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Brain tumor classification by CNN

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Abstract

In this paper, we proposed a disease classification method for brain images using CNN. The research dataset collects images of normal, blastoma, meningioma, adenoma, and glioblastoma by brain tumor disease from journals such as NEJM and AuntMinnie and files them in Exam_Brain.Zip. As a result of CNN processing the images for each file folder in the Exam_Brain.zip file 10 times, the AUC was found to be 0.8825. As a result of the experiment, the brain disease classification accuracy of brain magnetic resonance imaging was found to be 88.25%. These results indicate that the results of this study can be used to classify other diseases once the data set is established, and can also be used to classify objects in other industries.

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This study has the following limitations. A challenge in automatically classifying diseases is the vastness and integrity of the data sets. If the data is not prepared, the accuracy of classification will be problematic. Additionally, in the medical field, a doctor's decision-making (diagnosis) is not limited to image data but is made based on comprehensive data, and there is a limitation in that medical decisions cannot be made by machines without the intervention of a doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts, but the domain of experts in the field. Therefore, field medical staff must participate in the process of developing AI in medical settings. Future research tasks include developing applications that improve performance by developing the input stage of the program, and continuing research in connection with medical big data servers.

Key word: Brain MRI, Tumor Classification, CNN, AlexNet, Confusion Matrix, AUC

I. Introduction

Brain tumors have various types and characteristics. Tumor characteristics are classified in various ways based on cell origin, cell shape, tumor location, size, and malignancy level. Glioma is a tumor derived from glial cells, the connective tissue of the brain, and is one of the most common brain tumors. Among gliomas, Astrocytoma is a tumor derived from glial cells and appears in various forms depending on the grade, while Oligodendroglioma is a tumor derived from oligodendrocytes and occurs in the white matter of the brain. Lymphoma is a brain tumor derived from the lymphatic system that mainly occurs in patients with weakened immune function. Neoplastic medulloblastoma is a rapidly growing, isolated brain tumor that commonly occurs in children and originates in the cerebellum. Chordoma is a rare tumor that occurs in the pharyngeal gland and is located at the base of the brain. A brain cell tumor is a brain tumor that originates from the tissue surrounding the cerebrospinal fluid. Ganglioglioma is a benign tumor derived from nerve cells and glial cells and occurs mainly in children and adolescents. Some tumors are benign tumors that originate from the tissue surrounding the cerebrospinal fluid and are relatively less common. Although the types and characteristics of brain tumors are diverse, they are broadly classified into germinomas, meningioma, adenoma, and glioblastoma[1].

Imaging equipment for diagnosing brain tumors includes MRI, SPET, SPECT/CT, PET/CT, and PET/MRI. These devices acquire brain images as digital images, and the acquired images are managed by PACS. Brain tumor is one of the major causes of death among people. The chances of survival can be increased if the tumor is detected and classified correctly at its early stage. Conventional methods involve invasive techniques such as biopsy, lumbar puncture, and spinal tap method, to detect and classify brain tumors into benign (non-cancerous) and malignant (cancerous). A computer-aided diagnosis algorithm has been designed to increase the accuracy of brain tumor detection and classification, and thereby replace conventional invasive and time-consuming techniques.

Neural Network (NN) refers to a computational model that imitates the structure of the human brain to construct an information processing system that resembles a human[2]. NN consists of an input layer, a hidden layer, and an output layer, and a network with multiple hidden layers is called a deep neural network (DNN). Learning with DNN is called deep learning (DL), and DL is achieving high results in many fields such as image classification and object detection. Convolutional Neural Network (CNN) is a DL model that extracts and classifies image features and has recently been actively used in the imaging field[2]. DL models such as CNN have excellent computational capabilities for processing and understanding complex and large amounts of data.

In this paper, we attempt to classify digitally acquired brain images into normal, blastoma, meningioma, adenoma, and glioblastoma by modifying the CNN-based AlexNet using a transfer learning method. Datasets for research were constructed for each brain tumor disease from journals such as NEJM and AuntMinnie. The results of this study believe that it will be possible to automatically classify various types of brain tumors if a dataset is constructed for each disease.

II. Materials and Methods

1. Dataset for research

The dataset for research is collected images of normal, germinoma, meningioma, adenoma, and glioblastoma by brain tumor disease from journals such as NEJM and AuntMinnie, and file them as Exam_Brain.Zip. The data size was a total of 50 images, 10 for each disease.

2. CNN

CNN models are a type of artificial neural network used in DL to evaluate visual information, and these networks can handle a wide range of tasks related to images, sound, text, video, and other media. CNN was created in the late 1990s by Professor Yann Lecunn at Bell Labs[3]. CNN models have input layers, output layers, hidden layers, and millions of parameters, allowing them to learn complex objects and patterns. A convolution and pooling process is used to sample a given input before applying an activation function, where all inputs are partially connected to hidden layers and the fully connected layer at the end is the output layer. The output format itself is the same as the size of the input image. Convolution is a process that combines two functions to generate the output of another function, and the input image is changed by applying a filter to the CNN model. The CNN model was proposed to solve the problems of training time, network size, and number of variables. The CNN model combines the convolution and pooling parts that extract features and the extracted features, it is divided into classification parts[4]. Figure 1 shows the concept of the CNN model.

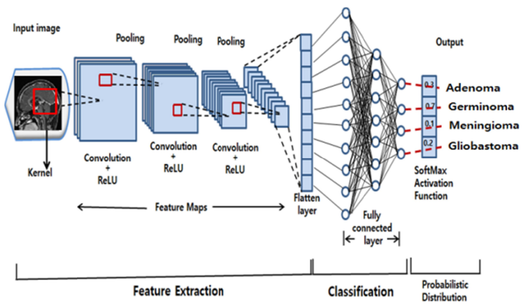


Figure 1. The concept of the CNN model

3. AlexNet

AlexNet is a CNN-structured Neural Network(NN) that won the ILSVRC (imageNet large scale visual recognition challenge) competition held in 2012[5]. The official paper is "ImageNet Classification with Deep Convolutional Neural Network"[5]. It is called AlexNet, named after the first author of the paper, Alex Khrizevsky, and AlexNet brought CNN to the spotlight again. AlexNet was designed as shown in Figure 2 with two GPUs in parallel structure to perform parallel computation[5].

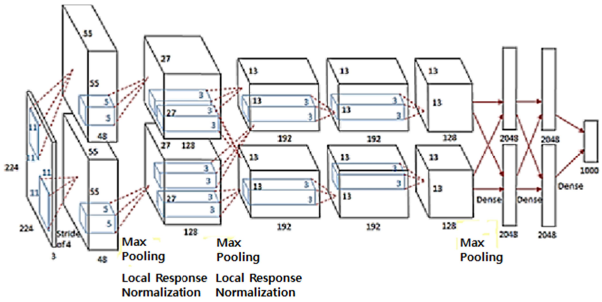


Figure 2. AlexNet with two GPUs in parallel architecture to perform parallel computations.

4. Transfer learning of AlexNet

AlexNet receives "Exam_Brain.Zip" as input and outputs the probabilities of labels and categories in the image. Transfer learning is widely used in DL applications[6]. A pre-trained neural network can be used as a starting point for learning new tasks. Fine-tuning a neural network with transfer learning is usually much faster and easier than training the network from scratch using randomly initialized weights. Learned features can be quickly transferred to a new task using a smaller number of training images, and the transfer learning process of AlexNet is shown in Figure 3[7].

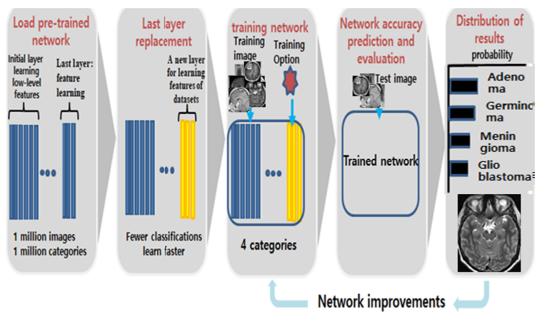


Figure 3. The transfer learning process of AlexNet

III. Experiment and Results

AlexNet CNN was modified and programmed using the transfer learning method to classify the grade of Brain tumor disease in Brain images of "Exam_Brain.Zip" into Adenoma, Germinoma, Meningioma, and Glioblastoma. The experiment used MatLab R2023B on a computer equipped with a GPU. The experimental procedure was performed as shown in Figure 4.

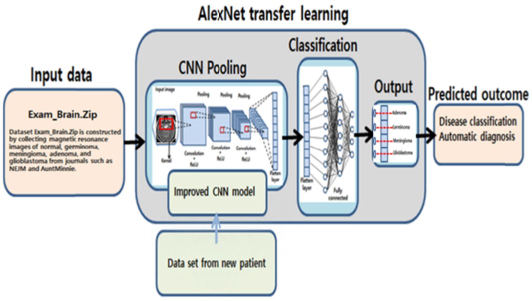


Figure 4. The experimental procedure

Unzipped the Exam_Brain.Zip file and loaded it into the data storage. The images were labeled based on the folder name and the data was saved as an ImageDatastore object. Data stored in the computer was divided into training datasets and validation datasets. The splitEachLabel function is a function that splits the data storage into two new data storages and stores them. The split data was divided into 70% training data and 30% validation data. Sample images were displayed using the algorithm below, with 2images in rows and 3 images in columns, a total of 6 images, as shown in Figure 5. The displayed image was converted from an RGB image to a gray image through a Matlab function, and the normalized image was displayed.

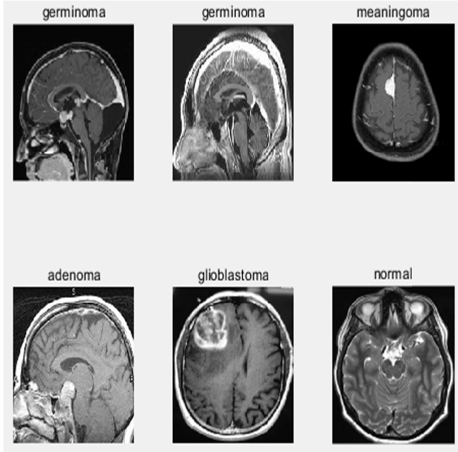


Figure 5. Display of sample images

An experiment was performed to classify brain diseases. The CNN training process for verification is shown in Figure 6. Looking at the CNN training process, the epoch period was short and the training time was also short due to the small amount of data.

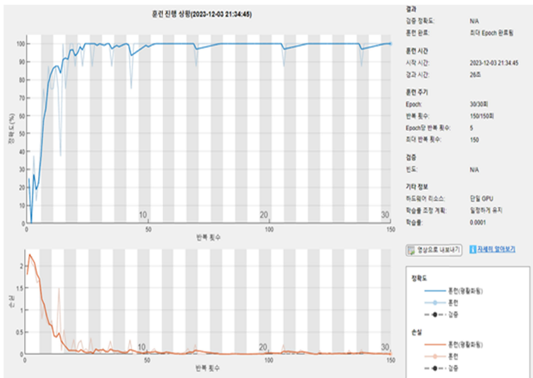


Figure 6. CNN training process

Finally, the verification image was classified using the classify function. The classification images with four disease names are shown in Figure 7 along with the predicted labeling.

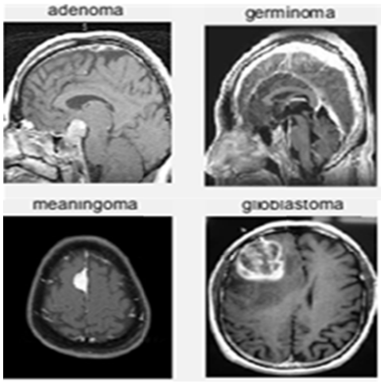
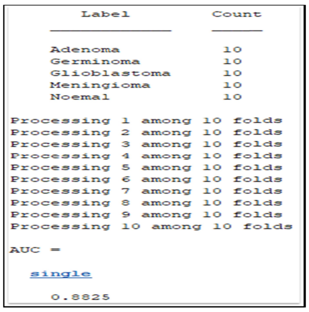


Figure 7. The classification images

CNN processed the images for each file folder in the Exam_Brain.zip file 10 times, and the AUC was found to be 0.8825, as shown in Figure 8.



```
    Label            Count
    ______________   _____

    Adenoma            10
    Germinoma          10
    Glioblastoma       10
    Meningioma         10
    Noemal             10

Processing 1 among 10 folds
Processing 2 among 10 folds
Processing 3 among 10 folds
Processing 4 among 10 folds
Processing 5 among 10 folds
Processing 6 among 10 folds
Processing 7 among 10 folds
Processing 8 among 10 folds
Processing 9 among 10 folds
Processing 10 among 10 folds
AUC =

  single

    0.8825
```

Figure 8. AUC

To evaluate the effectiveness of the CNN model that learned brain disease classification, a confusion matrix as shown in Figure 9 was obtained. The order of the confusion matrices was arranged alphabetically in the file folders in the Exam_Brain.zip file.

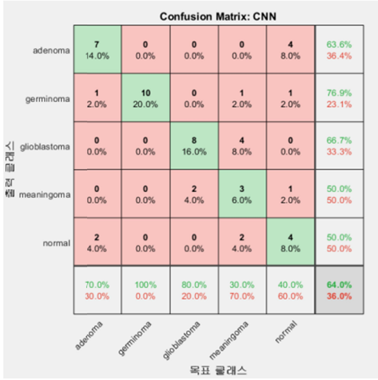


Figure 9. Confusion matrix

The ROC of CNN for brain disease classification is shown in Figure 10. Because the training data was small (50 pieces in total), the shape of the graph appeared in the form of stairs. The area under the x-axis curve (AUC) shown in the graph represents 88.25% of the total area of the graph.

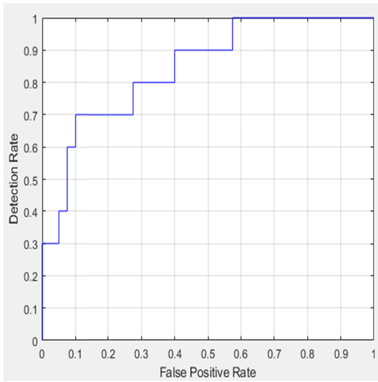


Figure 10. ROC

III. Discussion

In this paper, we proposed a disease classification method for brain images using CNN. Table 1 shows previous studies conducted before this study. The research contents of previous studies are as follows. Pauline John (2012) introduces an efficient method of brain tumor classification, where, the real

Magnetic Resonance (MR) images are classified into normal, non-cancerous (benign) brain tumors and cancerous (malignant) brain tumors. The proposed method follows three steps,(1) wavelet decomposition,(2) textural feature extraction, and (3) classification. The proposed method has been applied to real MR images, and the accuracy of classification using a probabilistic neural network is found to be nearly 100%[8]. Pauline John was conducted through three steps: wavelet decomposition, feature extraction, and classification. However, in this paper, the method of classifying diseases was improved using CNN without going through a separate feature extraction step[8]. Swapnali et al(2014 Swapnali et al(2014) propose an automatic support system for stage classification using an artificial neural network (learning machine) to detect Brain. They present a segmentation method, the k-means clustering algorithm, for segmenting Magnetic Resonance images to detect the Brain Tumor in its early stages and to analyze anatomical structures. A well-known segmentation problem within MRI is the task of labeling the tissue type which includes White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF), and sometimes pathological tissues like tumors, etc. A Probabilistic Neural Network with a radial basis function will be employed to implement an automated Brain Tumor classification. Decision-making was performed in two stages: feature extraction using GLCM and PCA and classification using the PNN-RBF network. The performance of this classifier was evaluated in terms of training performance and classification accuracies. The simulated results show that the classifier and segmentation algorithm provide better accuracy than the previous method. The research they conducted was on segmentation, which is different from research on distinguishing diseases[9]. Ahmed KHARRAT, Karim GASMI, Mohamed BEN MESSAOUD, et al. (2010) propose a hybrid approach for classifying brain tissue in magnetic resonance imaging (MRI) based on genetic algorithm (GA) and support vector machine (SVM). A set of wavelet-based texture features is derived. We extract optimal texture features from normal and tumor regions using spatial gray level dependence method (SGLDM). These features serve as input to the SVM classifier. Feature selection, a big problem in classification techniques, is solved using GA. These optimal features are used to classify brain tissue into normal, benign, or malignant tumors. The performance of the algorithm is evaluated on a series of brain tumor images. However, their study also went through an image decomposition step using the wavelet method, and it was found that images could only be distinguished into normal, benign, and malignant tumors[10]. N. Varuna Shree, T. N. R. Kumar (2018) focused on denoising techniques, gray level co-occurrence matrix (GLCM) feature extraction and DWT-based brain tumor region growth segmentation to reduce complexity and improve performance. Morphological filtering was then performed to remove noise that may have formed after segmentation. A probabilistic neural network classifier was used to train and test the performance accuracy of tumor localization in brain MRI images. The experimental results demonstrated the effectiveness of the proposed technique in identifying normal and abnormal tissues in brain MR images with almost 100% accuracy. In addition, the content of this study is different from the content of this study in that it is a technology for detecting disease areas within a single MRI image. It goes through a preprocessing step of segmentation using DWT[11]. Murugan Arunachalam and Sabeenian Royappan Savarimuthu (2017) state that detecting and segmenting tumor regions in brain images is an important task due to the similarity between abnormal and normal regions. Automatic computer-assisted detection and segmentation of brain tumors has been proposed. The proposed system consists of enhancement, transformation, feature extraction, and classification. The shift-invariant shearlet transform (SIST) is used to enhance brain images. In addition, NSCT (Nonsubsampled Contourlet Transform) is used as a multi-resolution transformation that converts a spatial domain enhanced image into a multi-resolution image. Texture features from Gray Level Co-occurrence Matrix (GLCM), Gabor, and Discrete Wavelet Transform (DWT) are extracted using approximate subbands of NSCT transformed images. These extracted features are trained using a feedforward backpropagation neural network and classified into normal or glioblastoma brain images. Additionally, K-means clustering algorithm is used to segment tumor regions in classified glioblastoma brain images. The proposed method achieved sensitivity of 89.7%, specificity of 99.9%, and accuracy of 99.8%. Their research also showed that the disease area was segmented using DWT within one image and that normal images were distinguished from diseased images (glioblastoma in the brain)[12].

<Table 1> Previous studies conducted before this study

Author	Journal (Year of publication)	Title
Pauline John	International Journal of Scientific & Engineering Research(2012)	Brain tumor classification using wavelet and texture based neural network
Swapnali Sawakare Dimple Chaudhari	International Journal for Research in Emerging Science and Technology (2014)	Classification of Brain Tumor Using Discrete Wavelet Transform, Principal Component Analysis and Probabilistic Neural Network
Ahmed KHARRAT, Karim GASMI, Mohamed BEN MESSAOUD, et al	Leonardo Journal of Sciences (2010)	A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and Support Vector Machine
N. Varuna Shree, T. N. R. Kumar	Brain Informatics (2018)	Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network
Murugan Arunachalam, Sabeenian Royappan Savarimuthu	International Journal of Imaging Systems and Technology(2017)	An efficient and automatic glioblastoma brain tumor detection using shift-invariant shearlet transform and neural networks

In this study, we proposed classifying diseases in brain images using CNN. As a result of the experiment, the classification of brain diseases in brain magnetic resonance images was found to be 88.25% accurate. These results indicate that the results of this study can be used to classify other diseases if a dataset is established and that they can be used to classify objects in other industrial fields. This study has the following limitations. The problem with automatically classifying diseases is the vastness and integrity of the dataset. If the data is not prepared, it will cause problems with the accuracy of classification. In addition, the doctor's decision-making (diagnosis) at the medical site is not limited to image data, but is based on comprehensive data, and has the limitation that medical decisions cannot be made by machines without the involvement of the doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts but of experts in the field. Therefore, medical staff in the field must participate in the process of developing AI in the medical field.

V. Conclusion

In this study, we proposed a method to classify diseases in brain images using CNN. We use transfer learning methods to modify CNN-based AlexNet to classify digitally acquired brain images into normal, blastoma, meningioma, adenoma, and glioblastoma. The research data set collects images of normal, blastoma, meningioma, adenoma, and glioblastoma by brain tumor disease from journals such as NEJM and AuntMinnie and files them with Exam_Brain.Zip. The data size was a total of 50 images, 10 for each disease.

As a result of CNN processing the images for each file folder in the Exam_Brain.zip file 10 times, the AUC was confirmed to be 0.8825. As a result of the experiment, the brain disease classification accuracy of brain magnetic resonance imaging was found to be 88.25%. These results indicate that the results of this study can be used to classify other diseases once a dataset is established, and can also be used to classify objects in other industrial fields.

This study has the following limitations. The challenge with automatically classifying diseases is the vastness and integrity of the data sets. If the data is not prepared, the accuracy of classification will be problematic. Additionally, in the medical field, a doctor's decision-making (diagnosis) is not limited to image data but is made based on comprehensive data, and there is a limitation in that medical decisions cannot be made by machines without the intervention of a doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts, but the domain of experts in the field. Therefore, field medical staff must participate in the process of developing AI in medical settings.

Future research tasks include developing an application that improves performance by developing the input stage of the program, and continuing research in connection with medical big data servers.

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