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Design of Medical Image Information Classifier to Improve the Accuracy of Lung Cancer Diagnosis

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Abstract. The incidence of lung cancer is increasing every year, and the first cause of death due to cancer is lung cancer. From 2012 to 2016, the most misdiagnosed of cancer among medical damage relief applications, and most of the damage cases were cancer but were misdiagnosed as non-cancer. In this paper, we propose a medical image information classifier to improve lung cancer diagnosis accuracy. The proposed classifier serves to assist the user in diagnosing lung cancer by reading medical images. They are data sets obtained from The Cancer Imaging Archive (TCIA) of the National Cancer Institute (NCI), USA. Pre-processing is performed using Houns Field Unit Changes. Then, classifiers are implemented as training using 3D CNN algorithms, one of the types of deep learning algorithms. As a result of the implementation, the performance of the classifier was 87.8%. Finally, the learned classifier model is applied to the AIoT device, and the medical image judgment result is provided to the user through the GUI on the screen.

Keywords; Lung Cancer, Deep Learning, CNN, IoT

1. Introduction

According to the Disease Policy Division of the Ministry of Health and Welfare, the incidence of lung cancer (people per 100,000 population) increased every year from 28 in 1999 to 55.8 in 2018, doubling. The death rate increased annually from 22.1 in 1999 to 34.8 in 2018. Lung cancer was the number one cause of cancer death in 2019[1].

According to the Korea Consumer Agency, out of 645 applications for medical damage related to misdiagnosis received from 2012 to 2016, 374 cases (58% of all applications) were misdiagnoses of cancer. Most of them were cancer, but they were misdiagnosed as non-cancerous (81.4%) [2]. This paper presents how to reduce the mortality r

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ate and the damage caused by misdiagnosis for the accuracy of a lung cancer diagnosis.

In this paper, we propose a medical image information classifier to improve lung cancer diagnosis accuracy. The proposed medical image information classifier classifies whether or not lung cancer is present when 3D medical image information is input and notifies the user. The proposed medical image information classifier was pre-processed by adjusting the houns field unit. The Houns Field unit is a unit that indicates the degree of attenuation of X-rays when penetrating the body. 0 is defined as passing through water. By adjusting the houns field unit, unnecessary information can be removed from the medical image. We also downsample all data sets to a size of 128 X 128 X 64.

As a deep learning model, a 3D CNN algorithm is used. Before the advent of the CNN algorithm, image recognition was learned after converting an image or video into a one-dimensional array. Spatial information is inevitably lost in the process of converting an image or video into one-dimensional. The neural network is inefficient in extracting and learning features, and there is a limit to increasing the accuracy. Therefore, a compensated version of the neural networks, a CNN algorithm, was developed. The accuracy of the CNN algorithm has improved because it learns using spatial information without dimensional change. Among the many images, medical images were used in the proposed content, and this medical image is composed of 3D images. Learning was carried out using a 3D CNN algorithm to learn these 3D images by taking spatial information without dimensional change.

2. Related Articles

In this chapter, we investigated and compared papers related to lung cancer detection using deep learning.

Table 1 shows the results of a comparative analysis of papers related to lung cancer. All related papers used CT images as data to detect lung cancer. The houns field unit was pre-processed by changing it, and if necessary, the houns field unit may be used without change. In Park Sung-wook's study [5], a data set of 888 lung cancer patients was constructed, and six CNN models were selected as the model used. The six models are LeNet-5, VGG-16, Inception-V3, ResNet-152, DenseNet-201, and NASNet. Learning and experiments were conducted using six algorithms. The highest accuracy was LeNet-5, VGG-16, and DenseNet-201 with 99.9% probability, and the lowest accuracy was ResNet-152 with 97.9%. Therefore, it has been proven that the performance of the existing CNN model is better than that of the customized CNN model. In Seungwon Oh's study [5], learning and experimentation were conducted with three models: Linear Softmax, Multi-layer Perceptron (MLP), and CNN was used. The experimental results were Linear Softmax 60.91%, MLP 62.73%, and CNN 65.45%, and the model usin g CNN showed the highest accuracy. In Kim Han-Woong's study [6], a data set of LIC D-IDRI lung cancer was constructed and consisted of 1010 chest CT images. The CT image includes the readings made by the specialist. During pre-processing, all pixels with a HU value of -1350 or less are displayed in black, and all pixels with a HU valu e of 150 or more are shown in white. Using a CNN model, this paper consists of 14 la yers, and the accuracy is 91.79%.

Table 1. Summary of related papers

	Sung-Wook Park [5]	Seung-Won Oh [6]	Han-Woong Kim [7]	QingZeng Song [8]	Wafaa Alakwaa [9]	Proposed Study
Number of data used for training	888	110	1010	1010	1397	400
usage model	LeNet-5	CNN	CNN	CNN	3D CNN	3D CNN
Prepro-cessing technique used	2D 48 X 48 Houns Field -1000, 400	histogram leveling	2D 36 X 36 Houns Field -600, 1500	2D 28 X 28	3D 64 X 64 X 64 Houns Field -1000,700	3D 128 X 128 X 64 Houns Field -1000,400
Charac-teristic	High accu-racy	Can select six types of lung cancer	32x data in-crease with data aug-mentation technique	Utilize NNE tech-nique	Learning 3D medi-cal im-ages as they are	Learning 3D medical im-ages as they are
Disad-vantage	Occurs when reading is not possible de-pending on the location of lung can-cer	Low accu-racy	Reading pulmonary nodules and non-nod-ules only	Low accu-racy	Low ac-curacy	Optimal model imple-mentation by comparing multiple models with low accuracy
Accuracy	95.6%	65.45%	91.79%	84.15%	86.6%	87.8%

3. Implementation and experiment of medical image information classifier to improve the accuracy of lung cancer diagnosis

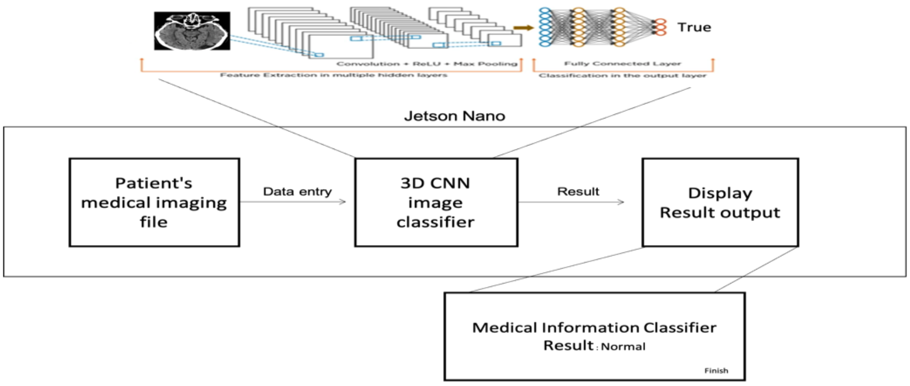

Fig. 1. Medical Imaging Information Classifier Diagram

In this chapter, we design a medical image information classifier to improve the accuracy of lung cancer diagnosis by applying a medical image information classifier model. Figure 1 is a diagram of a medical image information classifier.

The proposed classifier puts medical images into an AIoT device with a model trained by a 3D CNN by a reader or an ordinary person, runs a program in the AIoT device, and displays the results on the device.

3 - 1. 3D CNN model training

The data set consists of medical images obtained from The Cancer Imaging Archive (TCIA) of the National Cancer Institute (NCI). The constructed data set consists of 400 (about 100,000) data sets, including 200 normal lung CT images and 200 lung cancer CT images. The produced data set was down-sampled to a shape of 128 X 128 X 64 so that all data sets had the same size. Pixels with HU values below -1000 were pre-processed as black, and HU values above 400 pixels were pre-processed as white. The constructed data set is divided into a training set of 320 people and a test set of 80 people in a ratio of 8.5:1.5. The model used for training uses Keras and trains it using a 3D CNN algorithm [10]. Figure 2 shows the model configuration of the algorithm used for training. 3D CNN consists of a total of four layers, and all of the layers are three-dimensional.

```
Model: "ctcnn"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 128, 128, 64, 1)] 0
_________________________________________________________________
conv3d (Conv3D)              (None, 126, 126, 62, 64)  1792
_________________________________________________________________
max_pooling3d (MaxPooling3D) (None, 63, 63, 31, 64)    0
_________________________________________________________________
batch_normalization (BatchNo (None, 63, 63, 31, 64)    256
_________________________________________________________________
conv3d_1 (Conv3D)            (None, 61, 61, 29, 64)    110656
_________________________________________________________________
max_pooling3d_1 (MaxPooling3 (None, 30, 30, 14, 64)    0
_________________________________________________________________
batch_normalization_1 (Batch (None, 30, 30, 14, 64)    256
_________________________________________________________________
conv3d_2 (Conv3D)            (None, 28, 28, 12, 128)   221312
_________________________________________________________________
max_pooling3d_2 (MaxPooling3 (None, 14, 14, 6, 128)    0
_________________________________________________________________
batch_normalization_2 (Batch (None, 14, 14, 6, 128)    512
_________________________________________________________________
conv3d_3 (Conv3D)            (None, 12, 12, 4, 256)    884992
_________________________________________________________________
max_pooling3d_3 (MaxPooling3 (None, 6, 6, 2, 256)      0
_________________________________________________________________
batch_normalization_3 (Batch (None, 6, 6, 2, 256)      1024
_________________________________________________________________
global_average_pooling3d (Gl (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 512)               131584
_________________________________________________________________
dropout (Dropout)            (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 1,352,897
Trainable params: 1,351,873
Non-trainable params: 1,024
_________________________________________________________________
```

Fig. 2. Model configuration

3 - 2. Implementation of medical image information classifier

The proposed medical image information classifier requires an AIoT device to retrieve the learned model and derive the result. By applying the learned model to the AIoT device, the lung cancer classification result is displayed to the user. AIoT (AI of Things, Artificial Intelligence of Things) is a compound word of AI (Artificial Intelligence) and IoT (Internet of Things). The AIoT device was used for the reader to carry it and use it anywhere easily. The instrument used for the classifier was NVIDA's Jetson Nano. The learned CNN model is embedded in the AIoT device.

Using Python Tkinter, a GUI composed of a text box displaying the result value and a program end button was configured. After putting the user's medical image in the folder where the program is executed, when the program is run, the medical image is read, and the result is displayed in the text box. Figure 3 shows the implementation result.

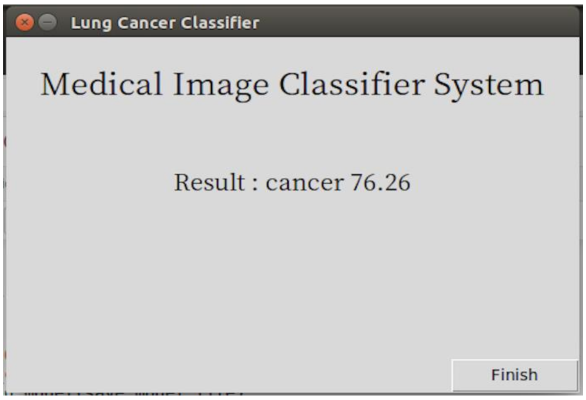

Fig. 3. Implementation result

3 - 3. Experiment

In this paper, a performance evaluation of the medical image information classifier was performed. The deep learning model training environment uses a computer with Intel® Core™ i9-10920X CPU @3.50Ghz (23 CPUs) and two NVIDIA GeForce RTX 3090.

Table 2. Performance evaluation results of classifier using Confusion Matrix

Inference Result	Normal (persons)	Cancer (people)
Normal	70	5
Cancer	12	77
Accuracy	85.4%	94.0%

Table 2 below shows the experimental results by constructing a data set of 82 patients, respectively, for normal lung CT and cancerous lung CT. The data set is a data set obtained from the National Cancer Institute's Tumor Imaging Archive.

Fig. 4. Normal lung CT picture

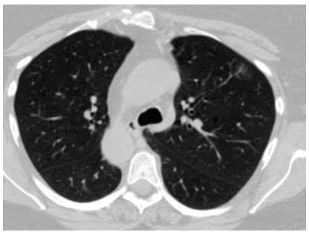

Fig. 5. CT scan of lung cancer

The following Figures 4 and 5 are CT images of the lungs read as usual and lung cancer among the data sets acquired for the experiment. In Figure 4, when the classifier implemented with the CT image of the lungs of an actual average person was executed, it was read as non-cancerous. However, in the case of Figure 5, when the classifier implemented with the lung CT image of natural lung cancer was completed, it was read as cancer. Thus, 14.6% of cases discriminated normal as cancer, and 6.0% of cases determining normal as cancer, and the accuracy of the medical image information classifier was 87.8%.

4. Conclusion

In this paper, a medical image information classifier is implemented. Deep learning used a 3D CNN model, and the AIoT device was implemented with NVIDIA's Jetson Nano. The trained model was embedded in the AIoT device. When a user inserts a medical image into the AIoT device and executes the program, on the other hand, the reading result of the medical image can be known.

The proposed medical image information classifier helps users read their own medical images using a reading program that only medical image readers can do. Also, medical image readers can have confidence in their reading results. As a future study, the accuracy of the 3D CNN model used in the medical image information classifier will be increased to increase the accuracy so that actual medical image readers can trust the program. In addition, the accuracy will be improved by training with an algorithm optimized for lung cancer medical imaging.

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