Evaluation of Artificial Intelligence Accuracy by Increasing the CNN Hidden Layers: Using Cerebral Hemorrhage CT Data

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ABSTRACT

Deep learning is a collection of algorithms that enable learning by summarizing the key contents of large amounts of data; it is being developed to diagnose lesions in the medical imaging field. To evaluate the accuracy of the cerebral hemorrhage diagnosis, we used a convolutional neural network (CNN) to derive the diagnostic accuracy of cerebral parenchyma computed tomography (CT) images and the cerebral parenchyma CT images of areas where cerebral hemorrhages are suspected of having occurred. We compared the accuracy of CNN with different numbers of hidden layers and discovered that CNN with more hidden layers resulted in higher accuracy. The analysis results of the derived CT images used in this study to determine the presence of cerebral hemorrhages are expected to be used as foundation data in studies related to the application of artificial intelligence in the medical imaging industry.

Keywords: AI, CNN, hidden layer, Computed Tomography, Cerebral Hemorrhage

I. INTRODUCTION

Deep learning has been applied in the medical field for appropriately handling complex clinical data. Deep learning is defined as a collection of machine learning algorithms that attempt to summarize key contents or functions in large amounts of data or complex data through a combination of several nonlinear transformation techniques[1].

Many studies are being conducted to express structured or unstructured human data in a manner computers can understand, learn, and interpret in a learning process. Such artificial intelligence (AI) offers the advantage of performing operations with high accuracy and fast processing speed that exceeds human capacity, integrated through enormous data learning. By promoting these advantages, AI is being grafted across the software-based industry[1]. In the medical imaging field, deep learning is being developed through AI analysis technology that enables the quantitative portrayal of intrinsic characteristics to distinguish lesions in medical images, such as brightness, contrast, spatial frequency, homogeneity, curvature, and length. The quantitative information grants objectivity to the quantitative evaluations of the lesions before and after surgery[3,4]. AI analyses allow pre-educated AI to extract features from medical images and diagnose lesions[5].

According to studies such as Liu, who diagnosed pancreatic cancer using AI, the accuracy was 99%, which exceeded the doctor’s diagnosis accuracy[6]. Modern AI medical-imaging analysis technology has been applied to various imaging equipment, starting from general radiography equipment to those used in CT, magnetic resonance imaging, ultrasound systems, and fluoroscopy; significant findings have been reported for various diseases[7]. Applying AI medical...
imaging analysis technology to examining patients can quickly provide information to the medical staff and help determine the treatment direction. CT must be performed as soon as possible when checking a patient for a possible cerebral hemorrhage. CT imaging transmits X-rays through the human body and reconstructs absorption differences to obtain a cross-sectional or a three-dimensional image of the human body. The fast scanning speed of CT favors its wide usage in the diagnosis and treatment of cerebral hemorrhage. Furthermore, the clarity of the acquired images enables a quick and accurate characterization of the bleeding area and the amount of bleeding\[8\]. However, CT images may be challenging to interpret depending on the severity of the cerebral hemorrhage; hence, in some cases, patients may have their emergency surgery delayed due to the extended examination time. Therefore, assistive tools must be available to automatically and quickly identify the bleeding area of the brain and provide quantitative information before the surgery\[9\]. Hence, CT images are digitized so that AI can be utilized, enabling automatic detection and recognition by computers to provide data for diagnosing bleeding sites. To evaluate the accuracy of determining the presence of cerebral hemorrhage, we compared the diagnostic accuracy of the AI, based on the number of hidden layers, by using normal cerebral parenchyma CT images and cerebral parenchyma CT images of areas where cerebral hemorrhage is suspected of having occurred.

II. MATERIAL AND METHODS

1. Brain CT dataset

The brain CT data used in the study utilized the Balanced Normal and Hemorrhage Head CT dataset shown in Fig. 1 (Creative Commons license (CC0 1.0 Universal Public Domain Dedication from Kaggle). For learning purposes, a total of 204 png images were classified into normal brain or brain hemorrhage images, and 64 training datasets, 16 validation datasets, and 20 test datasets were constructed.

(a) Normal brain CT image  (b) Hemorrhage brain CT image

Fig. 1. Balanced normal and hemorrhage head CT dataset.

2. Network configuration library


3. Convolutional neural network

A convolutional neural network (CNN) is considered a model suitable for image classification because AI learns the visual processing steps operating in humans to extract image characteristics. The general structure of CNN consists of a convolutional layer, pooling layer, and a fully-connected layer shown in Fig. 2. The basic image classification functions of CNN can be used to determine the presence of lesions in medical images\[10\]. The input layer uses 150 × 150 pixel input images, with the input image pixels being rescaled to the range of 0–1. In addition, the class mode was applied as binary. The training dataset was set to rotate the image at any angle between 0 and 20 degrees, and the width was set to move horizontally within 41 pixels. The height was set to move approximately 51 pixels vertically and was reversed horizontally. These augmentations of the training and
the validation datasets were applied in learning. The test dataset was used in the evaluation without augmentation. The basic CNN layer consists of three, four, five, or six layers, and the filter kernel size was set to $3 \times 3$. Max pooling $2 \times 2$ was applied to each convolution layer. ReLU was used for the activation function, and Adam was used for the optimization function. Binary cross entropy was used for the loss function, and training accuracy, training loss, validation accuracy, and validation loss were used as evaluation indicators to implement the model.

4. Evaluation of CNN models

In basic CNN, the epoch was set to 700, 450, 300, and 200 for three, four, five, and six layers, respectively. The evaluation was conducted by checking the training accuracy, training loss, validation accuracy, and validation loss to determine the accuracy and loss of each finalized model in determining the presence of cerebral hemorrhage through test datasets.

III. RESULT

When the basic number of CNN layers are there, four, five, and six, the accuracy is 60.00%, 64.99%, 80.00%, and 85.00%, respectively, and the loss is 13.87%, 6.37%, 1.54%, and 0.78%, respectively shown in Table 1 and Fig. 3. The application of six layers showed the highest accuracy and the lowest loss.

<table>
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<th>Layer</th>
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<th>Layer 4</th>
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<tr>
<td>Accuracy</td>
<td>60.00%</td>
<td>64.99%</td>
<td>80.00%</td>
<td>85.00%</td>
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<tr>
<td>Loss</td>
<td>13.87%</td>
<td>6.37%</td>
<td>1.54%</td>
<td>0.78%</td>
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Table 1. Result of each CNN layer's accuracy and loss comparison

![CNN structure](image)

Fig. 2. CNN structure.

![Results of deep learning process](image)

Fig. 3. Results of deep learning process.

IV. DISCUSSION

In this study, the accuracy of cerebral hemorrhage CT images for different numbers of CNN layers was evaluated. The accuracy was 60.00%, 64.99%, 80.00%, and 85.00% for three, four, five, and six layers, respectively, showing a tendency to increase with the number of layers. Although increasing the number of CNN layers increases demands on managing resources such as time and equipment, reducing the number of CNN layers results in less effective results and reduced accuracy. A similar study by Anjali Gautam reported the accuracy of hemorrhage determination up to 98.77% when deep
learning was applied to CT imaging\textsuperscript{[11]}. In addition, a study conducted by Ali Arab et al. deduced accuracies similar to our study in approximately 0.7 seconds\textsuperscript{[12]}. Likewise, doctors' clinical knowledge, experience, and understanding of patients combined with deep learning data reflected that assistive diagnostic tools maximized diagnostic efficiency and enhanced experts' accuracy and speed of deciphering medical images. In other words, AI assistance can significantly reduce the labor-intensive effort and time required to interpret medical images that entail complex diseases\textsuperscript{[5]}. The breast cancer decipherment experiments conducted by Mckinney et al. showed that the number of false-negative misdiagnoses was 9.4% lower when deep learning was used compared to those made in the radiology department\textsuperscript{[12]}. Since the prognosis is likely to worsen with an increase in the time taken to start combating the disease, we expect the assistance of deep learning to positively reduce the misdiagnosis caused by human error. Furthermore, a study conducted by Jared Hamwood et al. demonstrated that deep learning could be used to distinguish bony orbits in MRI images with high accuracy\textsuperscript{[13]}. Medical imaging technology using deep learning can be applied to CT and other imaging techniques such as MRI, ultrasonography, and fluoroscopy to achieve significant image deciphering improvements. However, large amounts of vivid images portraying the characteristics of specific lesions are required, and deep learning is sensitive to many parameters such as filter, weighted value, and learning rate. Therefore, future studies will need to apply optimizer functions different from the ones used in this study or the study conducted by Muhammad Faheem Mushraq et al., or use a more optimal model than CNN, like in the study conducted by Kim et al. Further, high-performance equipment will be needed to secure sufficient medical imaging data and reduce research hours before implementing the model\textsuperscript{[14,15]}. 

V. CONCLUSION

We expect this study's CT cerebral hemorrhage deciphering results can be used as foundation data for studies grafting medical imaging to AI. Consequently, experts' accuracy and speed of medical image reading can be improved to benefit patients and medical staff.

Acknowledgement

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Reference


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CNN 은닉층 증가에 따른 인공지능 정확도 평가 : 뇌출혈 CT 데이터

김한준, 강민지, 김은지, 나용현, 백수은, 심수만, 홍주완

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요 약

딥러닝은 다양한 데이터 속에서 블랙박스 내용을 요약해 학습하는 알고리즘의 집합으로 의료영상 분야에서 빌류를 진단하는 목적으로 사용되기 위해 발전하고 있다. 본 논문에서는 뇌출혈 진단 정확성을 평가하기 위해 CNN을 이용해 뇌실질 CT 영상과 뇌출혈이 의심되는 뇌실질 CT의 진단 정확도를 도출하였다. 은닉층 수에 따른 정확도를 비교한 결과 은닉층이 증가함수록 정확도가 높아졌다. 본 연구에서 도출된 CT 뇌출혈 유무 분석 결과는 앞으로 의료영상 분야와 인공지능 접목에 관한 연구에서 기초 자료로 사용될 것으로 사료된다.

중심단어: 인공지능, 컨볼루션 신경망, 은닉층, 전산화단층촬영, 뇌출혈

연구자 정보 이력

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