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학 술 논 문

Evaluation of Deep Learning Model for Scoliosis Pre-Screening Using Preprocessed Chest X-ray Images

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Abstract: Scoliosis is a three-dimensional deformation of the spine that is a deformity induced by physical or disease-related causes as the spine is rotated abnormally. Early detection has a significant influence on the possibility of non-surgical treatment. To train a deep learning model with preprocessed images and to evaluate the results with and without data augmentation to enable the diagnosis of scoliosis based only on a chest X-ray image. The preprocessed images in which only the spine, rib contours, and some hard tissues were left from the original chest image, were used for learning along with the original images, and three CNN(Convolutional Neural Networks) models (VGG16, ResNet152, and EfficientNet) were selected to proceed with training. The results obtained by training with the pre-processed images showed a superior accuracy to those obtained by training with the original image. When the scoliosis image was added through data augmentation, the accuracy was further improved, ultimately achieving a classification accuracy of 93.56% with the ResNet152 model using test data. Through supplementation with future research, the method proposed herein is expected to allow the early diagnosis of scoliosis as well as cost reduction by reducing the burden of additional radiographic imaging for disease detection.

Key words: Scoliosis, Chest X-ray, Deep learning model, Preprocessed image, Data augmentation

1. Introduction

Scoliosis is a three-dimensional deformation of the spine, which is otherwise defined as a temporary deformation due to physical or disease-related causes as the spine is rotated abnormally. More specifically, scoliosis can be classified into nonstructural scoliosis and structural scoliosis, the latter of which is a permanent deformation of the structure of the spine [1-4]. Structural scoliosis can then be classified into idiopathic scoliosis, congenital scoliosis, and neuromuscular scoliosis, of which idiopathic scoliosis, a scoliosis of unknown cause accounting for more than 80% of all scoliosis, is considered the most important [5]. In particular, adolescent idiopathic scoliosis has an incidence of 0.5–5.2% worldwide, although this prevalence is gradually increasing [6,7]. Adolescent idiopathic scoliosis is typically caused by a poor posture and lifestyle choices, and early detection has a significant impact on its treatment [8]. However, only 10% of patients with scoliosis are undergoing medical treatment, leaving 90% of patients only under observation through examination [14].

Scoliosis is mainly detected through spinal column X-ray images [4], wherein the angle of intersection on a vertical line is measured from the upper and lower vertebrae, and where the greatest inclination is observed at the curvature point exhibiting the greatest degree of concave. This intersection angle is known as the Cobb angle [1-5,10]. If the Cobb angle is greater than 10°, the patient is diagnosed as suffering from scoliosis. Such a diagnosis is followed by the appropriate treatment depending on the degree of spinal deformity and the risk of progression. The earlier the detection, the greater the effectiveness of non-surgical treatments [11,12]. However, manual measurement of the Cobb angle may

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result in errors since it is often dependent on the subjective experience of the radiologist. Such errors occur to an even greater extent when scoliosis is diagnosed using a chest X-ray image alone, as the Cobb angle value sometimes appears particularly small on a chest X-ray image [10,13,14]. In this context, Sugita [15] reported that scoliosis could be diagnosed from chest images in cases where the Cobb angle was ≥10°. However, Oh et al. [16] reported severe errors and misdiagnoses in cases where chest X-ray images alone were used along with the conventional passive scoliosis diagnosis method. Indeed, many cases are known wherein scoliosis patients were classified as "normal," since no image was recorded in the lumbar region where scoliosis occurred to the greatest extent, or alternatively, where the risk of scoliosis was judged incorrectly due to an inaccuracy in the Cobb angle measurement. In terms of adolescent idiopathic scoliosis in particular, the reliability of the diagnosis is generally insufficient, approaching an accuracy of only 27.9% when a chest image alone is used to determine the presence or absence of scoliosis [10,13,14,16].

To address these issues, research is being conducted to incorporate the machine learning technology into the diagnostic process, since this technology has attracted worldwide attention due to its high accuracy in the medical imaging field. This research trend has been inspired by the fact that deep learning techniques, unlike existing machine learning methods, have a structure similar to that of a human neural network, and so can learn and read patterns after directly studying data [17]. Indeed, previous studies in this area have proven the effectiveness of learning through a deep learning model itself [13,18-20]. However, the accuracy of the Cobb angle measurements and the use of chest images alone for diagnosis continue to result in incorrect diagnoses, and so no meaningful results have been published regarding whether scoliosis can be accurately diagnosed using chest X-ray images alone.

With reference to existing deep learning studies related to scoliosis, this study aims to train a deep learning model that enables the diagnosis of scoliosis using chest X-ray images taken from pulmonary tuberculosis tests, which are conducted on a regular basis in South Korea. More specifically, three CNN models (VGG16, ResNet152, and EfficientNet B0), which have been reported to be effective for medical data learning, are selected for comparison according to the differences among deep learning models [21]. For these models, the learning potential of the model for chest X-ray images is evaluated based on how the difference in image preprocessing and the training data size affect the accuracy of deep learning model training for scoliosis classification.

II. Methods

In this study, a total of 111 chest X-ray images (dimensions: 224 × 224), in which the presence or absence of scoliosis had already been identified by an orthopedic surgeon, were used.

1. Image generation

The majority of previous studies have been conducted without any additional pretreatment of the chest X-ray images [17-20]. However, recent research results have suggested that learning models using preprocessed X-ray images are more efficient than those using the original non-processed images [22].

In this study, image preprocessing was performed prior to training the deep learning model. Initially, for Gaussian sharpening, a difference image was generated using the original image and the image that had undergone Gaussian smoothing through a Gaussian filter. By adding the difference image to the original image once again, image sharpening was achieved. Thus, Gaussian smoothing derived a result based on a constant that was multiplied while adding a difference image to the original image, and this constant could be adjusted according to a range of characteristics, such as the brightness or resolution of the image [23]. Subsequently, a multi-frequency enhancement image was obtained by repeating this process (i.e., adding the difference image back to the original image) [24] (Fig. 1).

For these preprocessed images, the result of the input image "s" was returned as the result image "r" using the sigmoid function transformation equation (i.e., Eq. (1)). In this case, "a" represents the slope and "c" represents an average value, and by adjusting these two values, specific parts of the image can be brightened or darkened. In addition, the result image of the sigmoid function transformation was characterized by

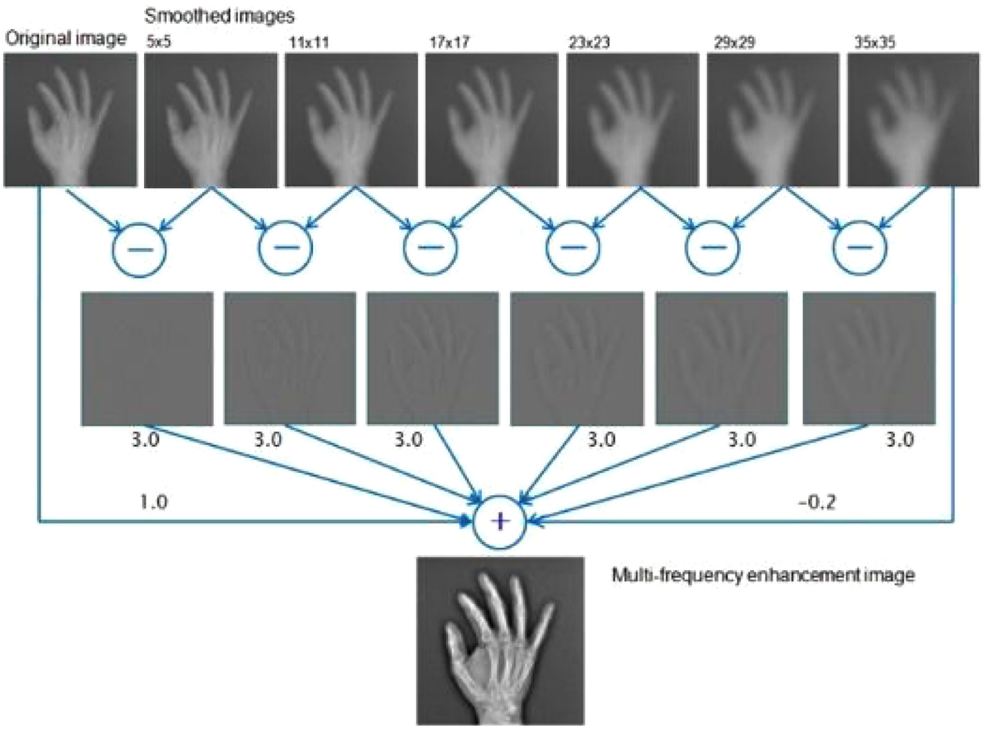

Fig. 1. Multi-frequency enhancement to produce a sharpened image and the Gaussian smoothing images.

normalization between 0 and 1. Using this method, the spine in the chest image was emphasized by brightening the bone part with high-level pixels and darkening the tissue part with low-level pixels [25].

$$r = f(s) = \frac{1}{1+\exp^{-a(s-c)}} \tag{1}$$

As a result of multi-frequency image sharpening and sigmoid function transformations, only the spine and rib cage were left in the original image. Thus, to use grayscale image data for the further training of deep learning models, a training data set was constructed with 49 normal subject images and 33 scoliosis images by classifying them as normal and scoliosis images, respectively. Furthermore, the test data set for verification of the learning results was composed of 16 normal images and 14 scoliosis images (Fig. 2).

Deep learning model training is mainly used with big data to prevent overfitting. However, for data such as medical images, data usage is often limited due to issues related to big data access rights [26]. To address this problem, we attempted to use data augmentation

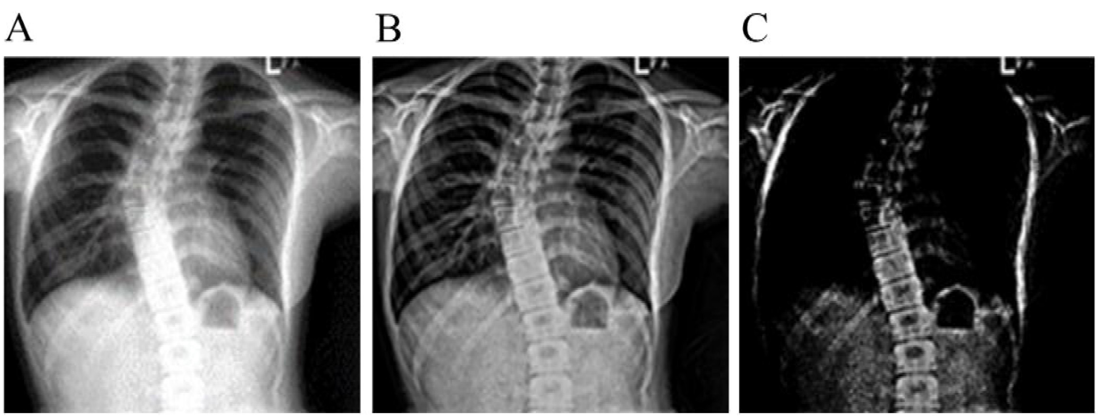

Fig. 2. (A) Example of an original image, (B) a multi-frequency enhancement sharpened image, and (C) a preprocessed image.

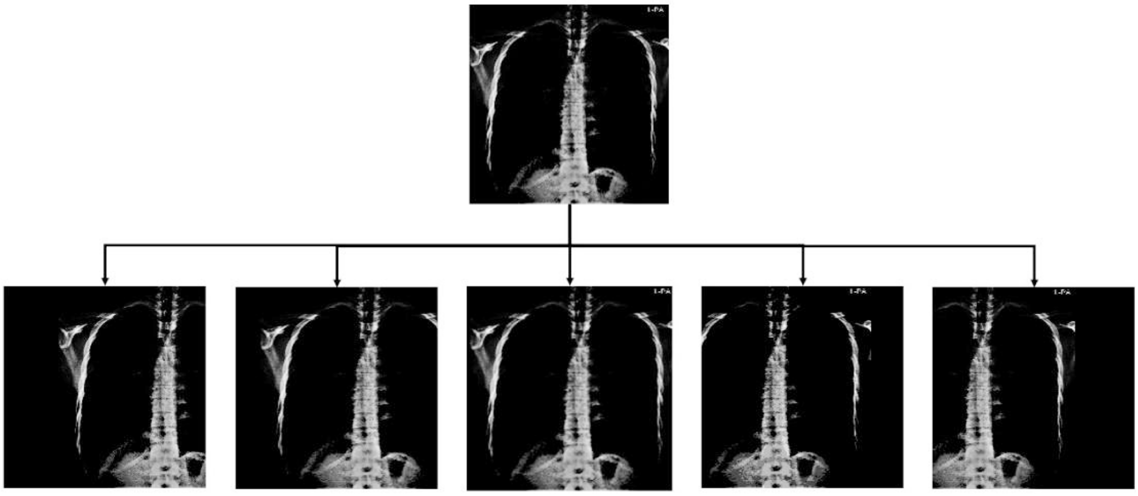

Fig. 3. Preprocessed image (top) and the generated images (bottom).

to achieve image generation. However, the loss of the angle of the spine, which is the most important feature in the image, could be problematic during the learning process [1-6,13], and so image generation was performed at 20 times the original images, and the resulting images were used in training along with the original images. In this case, images were randomly generated by changing the width range of the images by up to 30% and the brightness by up to 40% while avoiding the angular displacement of the images themselves [27] (Fig. 3 and Table 1).

2. Deep learning model

(1) VGG16

VGG16 is a type of VGG model with 16 layers that has a feature enabling the learning of a deeper neural network compared to existing models. This is achieved using a 3 × 3 filter as a learning parameter in all convolution layers. The feature discrimination of the model is enhanced by increasing the nonlinearity of the ReLU function included in the convolution operation through 3-layer 3 × 3 filtering, and the accuracy of image classification is dramatically improved through a reduction in the learning parameters, even when a small filter is employed. In this study, a VGG16 model was configured with 13 convolution layers and three fully-connected layers, and the softmax function for classification was used in the output layer for classify the two categories [28].

(2) ResNet152

ResNet152 is a model characterized by having a deeper neural network structure than previously used models, which is achieved by adopting a novel method (i.e., the residual learning framework) to facilitate the learning of a much deeper network. Unlike the general CNN model structure in which the output “x” is received through two weight layers and the output is input into the next layer, ResNet connects additionally the input of the image layer directly to the output of the layer in ResNet block. This facilitates optimization of the model parameters, and a higher accuracy can be

Table 1. Number of images used for deep learning

Image type	Spine condition	Training images	Test images
Original image	Normal	49	15
	Scoliosis	33	14
Preprocessed image	Normal	49	15
	Scoliosis	33	14
Generated image	Normal	1,029	315
	Scoliosis	693	294

obtained through a significantly deeper model structure [29]. In this study, the ResNet152 model, consisting of a maximum of 152 layers, was used for learning to determine how the layer depth of the model affected the learning process.

(3) EfficientNet B0

In existing deep learning models, the depth, width, and resolution of the models are generally adjusted to improve the accuracy. However, it was not easy to obtain an optimal performance as this method was carried out passively. EfficientNet is a model aimed at solving this problem, since it exhibits an improved performance through more efficient scaling by experimentally verifying that the depth, width, and resolution have a proportional relationship with one another, and then carrying out their careful adjustment. This is known as compound scaling, and is a scale-up method that uniformly scales the depth, width, and resolution of the EfficientNet network at a constant integer ratio [30]. According to the data size, this EfficientNet model was composed of B0–B7; since 224×224 image data was used for the purpose of this study, the B0 model was used for training to effectively detect minute changes in the rotation of the spine from the chest image used as input data.

3. Training method

The deep learning model was trained on the GTX2080, tensorflow 2.3.1, and Keras 2.4.3 environments. A total of four types of training methods were set according to the presence or absence of data preprocessing for learning and whether generation images were used:

Type 1: Checking the classification accuracy for the original images after training the model with the original image data set(82 train images and 29 test images) without preprocessing;

Type 2: Checking the classification accuracy for the preprocessed images after training the model with the preprocessed image data set(82 train images and 29 test images);

Type 3: Checking the classification accuracy only for the preprocessed images after training the model with the additional images generated in addition to the preprocessed image data set(82 train images and 29 test images);

Type 4: Checking the classification accuracy for the preprocessed images as well as the generated images after training the model with the additional images generated and with the preprocessed image data set (1,722 train images and 609 test images) as for Type 3.

As a result, the accuracy was obtained based on the result of learning through 1,000 epochs, and the average accuracy for 50 repetitions of learning was employed. In addition, the learning order of the training data was set randomly. Finally, the difference in the average value of the learning accuracy in each model was examined according to the state of the training data.

4. Statistical significance analysis

Statistical analysis was performed using the SPSS (version 25.0; SPSS Inc, Chicago, IL) software to verify the validity of the data used in this study and the study results obtained through repeated experiments. The homogeneity of the experimental results was verified through one-way analysis of variance (ANOVA), and the invariance was tested through an independent sample T-test. The statistical significance level was defined as $p < .05$.

III. Results

1. Type 1

For the Type 1 method, the VGG16 model showed an accuracy of 51.7%, ResNet152 gave an accuracy of 59.8%, and EfficientNet B0, which exhibited the highest performance, showed an average accuracy of 55.8% (see Table 2). However, statistical significance was only identified in the case of the VGG16 model.

2. Type 2

For the Type 2 learning method, the scoliosis classification accuracy was slightly improved compared to the Type 1 method when image preprocessing was performed (see Table 3). However, the VGG16 model gave comparable results before and after pretreatment, and it was found that training was not performed properly, with all images being classified as normal.

3. Type 3

Subsequently, for the Type 3 method, in which addi-

Table 2. Training results for the Type 1 method

Model	Accuracy	Standard deviation	*p*-value
VGG16	51.7%	±0.001	<.05
ResNet152	59.8%	±0.129	>.05
EfficientNet B0	55.8%	±0.169	>.05

Table 3. Training results for the Type 2 method

Model	Accuracy	Standard deviation	*p*-value
VGG16	51.7%	±0.001	<.05
ResNet152	63.5%	±0.096	>.05
EfficientNet B0	68.7%	±0.074	<.05

Table 4. Training results for the Type 3 method

Model	Accuracy	Standard deviation	*p*-value
VGG16	51.7%	±0.001	<.05
ResNet152	49.6%	±0.018	<.05
EfficientNet B0	51.1%	±0.042	<.05

Table 5. Training results for the type 4 method

Model	Accuracy	Standard deviation	*p*-value
VGG16	51.7%	±0.001	<.05
ResNet152	93.6%	±0.057	<.05
EfficientNet B0	71.7%	±0.033	<.05

tional generated images were added to the training data set for the training of the model, the accuracy was reduced compared to that of the Type 2 method (see Table 4). This observation indicated the importance of the learning results obtained for the preprocessed image due to the extreme data differences between the training and validation data sets. In terms of the learning accuracy, our results for the Type 3 method also revealed a significant bias, with images being classified into only one side. As in the case of the VGG16 model, it appeared that training had not been successfully performed.

4. Type 4

Finally, the results for the Type 4 method, in which the additional images generated were added to the verification data set as well as to the training data set, showed the highest accuracy of all training cases. In particular, a large increase in the accuracy was observed for the ResNet152 model (see Table 5).

IV. Discussion

The aim of this study was to train the deep learning model to detect scoliosis using chest X-ray images alone instead of the full-length spine images that are commonly employed. In addition, we also aimed to evaluate the performance of the developed method through comparison of the classification accuracies obtained by training the CNN models that were classified according to their characteristics. Initially, to train an accurate and effective deep learning model and to verify the results, data was used that consisted of 111 images in which the spine was emphasized through preprocessing of the chest radiographic images. This preprocessing stage involved multi-frequency sharpening based on Gaussian sharpening, sigmoid function transformation, and the use of an unsharp mask filter.

Based on previous results [24], which suggest that an insufficient training data capacity may cause issues related to overfitting in the training of the deep learning model, data augmentation was performed to prevent such overfitting in the model, thereby improving the model accuracy.

Indeed, the obtained results suggested that the classification accuracy of chest X-ray images obtained from patients suffering from scoliosis can be improved by extracting features through image preprocessing and by adjusting the height and width ranges of the images. This was particularly true for images that are often classified as “normal” by the deep learning model. However, it is important to note that appropriate image processing and generation must be carefully performed while maintaining the characteristics according to the disease of each patient.

Following comparison of the results obtained for the Type 1 and Type 2 methods, the accuracy of the deep learning model was expected to be improved by training with the preprocessed image. However, the observed difference was insignificant, and the results obtained following training with the original non-preprocessed images also showed no statistical significance. This could be accounted for by considering that the loss rate was particularly high during learning, and the stability of the learning was also insufficient, thereby resulting in a large deviation in accuracy. In the training for each model, the deviation of the result was particularly large when the original image was used for learning. However, no significant difference was found when using the VGG16 model, likely due to the underfitting [31] that occurred from the use of a simple model. This analysis is supported by the fact that no such issue was observed for the ResNet152 and EfficientNet B0 models trained using the same data set.

Subsequently, the results of the Type 3 and Type 4 methods, which were obtained by training the models after data augmentation, suggested the possibility of improvement in the classification accuracy of the scoliosis diagnosis model. Comparison of these results with those of previous studies [32], the verification data gave an extremely large ratio difference (98.3:1.7) compared to that of the training data, and this was attributed to an issue with the ratio of the training data [32]. Furthermore, as in the cases of the Type 1 and Type 2 method results, it was suggested that the learning efficiency of the deep learning model could be further increased through image preprocessing. This may also support the argument that an increase in the size of the data will lead to more accurate results.

When comparing the Type 2 and Type 4 methods using the ResNet152 and EfficientNet B0 models, the accuracy increased in the Type 4 method compared to that of the Type 2 method for both models, although the increase was greater for the ResNet152 model. These results indicate that some overfitting occurred in the learning process for the ResNet152 model, wherein the existing training data set consisted of 82 images. It was therefore considered that the accuracy could be greatly improved through application of the Type 4 method, since this issue was easily addressed through data augmentation.

The results of this study also indicate that research that has previously not been possible using deep learning models could be considered in the future due to advances in the preprocessing technologies and the deep learning models, which could ultimately improve image classification. The main aim of this study was to achieve the detection of scoliosis through chest X-ray images, which had not presented accurate results in previous studies, and as a result, we successfully demonstrated the feasibility of this technique with the ongoing advances in technology. As a result, other diseases that could not previously be detected in early medical deep learning studies could therefore be examined in the future following additional research into their detection methods and subsequent combination with the deep learning approach.

In terms of the image preprocessing method, superior results will be expected following future research based on the application of additional methods to the deep learning image classification model, while continuing to maintain the characteristics of scoliosis.

It should also be noted that since the chest X-ray images used in this study were taken from the front of the patient during the examination, there was a limitation in that only the curvature of the spine, which is identifiable in a two-dimensional image, could be detected. This means that any abnormal rotation occurring from the side to the front or back (i.e., anterior or posterior rotation) will not be detectable when viewed from the front, and so three-dimensional spinal deformities on the x, y, and z axes should ideally be examined. Thus, since patients with anterior and posterior rotations may appear normal on anterior chest X-ray images, the use of such images and their clinical diagnoses to generate the artificial intelligence algorithm trained in this study creates limitations in the final method. As a result, an accuracy of ~93.56% was achieved using the deep learning model developed herein, which is somewhat insufficient for application in the diagnosis of scoliosis. However, it still has potential for the identification of adolescent idiopathic scoliosis risk groups or expected groups using chest X-ray images, which are generally taken for health screening during adolescence. As a result, the efficiency of early diagnosis and non-surgical treatment could be greatly improved.

V. Conclusion

We herein reported our investigation into the training of a deep learning model with preprocessed images and subsequent evaluation of the results with and without data augmentation to enable the diagnosis of scoliosis based only on chest X-ray images. The results of this study demonstrated that a higher accuracy could be obtained using a deep learning model than by the passive measurement method based on the measurement of chest X-ray images. The technique proposed in this study is expected to develop into a more useful method for the early diagnosis of scoliosis with the use of images taken from various viewpoints, such as the front and the side. Overall the results of this study suggest the possibility of reducing the cost burden to the patient through the use of chest X-ray images obtained during periodic screening, thereby avoiding the requirement to obtain additional full-length images of the spine for scoliosis diagnosis. Moreover, the effectiveness of the early diagnosis and non-surgical treatment of scoliosis is also expected to be enhanced through detailed examinations.

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