an emergency patient in the early stage of stroke. The Alberta Stroke Program Early CT Score (ASPECTS) is widely used to assess the progress of stroke based on the CT imaging. It is problematic because of its presence of a scoring variability depending on a specialist's career and individual variations. To resolve this issue, the scoring system proposes the deep learning system which can estimate ASPECTS automatically based on the CT imaging in order to help reduce the occurrence of scoring variability between specialists, as well as to improve decision making. The system uses NCCT brain scan images as inputs and creates outputs which estimated patient's ASPECTS through three phases of imaging – preprocessing, segmentation and deep learning. Each phase is designed to imitate experienced specialists' stroke identification techniques by standardizing dataset and applying appropriate feature extractions on the neural network, based on image processing and deep learning.**

I. Introduction

Stroke is the most common single-organ disease which claims 6.2 million lives globally each year. Stroke occurs above the age of 65 at a rapid pace, therefore, advanced countries where population ageing is taking place are gradually taking more social burden due to stroke[1][2]. Moreover, this disease is likely to happen commonly in people in their 30s and 40s, therefore, it occurs extensively almost in all age groups and is considered very dangerous. Stroke is divided into an ischemic stroke that occurs when an artery in the brain becomes blocked and cerebral hemorrhage which is caused when an artery in the brain bursts.

Various tests have been developed for diagnosing the stroke and methods depending on computed tomography (CT) can diagnose the stroke in a relatively short time. It is considered to be an appropriate test method for the stroke because a rapid response is essential for treating the stroke and this method diagnoses the stroke quickly. Since the bleeding of hemorrhagic stroke can be observed on CT immediately, CT is used as a useful tool to identify the hemorrhagic stroke prior to the use of a thrombolytic agent (a drug that breaks blood clots) for treating the hemorrhagic stroke. Moreover, it is important to monitor the progress of the hemorrhagic stroke after using a thrombolytic agent.

Studies conducted indicate that when carrying out a test using CT as shown above, excluding the area where a cerebral infarction has rapidly developed may increase the effectiveness of stroke diagnosis and treatment [3][4]. This is implemented with more detail in so-called ASPECTS (Alberta Stroke Program Early CT Score) [5][6].

But, the determination of early signs of ischemia and their translation into the ASPECTS have a considerable inter-rater variability, which is, among other factors, influenced by rater's experience[7]. Hence, inter-rater variability depending on rater's experience has a very negative impact on decision making about the patient's stroke identification. One solution to improve ASPECTS readings is to train doctors to be aware of these issues and provide strategies that enhance the reliability and validity of these readings. Another solution is to develop an automated solution for interpreting ASPECTS using new technologies such as machine learning and feature extraction.

The objective of this study was to develop an objective and automated ASPECT Score estimation system based on the image processing and deep learning technology. It will reduce the scoring variability that can occur while a physician calculates the ASPECT Score for a stroke patient

II. Proposed Method

Data for purposes of system training and assessment was collected from the patients who have gone through a stroke test through non-contrast computed tomography (NCCT) at The Gachon University Gil Hospital in South Korea. Upon arrival at the hospital's emergency room, the patients had NCCT brain scan and the ASPECTS scores were calculated using the corresponding initial CT scanned images. Besides, excluded from this study were the patients who : showed symptoms of transient ischemic stroke with negative imaging findings, had posterior circulation stroke, or had a contraindication for administration of intravenous alteplase [8].

The scoring system largely performs a 3-step process to estimate the ASPECTS based on CT scans of stroke patients. The first step is the preprocessing that involves the performing of the normalization process between CT image data, highlighting primary features in stroke determination in the image and simplifying data by deleting unnecessary features. The second step is the segmentation involving taking apart a total of 10 lesions to calculate the ASPECTS in CT scan. Each lesion is segmented into 3 or 7 territories in supraganglionic and ganglionic levels, each segmented territory being utilized at a deep learning level independently to learn and classify per-territory features. The third step involves the ASPECTS scoring with the use of the deep learning.

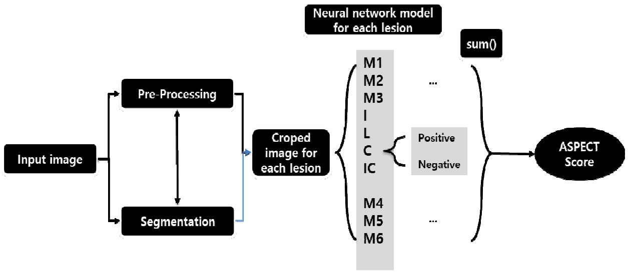

Fig. 1. System Flow Chart

In other words, it plays a role in performing the classification by receiving input images which went through preprocessing and segmentation steps and taking the supervised learning of positive/negative images for each lesion that constitutes the ASPECTS.

This study explains each step of the whole algorithm. Moreover, this study evaluated the results of the test S/W of the deep learning based diagnosis of lesions step. Additionally, this study verified the whole algorithm.

A. *CT Image Pre-Processing*

The pre-processing is carried out to ensure more accurate results in the segmentation and deep-learning steps through the normalization and standardization of a dataset. The pre-processing step includes the step of locating the skull in the brain CT images based on the image processing, the alignment step (rotation degree and center point), and the horizontal invert step according to the lesion-side.

After the pre-processing step, an image is standardized so the image is aligned to the center with having the center vertical line as the symmetry line and making the left brain as the lesion. The purpose of the pre-processing step is to optimize the image so it is easy to specify main features for diagnosing the stroke in the following deep learning step.

The purposes and results of each sub-step of the pre-processing step are as follows.

- The first sub-step is image blurring which is performed to eliminate the noise produced primarily by CT scan. The filter used for convolution operation is a Gaussian filter. Noise does not put a significant impact on learning and classifications in the deep learning step. However, it can cause the accuracy of search to drop when searching for a reference point (skulls, left-right brain symmetry, the location of an infraction territory) in the preprocessing step. Therefore, the overall system performance can be improved when removing it from the corresponding step.

- The second sub-step is to locate the skull in the brain images of a patient. It includes auto-thresholding, contour finding, and skull ellipse exploration. It separates each function in order to locate the inner and outer ellipses of the skull from the noise-removed images. The auto-thresholding function makes it remain only the pixel information corresponding to the skull by exploring the adaptive threshold value with considering the pixel value distribution of the divided image.

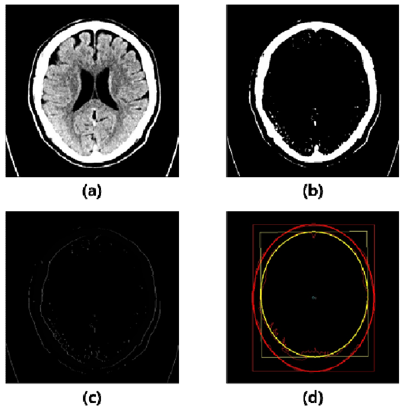

Fig. 2. Blurred Image (a), Thresholding Image (b) Contour detection Image (c), Inner-Outer skull ellipse (d)

- The edge detection is performed based on the thresholding completed image through the contour finding. The information of the inner-outer skull ellipse is obtained by exploring the inner-outer skull ellipse from the image only containing edge information.

- The third sub-step is the alignment, which is included for the consistency of the dataset. The consistency of the dataset is essential to improve the learning and classification accuracy in the deep-learning step, which determines the stroke. Since the location of patient's skull is different when a brain CT image of a stroke patient is taken by a medical specialist, the consistent position and rotation of a dataset should be obtained by conducting the center-point alignment and rotation alignment of the skull. Each alignment is calculated based on the skull ellipse information obtained in the pre-processing step.

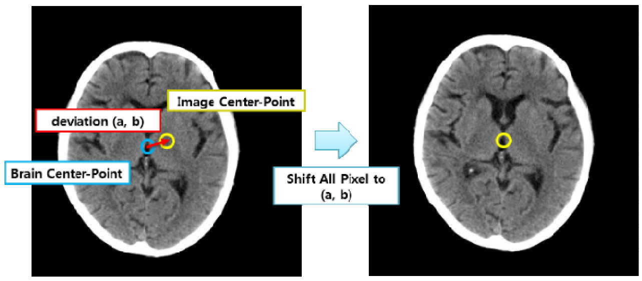

Fig. 3. Center-Point Alignment

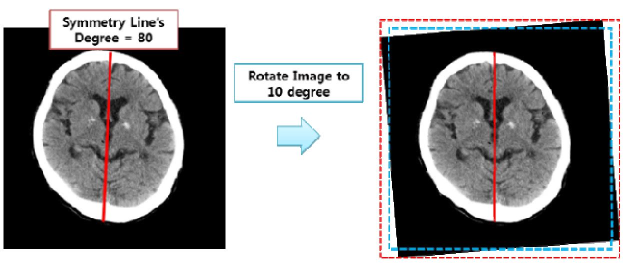

Fig. 4. Rotation Alignment

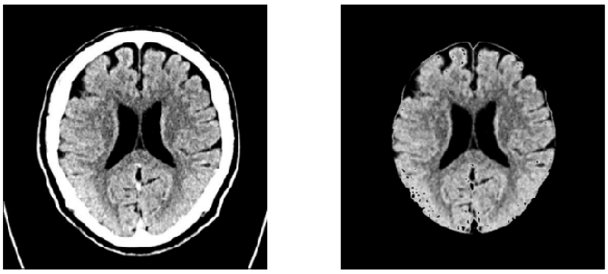

Fig. 5. Before-After Padding Processing

- The final sub-step is padding. It is a process to enhance the learning and classification accuracy in the deep-learning step by deleting the skull area, which is an unnecessary feature in determining the stroke. Based on the skull ellipse information obtained in the pre-processing step, ROI is set for a predetermined width of a region from the skull ellipse. Moreover, the padding calculation is conducted by calculating the threshold value corresponding to the skull in the CT image adaptively.

B. Lesion Segmentation

The segmentation step, which refers to the process performed following the preprocessing step, involves carrying out the task of acquiring a contour for 10 territories used in calculating the ASPECTS on the basis of the original CT scan where the preprocessing is not applied. Out of the 10 territories, 7 are searched in the image on the ganglionic level and 3 on the supraganglionic level, respectively.

Ganglionic and supra Ganglionic level images have feature points that are always present. Segmentation for each lesion is carried out based on the image processing technology by using the skull ellipse information and feature points obtained in the pre-processing step. The following figure shows the segmentation standard based on the feature points and the red points present the feature points used in each level.

The system segments the lesion by connecting feature points geometrically after exploring features points based on the segmentation standards. The figure below shows the segmentation results of the ganglionic level. It can be confirmed that it is segmented for the seven lesions of the ganglionic level. Since each lesion has a shape that is not clearly distinguishable from the pixel value, it is optimized to approach the segmentation standards, which were established according to the opinions of the medical specialists.

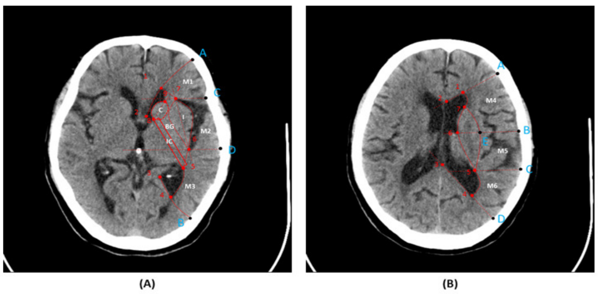

Fig. 6. Ganglionic Level Segmentation (A), Supra Ganglionic Level Segmentation (B)

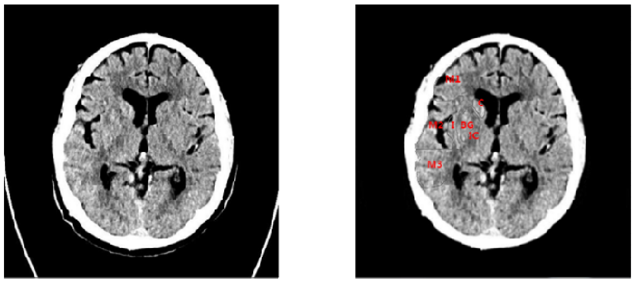

Fig. 7. Before-After Segmentation

C. Feature extraction

CT images are atypical data and contain a large quantity of information. In order to calculate ASPECTS from CT images, it is necessary to explore the cerebral infarction, swelling, and occlusion, and to judge the presence of a stroke based on the reading.

The ASPECTS is basically an intuitive, simple method, but it is particularly difficult for inexperienced specialists to determine early ischemic changes based on the NCCT brain scan images. This is because the ASPECTS scores can be influenced by a variety of factors to consider in determining ischemic changes, such as a patient's medical history, long-term infarction, brain atrophy and leukoaraiosis [9].

The CNN neural network can find meaningful patterns from complex, irregular data. However, it is also difficult to classify the presence of a stroke only using pre-processed CT images. Moreover, it shows low accuracy. Therefore, this study decreased the complexity of images by only using the target region of CT images and specific features for detecting cerebral infarction, swelling, and occlusion regions. These are important features determining the stroke before inputting CT images to the neural network.

To extract the features, the radiologist created gold standards for the cerebral infarction, swelling, and occlusion regions using the dataset of patients' CT images. Moreover, the histogram of the feature regions was learned based on it. This study used the Weka segmentation algorithm for learning regions and classification[10]. Feature extraction is shown in Fig. 8. Brain CT images were segmented into four groups based on the previously learned models to detect the regions suspected as cerebral infarction, swelling, and occlusion in purple color.

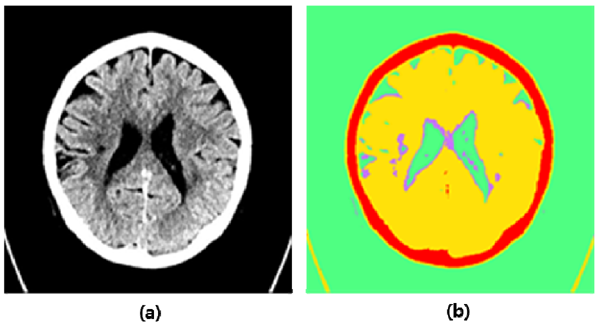

Fig. 8. Feature extraction (a) original image (b) segmented image (by 4 groups)

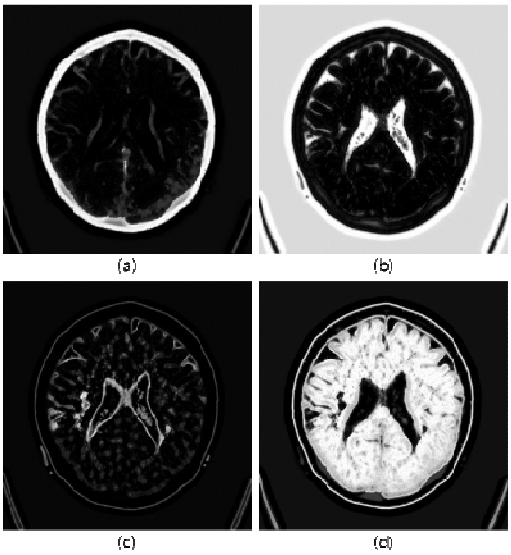

Fig. 9. Probability maps of each group

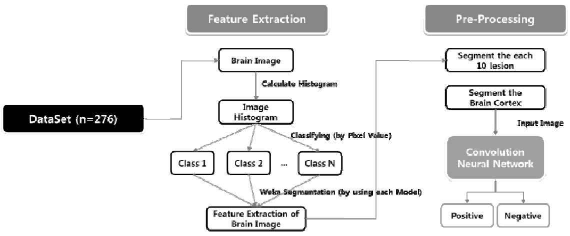

Fig. 10. Conceptual diagram of the proposed system using the feature extraction phase

Fig. 9 shows the probability map of each group. The system uses the probability map image of (c) group, which was used as a feature.

Fig. 10 presents the conceptual diagram of the entire system, including the feature extraction phase.

D. *Deep Learning based diagnosis of lesions*

According to the segmentation result, each lesion image is cropped from the whole image (image crop) and the cropped image is subjected to the map learning using the neural network consisted by each lesion with containing the positive/negative information. Each neural network learns based on CNN and consists of six hidden layers and two DropOut layers to prevent overfitting. Moreover, ReLU is used as an activation function.

Each lesion conducts learning and classification in an independent neural network. The number of neural networks that judged a lesion as positive is the number of lesions with the stroke, so the final ASPECT Score is calculated based on the number.

$$\boldsymbol{AspectScore = 10 - \sum_{k=1}^{10} if(L_k == positive)} \quad (1)$$

III. Results

This study determined the ASPECT scores of 276 CT images of patients suspected with acute ischemic cerebral diseases (within 6 h of the onset). Experienced neurosurgeons and radiologists independently diagnosed the presence (positive/negative) of stroke for 10 independent lesions (i.e., caudate, putamen, inside capsule, insular cortex, and M1-6) and it was used as a ground-truth dataset. Of this dataset, 80% (n=220) was used as a training dataset, and the other 20% (n=56) was used as a test dataset. The accuracy of the results was calculated by comparing the classification results of the system with the ground-truth dataset. The accuracy of the results (performance index) was estimated by averaging the accuracies of the ten lesions.

The performance of the system was measured by calculating sensitivity, specificity, PPV, NPV, and accuracy. Table. 1 shows the positive/negative results for 560 samples of 56 patients, which examined the 10 lesions of each patient.

TABLE I
POSITIVE/NEGATIVE RESULTS
BETWEEN SYSTEM RESULTS AND GROUND TRUTH

	Ground Truth (+)	Ground Truth (-)	Sub Total
System Result (+)	239	136	375
System Result (-)	62	123	185
Sub Total	301	259	560

The results of the evaluation had sensitivity of 79.40, specificity of 47.49, PPV of 63.73, NPV of 66.49, and accuracy of 64.64. The overall performance of the system is similar to that of Brainomix, which is a representative automatic ASPECTS estimation system. In terms of accuracy index, it showed a performance of approximately 96.5%, compared to that of Brainomix (67%).

When a neuroradiologist, who had 32 years of experience, examined the stroke ASPECT score, the accuracy was 77% on average[11]. Considering this, it is believed that the system may show an accuracy close to that of skilled neuroradiologists if the accuracy of the neural network is increased by securing more datasets and more reliable ground-truth data (if many neuroradiologists participate in ground-truth production and DWI–MRI , which has a higher reliability in stroke judgment, is used).

IV. Conclusion

This study proposed an automated system that can estimate the ASPECT Score, which is an objective index for diagnosing the status of stroke patients, solely based on CT images. The ASPECT Score automation calculation program for the stroke is expected to provide a reliable index that can prevent an issue associated with the scoring variability among professionals and will make the treatment decision-making easier in the medical treatment. It will be beneficial because the stroke requires a prompt treatment.

Given that the results of a neural network are highly affected by the quality of the dataset, the current size of the dataset (276 patients) seems insufficient for providing reliable learning. Additionally, a more reliable ground-truth should be obtained because, owing to the nature of supervised learning, the labeling of the dataset directly influences the classification results. It is expected that it will be possible to improve the performance of the neural network greatly if a highly reliable ground-truth is produced by using DWI–MRI instead of creating a ground-truth dataset using CT images, which may pose discrepancies regarding the presence or absence of the stroke between neuroradiologists. Additionally, it will be possible to obtain higher accuracy results by extracting the texture features of images and diversifying the input features of the neural network, instead of only using the infarction, swelling, and occlusion regions in the feature extraction phase. In the future, we will develop a system providing an accuracy close to that of the diagnosis of a skilled neuroradiologist by overcoming the current shortcomings.

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