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Disease Classification of CXR Images by AlexNet Transfer Learning

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Abstract

The purpose of this study is to classify COVID-19 CXR(Chest X-Ray) images using a CNN(Convolutional Neural Network) modified from AlexNet using a transfer learning method so that it can be used as an auxiliary method when diagnosing diseases in medical settings. The Dataset used in the experiment uses "COVIDGR-1.0 Dataset". "COVIDGR-1.0 Dataset" is a collection of 784 anonymized X-ray images and, in collaboration with a team of radiologists, built into the dataset in accordance with labeling protocols.

The proposed CNN is a fine-tuned build of pre-trained AlexNet, which takes the "COVIDGR-1.0 dataset" as input and categorizes it into Normal, Mild, Moderate and Sever according to the labels and categories. Experimental results of the disease classification of CXR images show that the AUC(Area Under the Curve) is 0.8781, with accuracy of 87.81%.

It is believed that the results of this study can be used in the following fields. First, it can be used as an auxiliary tool for diagnosing lung diseases. Second, if the data set is ready, it can be used to classify other diseases. Third, data can be stored separately through classification. Fourth, in the medical field, the object to be classified can be imaged using a smartphone and then classified and stored.

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. And in the medical field, doctors' decision-making (diagnosis) is not limited to image data. There is a limitation in that doctors make decisions based on comprehensive data and that medical decisions cannot be made by machines without the doctor's intervention. Determining the decision threshold in decision making problems by AI 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.

Future tasks include continuing research in connection with program input stage development, performance improvement, app development, and medical big data servers.

Key word: COVID-19 Chest X-Ray, CNN, Disease Classification, Confusion Matrix, AUC

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I. Introduction

The importance of early diagnosis and appropriate treatment for lung disease, which is considered a serious health problem, is being emphasized, and the development of deep learning (DL) technology is providing innovative solutions for this. Chest X-Ray(CXR) devices are installed in most medical institutions and mobile devices are also available, CXR imaging has become an important tool to determine whether lung disease has progressed due to infection. The “COVIDGR-1.0 Dataset” was used as the dataset for the study[1]. This is a dataset built by Spanish radiologists to support COVID-19 diagnosis. 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.The purpose of this study is to classify the disease grade of COVID-19 CXR images into normal, mild, moderate, and severe using a transfer learning method using Alexnet, a type of CNN.

II. Materials and Methods

1. Dataset for research

The dataset used for learning in the study was “COVIDGR-1.0 Dataset”. “COVIDGR-1.0 Dataset” was constructed as a dataset by collecting 784 anonymized X-ray images in close collaboration with a team of radiologists at “Hospital Universitario San Cecilio” in Spain and following a strict labeling protocol. The collected 784 images were classified into 431 negative cases and 353 positive cases. Positive images are images of patients who tested positive for COVID-19 through Reverse Transcription Polymerase Chain Reaction(RT-PCR) within up to 24 hours between the X-ray image and the test. All images were taken with the same type of equipment and in the same format, and only posterior-anterior imaging (P-A projection) was considered. Images were categorized as normal, mild, moderate, and severe [1]. The figure below shows some of the images in the dataset by disease grade.

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. 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[2]. Figure 1 shows the concept of the CNN model.

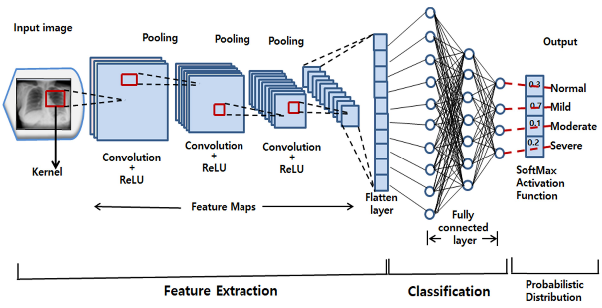


Figure 1. The concept of the CNN model

3. AlexNet

AlexNet is a CNN-structured Neural Network(NN) that won the ILSVRC (imageNet large scale visual recognition challenge) competition held in 2012[3]. The official paper is "ImageNet Classification with Deep Convolutional Neural Network"[4]. 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[4].

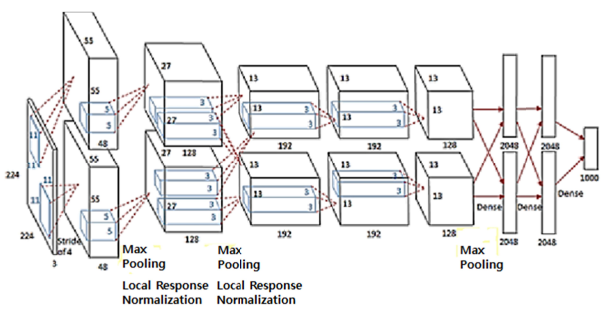


Figure 2. AlexNet with two GPUs in parallel

architecture to perform parallel computations.

4. Transfer learning of AlexNet

AlexNet receives "COVIDGR-1.0 Dataset" as input and outputs the probabilities of labels and categories in the image. Transfer learning is widely used in DL applications[5]. 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[6].

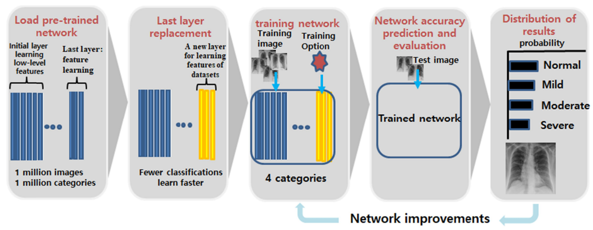


Figure 3. The transfer learning process of AlexNet

III. Experiment and Results

AlexNet CNN was modified and programmed using the transfer learning method to classify the grade of lung disease in CXR images of "COVIDGR-1.0 Dataset" into normal, mild, moderate, and severe. The experiment used MatLab R2023B on a computer equipped with a GPU. The experimental procedure was performed as shown in Figure 4.

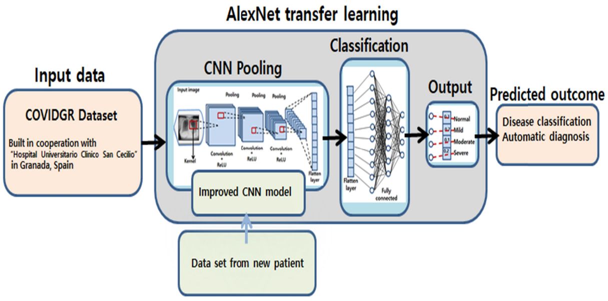


Figure 4. The experimental procedure

Unzipped the COVIDGR_Dataset.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 4 images in rows and 4 images in columns, a total of 16 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.

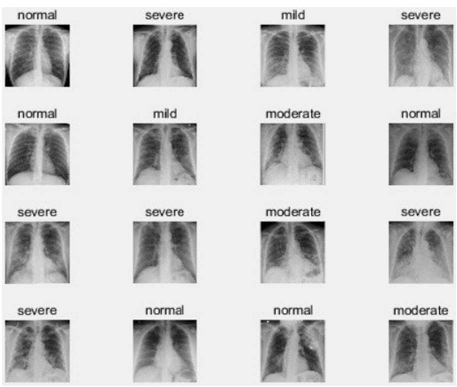


Figure 5. Sample images display

Finally, the verification image was classified using the classify function. The classification images with four disease names are shown in Figure 6 along with the predicted labeling.

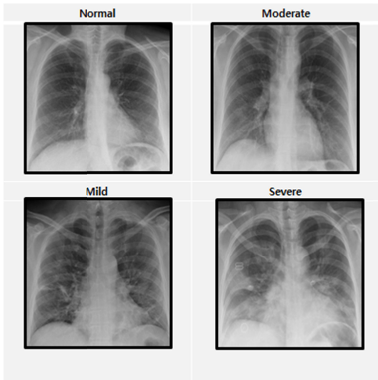
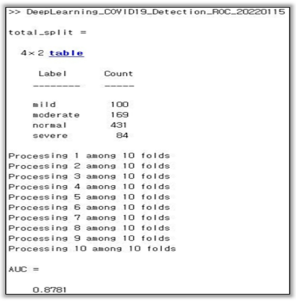


Figure 6. The classification images

Accuracy refers to the percentage of labels that a NN predicts correctly. The experimental results showed an accuracy of 87.8%, as shown in Figure 7.


```
>> DeepLearning_COVID19_Detection_ROC_20220115

total_split =

  4×2 table

     Label        Count
    ________     _____

    mild          100
    moderate      169
    normal        431
    severe         84

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 =

    0.8781
```

Figure 7. Experimental result accuracy.

Figure 8 is a confusion matrix for evaluating the effectiveness of the CNN model. We can find out the accuracy and error rate of training through this confusion matrix.

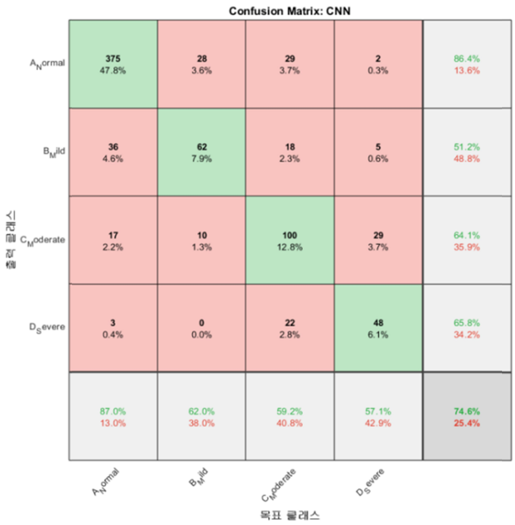


Figure 8. A confusion matrix for evaluating the effectiveness of the CNN model.

In the confusion matrix, as shown in <Table 1>, the accuracy was 74.0% and the error rate was 26.0%.

<Table 1> Accuracy and error rate

Accuracy	74.6%
Error rate	25.4%

To evaluate the performance of the CNN built for the study, precision, recall, and F1-Score are shown in <Table 2> for each disease classification.

<Table 2> Precision, Recall, F1-Score by classified disease

Evaluation items / Classification	Precision	Recall	F1-Score
Normal	87%	86%	43%
Mild	62%	51%	27.98%
Moderate	59%	64%	30.70%
Severe	57%	66%	30.59%

In this study, through experiments, ROC was obtained as shown in Figure 9 below. In the graph, the x-axis represents the false positive rate (FPR), and the y-axis represents the true positive rate (TPR), that is, the decision rate. The area of the x-axis in the ROC graph is called the area under the curve (AUC), and here it is found to correspond to 87.81% of the total area, as shown in Figure 7.

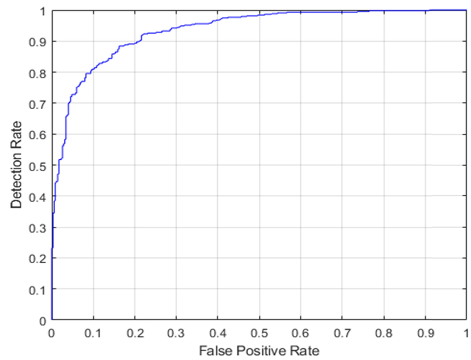


Figure 9. ROC graph

IV. Discussion

Classifying medical imaging diseases is being studied in the form of Computer Aided Diagnosis(CADx)[7]. Since the COVID-19 pandemic, many attempts have been made to detect CXR images by CNN. <Table 3> shows CNN-related research for detecting disease in COVID-19 chest X-ray images. The results from the paper described in <Table 3> are as follows. Ahmed Abdelgawad, et al.

(2020) proposed a CNN model to detect COVID-19 patients in chest X-ray images. This model was evaluated through a comparative analysis of two other CNN models. The proposed model performed with an accuracy of 97.56% and a precision of 95.34%. This model resulted in a receiver operating characteristic (ROC) curve area of 0.976 and an F1-score of 97.61. It was stated that this result could be further improved by increasing the dataset for model training[8]. Appasami S. Nickolas (2022) proposed a deep learning-based CNN model to detect COVID-19 in CXR. CXR collected data from various sources to train with augmentation and evaluate models widely used for COVID-19 detection and diagnosis. A Deep Convolutional Neural Network (DCNN)-based model was proposed for COVID-19 analysis with data augmentation. This model used the patient's CXR for COVID-19 diagnosis to help support doctors' diagnostic process in high workload conditions. The overall accuracy of COVID-19 classification was achieved at 93% by selecting the optimizer[9]. Zohreh Mousavi (2022) and others reported that on the test set, the proposed network achieved over 90% accuracy (i.e., Healthy against COVID-19 against the virus) for all scenarios except scenario V. An accuracy of 99% was achieved for separating COVID-19 in the Healthy group. The results showed that the proposed network is robust to noise up to 1 dB. It is worth noting that the proposed network also achieved over 90% accuracy for two additional databases that were only used as test databases. They also claimed that compared to state-of-the-art pneumonia detection approaches, the final results obtained from the proposed network are very promising[10]. Nigam et al. (2021) used VGG16, DenseNet121, Xception, NASNet, and EfficientNet on a dataset consisting of 16,634 images. This dataset is slightly larger than COVIDx8B, but unfortunately the authors have not released it publicly. The accuracy obtained with EfficientNetB7 was the highest at 93.48%[11]. Ismael and şengür (2021) used ResNet18, ResNet50, ResNet101, VGG16, and VGG19 for deep feature extraction and support vector machine (SVM) for CXR image classification. The highest accuracy was 94.7% obtained with ResNet50. However, they used a small dataset with only 380 CXR images[12].

<Table 3> CNN-related research for disease detection in COVID-19 CXR

Author	Journal (Year of publication)	Title	Accuracy
Ahmed Abdelgawad, Fatin Farhan Haque, Khandaker Foysal Haque, Lisa Gandy	**IEEE (2022)**	**Automatic Detection of COVID-19 from Chest X-ray Images with Convolutional Neural Networks**	97.56%
Appasami S. Nickolas	**The European Physical Journal Special Topics (2022)**	**A deep learning-based COVID-19 classification from chest X-ray image: case study**	**93%**
Zohreh Mousavi, Nahal Shahini, Sobhan Sheykhivand, Sina Mojtahedi, Afrooz Arshadie	**Pub Med (2022)**	**COVID-19 detection using chest X-ray images based on a developed deep neural network**	90%
Nigam, B., Nigam, A., Jain, R., Dodia, S., Arora, N., Annappa, B	**Expert Systems with Applications (2021)**	**Covid-19: Automatic detection from x-ray images by utilizing deep learning methods**	93.48%.
Ismael,A.M., Sengur,A.	**Expert Systems with Applications (2021)**	**Deep learning approaches for covid-19 detection based on chest x-ray images**	94.7%

Compared to previous studies, this study produced a result of 99.23%, which is a high value in terms of accuracy in determining the presence of disease. The difference between the previous studies and this study is that the size of the data used was larger in the previous study. To evaluate the performance of the CNN constructed in this study, the precision, recall, and F1-Score for each disease were calculated and shown in <Table 2>. As shown in <Table 2>, in the normal image, precision was 87%, recall was 86%, and F1-Score was 43%. Mild images showed precision of 62%, recall of 51%, and F1-Score of 27.98%, while moderate images showed precision of 59%, recall of 64%, and F1-Score of 30.70%. And in severe images, precision was 57%, recall was 66%, and F1-Score was 30.59%. The evaluation of this experiment shows that it is an excellent result.

Limitations

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

The purpose of this study was to classify COVID-19 CXR images using a CNN modified from AlexNet so that it can be used as an auxiliary method when diagnosing diseases in medical settings. The dataset used for learning was the “COVIDGR-1.0 Dataset”. This dataset was constructed from anonymized X-ray images in close collaboration with a team of radiologists at “Hospital Universitario San Cecilio” in Spain. As a result of the experiment, the AUC was 0.8781 in disease grade classification of CXR images, showing an accuracy of 87.81%, which was ahead of the previous studies reviewed and showed that the experimental results were excellent. To evaluate the performance of the CNN constructed in this study, precision, recall, and F1-Score were calculated for each disease. As a result of the calculation, in the normal image, the precision was 87%, the recall rate was 86%, and the F1-Score was 43%. For mild images, the precision was 62%, the recall was 51%, and F1-Score was 27.98%, and for moderate images, the precision was 59%, the recall was 64%, and F1-Score was 30.70%. In severe images, it showed excellent performance with precision of 57%, recall of 66%, and F1-Score of 30.59%. The research results are expected to be useful in the following fields: First, it can be used as an auxiliary tool for diagnosing lung diseases. To diagnose a disease, the diagnosis is made based on a lot of comprehensive data such as the patient's history, various clinical data, and the patient's living environment. The classification of diseases obtained in this study can be used as an auxiliary tool during the diagnosis process. Second, it was proven through experiments that if the dataset is prepared, it can be used to distinguish diseases other than lung diseases. Third, many medical images are being produced in hospitals. In terms of data management, it is a very important issue to classify and store these videos separately. At this time, if the results obtained in this study are utilized, it will be possible to automatically classify and save images. Fourth, in the medical field, the object to be classified can be imaged using a smartphone and then classified and stored.

Despite these expectations, this study has the following limitations. Preparation of a large dataset for automatic classification of diseases and data integrity. If the data is not prepared or the prepared data is contaminated, it causes problems in the results. 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.

Future research tasks include developing application programs by developing the input stage of the program improving performance, and continuing research in connection with the medical big data server.

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