A study of the estimation of Stroke ASPECTS Scores based on NCCT brain scan images using deep learning

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ABSTRACT

Stroke is a high-risk disease causing death, permanent disability in patients, and is the leading cause of death worldwide. Stroke can be quickly examined for disease through CT, an imaging diagnostic tool. However, the diagnosis of Ischemic Stroke using a CT image has the advantage of being able to take a picture in a short time with less restrictions in place, but there is a problem that diagnosis through an image is very difficult. In this paper, we propose a deep learning system capable of learning and classifying ischemic stroke diseases that are small datasets and difficult to learn about image data. We propose a preprocessing algorithm optimized for ischemic stroke based on Non-Contrast CT data in Middle Cerebral Artery (MCA) area.

CCS CONCEPTS

• Computing methodologies → Biometrics

KEYWORDS

Stroke, Deep learning, Brain CT, Pre-Processing

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1 INTRODUCTION

Stroke is a disease in which blood vessels supplying blood to the

brain are blocked or burst, causing brain damage, and resulting physical disability. In the past, it was mainly recognized as a disease for the elderly, but these days, it is a trend that is common in younger generations, and is recognized as a very fatal disease[1,2]. CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) are representative methods for diagnosing stroke[3].

Figure 1: Examples of stroke on CT and MRI images

Among them, the method using CT can perform the examination in a relatively short time. Due to the advantage of being able to test quickly, it is considered to be a test method suitable for the characteristics of stroke disease, which requires quick response.

Figure 2: Examples of stroke through MRI (DWI, FLAIR) images

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In 2000, Barber et al introduced the Alberta Stroke Program Early CT Score[4,5]. ASPECTS Score divides the Middle Cerebral Artery (MCA) territory into 10 predefined anatomic areas and grades the presence of early infarct signs by parenchymal hypodensity on NCCT.

Figure 3: Example of ASPECTS Calculation from Non-Contrast CT Images

Aspect Score has proven to be a powerful predictor of the condition of stroke patients, but the determination of early signs of ischemia and their translation into the ASPECTS have a considerable interrater variability, which is, among other factors, influenced by rater experience[6]. Therefore, such scoring variability has a disadvantage of negatively affecting the decision-making process for patient clinical outcomes. To solve this problem, in this paper, we developed an automated solution to interpret ischemic stroke in patients using new technologies such as machine learning and feature extraction.

However, due to the characteristics of deep learning technology that performs feature learning based on data, in order to converge to a certain performance, a large-capacity data set with little deviation between data must be required. But in the case of rare diseases, patient data is insufficient, and data is independently managed for each hospital due to problems such as protection of patient personal information, so it is very difficult to construct a large data set for a specific disease. Deep learning training using insufficient training data not only does not converge the weight of the neural network to sufficient performance, but also shows the disadvantage that the recognition rate for the actual dataset is significantly lowered due to over-training on the training dataset. It is not possible to apply to the dataset.

Therefore, in this paper, we propose a data preprocessing and deep learning system that can perform learning and classification for ischemic stroke diseases that are difficult for artificial intelligence to learn because it is a small dataset and has high image complexity.

2 EXPERIMENTAL AND COMPUTATIONAL DETAILS

2.1 Overview of the suggested algorithm

The proposed system classifies the patient's stroke based on image processing and deep learning technology using Non-Contrast CT images acquired from patients with suspected stroke symptoms, and provides appropriate medical measures according to the patient's stroke type and stage. We propose a deep learning CAD system that provides the basis for judgment prior to diagnosis by medical staff.

The proposed deep learning-based stroke classification CAD system aims to improve using the following method.

- In order to consider serial 2D data of CT image for MCA region, through concatenation for consecutive slices, it was induced to detect and learn cerebral infarction that occurred locally only in part of the brain.

- The data input to the neural network was preprocessed by optimizing the windowing algorithm that converts data from Hounsfield Units, which is the original CT data by acquiring the data distribution for each type of cerebral infarction through the histogram analysis of the cerebral infarction area of the patient subject to ischemic stroke. Through this, the performance of neural network learning for the cerebral infarction region of ischemic stroke is improved.

Because ischemic stroke has a great difficulty in data composition due to lack of data, this problem was intensively improved, and the best performance was derived by optimizing the preprocessing and neural network structure using the proposed improvement algorithms. Figure 4 shows the structured process of the ischemic stroke classification system.

Figure 4: A structure of ischemic stroke classification CAD system

2.2 Lesion Concatenation

Data preprocessing includes template conversion of CT Raw Data for normalization between datasets, Data Augmentation, Lesion Concatenation between Multi Slices, and Windowing. The proposed system reconstructs and normalizes the brain NCCT image to organize the data into several slices per patient. The neural network receives each target slice data, trains the model, and classifies whether the data has a stroke. The target slice input to the neural network is based on a 2D image, but the actual brain NCCT image is composed of serial data (Sequence Data) from the top of the head to the MCA area.

Also, in the proposed system, each area of the brain is segmented to classify whether each area has cerebral infarction. In the case of a specific area, it is composed of up to 3 consecutive slices based on a slice thickness of 3mm. Therefore, when infarction occurs in at least one of the plurality of slices, the neural network must determine the patient's area as a cerebral infarction. Figure 5 is an example of Old Infarction occurring only in the last slice in three consecutive slices of the Insula area. Infarction did not occur in slices 1 and 2, but since infarction occurred in slice 3, the area should be classified as Old Infarction.

Figure 5: Examples of infarction occurrence in sequential slices of a region

In this paper, in order to apply the clinical know-how for diagnosis of stroke to a deep learning system, continuous slices for one area are searched for before and after the target slice based on the relative position value metadata of medical image data. Multiple images are input to the neural network. The neural network performs concatenation on the input consecutive slices and transforms it into one image to perform model training and prediction.

Figure 6 shows the data applied to the single target slice and the target slice with Lesion Concatenation. The image to which the Lesion Concatenation is applied is calculated using the images before and after the target slice.

Figure 6: Slices before and after lesion concatenation (a): a single target slice and (b) a lesion concatenated slice

2.3 Optimal Windowing

CT data has a CT numerical value for each pixel, and this CT numerical value is called Hounsfield Units (HU) according to the name of Godfrey N. Hounsfield of England, the inventor of the CT technique. It is a value that is a relative expression of the degree of absorption due to density. 0 for water, 1000 for bones and -1000 for air. The range of Hounsfield Units ranges from -1000 to 3000, and for visualization of a specific area in radiology, the image is reconstructed with data of a certain range of Hounsfield Units without considering the data of all Hounsfield Units ranges. This process is called Windowing or Window Leveling. Windowing method displays only the value of a specific width (Window Width) centered on the Hounsfield Units value (Window Center) of interest. Among Hounsfield Units values, the values outside the Window Width are converted to 0 or 255, and the values within the Window Width are distributed and expressed from 0 to 255.

Figure 7: Comparison of CT images with windowing applied according to windowing parameter change

In the case of ischemic stroke, the difference in the distribution of Hounsfield Units between the normal group and infarction is

very small. Figure 8 shows the average histogram of the data of each class, showing that the distribution of the data is similar and the difference between the average values is very small. For this reason, it can be seen that the importance of limiting the data range of HounsField Units through appropriate windowing is very high.

Figure 8: Mean histograms of datasets by normal and infarction

In this paper, we propose an optimal windowing parameter that can classify the Early Ischemic Sign class (Frank Hypodensity, Territorial Infarction), the main target infarction of ischemic stroke, with high performance, and each value is Window Width 20-30, Window Center It is 40. Figure 9 shows the histogram of HounsFields Units in the left-right brain. One side is the Infarction corresponding to the Early Ischemic Sign class, and if the two histograms are differentially calculated when the symmetrical brain is normal, the difference between HounsField Units appears in a certain pattern. By setting each parameter based on the pattern, the image is reconstructed using only the Houns-Fields Units value in the range of 25 to 55 in the total range of -1000 to 3000 HounsField Units. Through the proposed windowing, optimal learning can be expected using only pixel information corresponding to the characteristic of ischemic stroke in the image.

Figure 9: Histograms in the infarction and normal ranges and the difference between them

3 RESULTS AND DISCUSSION

3.1 Experimental Environment

The system used in the experiment is an AMD Ryzen9 3900X 12-Core Processor desktop, and the operating system is Windows 10 Home. The GPU used 1 Geforce RTX 2080 Ti. Python 3.7 was used to implement the algorithm, and Python-OpenCV 3.0 was used to develop preprocessing algorithms. Pytorch 1.4.0 was used for learning and testing the deep learning algorithm.

In order to evaluate the algorithm proposed in this paper, the data of 356 stroke patients accumulated for 8 years in an actual hospital were used. Each patient's data is composed of 40-50 2D images according to the slice thickness during CT scan, and 8 images per patient are used among the 2D images reconstructed through template normalization, and ASPECTS from 8 2D images. For the 14 regions of the subject, 46 2D images were obtained by separating each left-right brain.

3.2 Lesion Concatenation Application and Performance Evaluation

The neural network was trained and tested by applying inter-image concatenation in order to more effectively classify the presence of cerebral infarction using the information of slices before and after the regions consisting of consecutive slices among stroke candidate regions. Table 1 compares the performance of a neural network trained using only a single slice without using Lesion Concatenation and a neural network trained using data applied with Lesion Concatenation for consecutive slices.

Table 1: Performance evaluation before and after applying lesion concatenation

Evaluation Index	Without Lesion Concatenation	Applied Lesion Concatenation
Number of Train Image	5,210	5,210
Precision	0.7784	0.7841
Recall	0.7390	0.7407
(Sensitivity)		
F-1 Score	0.8088	0.8260
AP*	0.6810	0.6994
Accuracy	0.8048	0.8269
AUC**	0.8592	0.8634

* : Average Precision

** : Area Under the Curve (ROC Curve)

When applying Lesion Concatenation, it showed a significant performance improvement of about 2.02% compared to the previous one.

3.3 Optimal Windowing Application and Performance Evaluation

This paper sets windowing parameters suitable for neural network feature learning based on the distribution of HounsField Units for each normal group and cerebral infarction classification, and compares and evaluates the neural network performance accordingly to explore the optimized parameters.

Table 2 shows the results of classification performance evaluation for the normal group and the Infarction group according to the windowing parameter setting.

Table 2: Performance evaluation according to windowing parameters

Evaluation Index	WC:40, WW:40	WC:40, WW:30	WC:40, WW:20
Number of Train Image	5,210	5,210	5,210
Precision	0.7784	0.7924	0.6426
Recall (Sensitivity)	0.7390	0.7497	0.6071
F-1 Score	0.8088	0.8308	0.7098
AP*	0.6810	0.7073	0.5900
Accuracy	0.8048	0.8307	0.6912
AUC**	0.8592	0.8691	0.7207

* : Average Precision

** : Area Under the Curve (ROC Curve)

Normal group and Infarction classification show the highest performance in case of Window Center 40 and Window Width 30, and the windowing range is [25, 55]. Infarction's Houns Field Units distribution has an average of 4.11 lower values and large standard deviation compared to the normal group. In this paper, we propose a windowing parameter optimized for ischemic stroke, and the parameter values are Window Center 40 and Window Width 30.

4 CONCLUSIONS

In medical images, the data varies greatly depending on the imaging device, and there is a problem of lack of data to build a reliable deep learning system due to problems such as patient medical information security and independent data management of medical service providers. In addition, compared to deep learning systems based on MRI images that have high reliability of data and provide a variety of information, deep learning systems using CT and X-ray medical images have fewer studies to date, and to secure performance for marketability. It is difficult. For diseases that require rapid medical measures such as stroke due to such problems, the demand for deep learning systems based on X-ray and CT images that can be quickly photographed is very high.

In this paper, a deep learning-based stroke classification model using Non-Contrast CT medical images was proposed to solve these problems. In this paper, we performed neural network learning through Lesion Concatenation to consider serial data of CT images in Voxel format. In addition, optimal windowing parameters for infarction detection of ischemic stroke were presented. The proposed method used non-contrast CT images of 356 stroke patients acquired for 8 years in the actual medical field to train and evaluate the patient's stroke status and type. The experimental data were classified into normal, Old Infarction, and Early Ischemic Sign (Frank Hypodensity, Territorial Infarction) classes, and their performance was evaluated by applying the proposed algorithm, respectively, and compared with the performance of the existing SEResNext neural network without the proposed algorithm under the same conditions. I did. As a result of learning and classifying stroke CT data based on the preprocessed data and the improved neural network system by applying the algorithm proposed in this paper, the performance improvement of about 8.21% compared to the existing neural network learning and testing for the original NCCT image. Showed. For performance evaluation, the class with the highest predicted value is determined as the predicted class based on the prediction value for the stroke class, and four performance indicators of Average Precision, F-1 Score, Accuracy, and ROC Curve AUC are calculated. I did.

In this paper, we proposed a deep learning-based stroke classification automation system that can calculate Aspect Score, an objective index for diagnosing the condition of a stroke patient, using only CT images. Stroke disease classification program is a reliable indicator that can prevent problems due to scoring variability among experts and facilitate patient treatment decisions in the medical field due to the nature of stroke diseases that require rapid prescription. It is expected to be available as

As a future research project, a study is needed to improve the classification neural network of the current system that only classifies the existence of stroke in medical images into a neural network in the form of semantic segmentation. When improving the system through the semantic segmentation neural network, it is possible to overcome the deterioration of the performance of neural network learning due to the preprocessing accuracy, which is a disadvantage caused by replacing the ROI process for the region in the medical image with the brain region segmentation preprocessing. In addition, it is believed that marketability can be secured because it can have clinical advantages through clear lesion detection.

In addition, the preprocessing module neural network performance improvement module for NCCT data in the middle cerebral artery region tested and evaluated in this paper is expected to be used in the deep learning field using medical images. In

particular, it is expected that it can be actively used as a performance improvement module for neural network learning using a small amount of limited data.

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