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Development of convolutional neural network model for diagnosing tear of anterior cruciate ligament using only one knee magnetic resonance image

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Abstract

Deep learning is an advanced machine learning approach used in diverse areas such as image analysis, bioinformatics, and natural language processing. In the current study, using only one knee magnetic resonance image of each patient, we attempted to develop a convolutional neural network (CNN) to diagnose anterior cruciate ligament (ACL) tear. We retrospectively recruited 164 patients who had knee injury and underwent knee magnetic resonance imaging evaluation. Of 164 patients, 83 patients' ACLs were torn (20 patients, partial tear; 63 patients, complete tear), whereas 81 patients' ACLs were intact. We used a CNN algorithm. Of the included subjects, 79% were assigned randomly to the training set and the remaining 21% were assigned to the test set to measure the model performance. The area under the curve was 0.941 (95% CI, 0.862–1.000) for the classification of intact and tears of the ACL. We demonstrated that a CNN model trained using one knee magnetic resonance image of each patient could be helpful in diagnosing ACL tear.

Abbreviations: ACL = anterior cruciate ligament, AUC = area under the curve, CNN = convolutional neural network, DL = deep learning, ML = machine learning, MR = magnetic resonance, MRI = magnetic resonance imaging.

Keywords: Anterior cruciate ligament, Convolutional neural network, Deep learning, Tear

1. Introduction

The anterior cruciate ligament (ACL) is a key ligament that stabilizes the knee and connects the femur and tibia. It limits the forward displacement of the tibia and prevents excessive internal or external rotation of the leg as well as excessive flexion and extension of the knee joint.[1] It is most typically torn during sports activities that involve abrupt stops and changes in direction.[2] ACL tears are one of the most typical knee injuries and a major problem worldwide, with approximately 2,00,000 cases per year in the United States.[3]

For diagnosing ACL tears, arthroscopy is the most accurate tool because it allows a direct visualization of the ACL.[4] However, it is a relatively invasive and expensive procedure. Magnetic resonance imaging (MRI) is a noninvasive diagnostic tool with good soft tissue contrast, high spatial resolution, and multi-parameter and multi-range imaging for the evaluation of knee lesions.[4] It is typically the first method used for investigating suspected knee injuries and can effectively display the site and degree of ACL tears. However, its sensitivity and specificity in the diagnosis of ACL tears are limited.[5] In 2017, Li et al performed a meta-analysis and reported that the sensitivity and specificity of MRI in the diagnosis of ACL tears were 87% and 90%, respectively.[5]

Machine learning (ML) is a computer algorithm that can automatically learn from data without requiring explicit programming.[6] ML can overcome the limitations of existing techniques and enables breakthroughs in several fields, such as image analysis, bioinformatics, and natural language processing.[7] In addition, several studies have shown the usefulness of ML in diagnosing musculoskeletal disorders and predicting disease prognosis.[8–10]

The deep learning (DL) technique is an advanced ML approach. In particular, it involves the construction of artificial neural networks with structures and functions similar to those of the human brain using a large number of hidden layers.[11] The DL technique can outperform traditional ML techniques as well as learn unstructured and perceptual data, such as images and languages. A convolutional neural network (CNN) is a representative DL model that is highly advantageous for imaging recognition and classification.[12] Previously, a CNN model has been developed for detecting ACL tears using almost all magnetic resonance (MR) images of a patient.[13–16] If a model learns or decides the occurrence of an ACL tear based on only one image instead of tens of images, then the computer system involved would be more efficient.

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The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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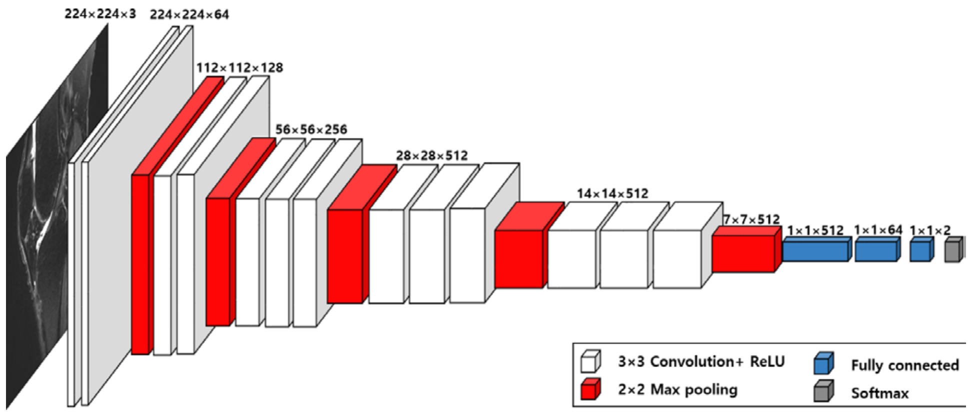

Figure 1. Architecture of deep learning model used in our study.

In the current study, we developed a CNN model to diagnose ACL tear using only one knee MR image of each patient.

2. Methods

2.1. Subjects

We retrospectively recruited 164 patients who had knee injury and underwent knee MRI evaluation at our university hospital from January 2010 to December 2020 (mean age, 43.6 ± 17.5 M 108:56). We included patients aged ≥ 20 years who had no previous history of knee surgery. Among the 164 patients, 83 patients' ACLs were torn (20 patients, partial tear; 63 patients, complete tear), whereas 81 patients' ACLs were intact. The findings of knee MRI were described by a radiologist with 15 years of experience in musculoskeletal radiology. The study protocol was approved by the institutional research board of Yeungnam university hospital. Written informed consent was waived because this study was performed retrospectively using anonymous data. The Helsinki Declarations were adhered to in this study.

2.2. Images used for deep learning (input variables)

All MRI examinations were performed using a 1.5T MR scanner (Phillips Medical Systems, Eindhoven, the Netherlands). We used fat-suppressed T2-weighted oblique-sagittal imaging along the longitudinal course of the ACL (repetition time, 2480–5000 ms; echo time, 19–25 ms; section thickness, 4 mm; NEX, 3.0; 192 × 2; matrix, 192 × 256). One image on which the largest ACL area was observed was selected and used for analysis.

2.3. Deep learning model

We used the VGGNet model[17] to determine whether the ACL was intact or torn from the MR images. The model comprised 13 convolution layers (with Rectified Linear Unit) and 3 fully connected layers. The region of interest was set around the ACL. The architecture is illustrated in Figure 1. A 3 × 3 filter was used in each convolution layer to create a feature map of the image and the highest pixel value was selected through max pooling. We used fully connected layers (sizes 512, 64, and 2) for the classification, and softmax was used as the last activation function. Knee MRI was classified as intact or tear.

2.4. Experiment

Among the 164 images, 79% of them, i.e., 130 images were randomly selected as training sets, whereas the remaining 21% (34 images) were assigned to the test set to evaluate the model performance. The details of the dataset configurations are listed in Table 1.

Table 1

Dataset configuration.

	Train set	Test set
Intact	64	17
Tear	66	17
Total	130	34

Table 2

Performances of the model for diagnosing anterior cruciate ligament tear.

	Input image size 224 × 224
Model details	Data augmentation (used the width, zoom, and shear function) Binary classification with softmax activation Adam optimizer (the initial learning rate of 10^{-5})
Performance	Batch size 8 Dropout regularization Training accuracy: 100% Test accuracy: 94.12% Test recall: 94.12% Test precision: 94.74% Test AUC: 0.941 with 95% confidence interval [0.8622–1.0]

ACU = area under the curve.

The deep learning model was implemented in Keras using TensorFlow as the backend. We used the Adam optimizer to optimize the learning model, and we devised a method to adjust the learning rate automatically when learning plateaued. The initial learning rate was set to 10^{-5}. The model was trained using pre-trained weights as the initial weights. In addition, built-in data augmentation methods in Keras were used to augment the input data samples. In this study, the width, zoom, and shear functions were used for data augmentation. The details of the model and performance are provided in Table 2.

In most recent medical imaging studies, the class activation map was plotted and visualized using the Grad-CAM method.[18] The results visualized using this method provided information regarding the focus of the model for achieving effective prediction. Figure 2 shows the visualization results for intact and tear images in the trained model using the Grad-CAM method. These visualizations can facilitate radiologists and doctors in performing assessments.

A receiver operating characteristic curve analysis was performed, and the area under the curve (AUC) was calculated using scikit-learn. The 95% confidence interval (CI) for the AUC

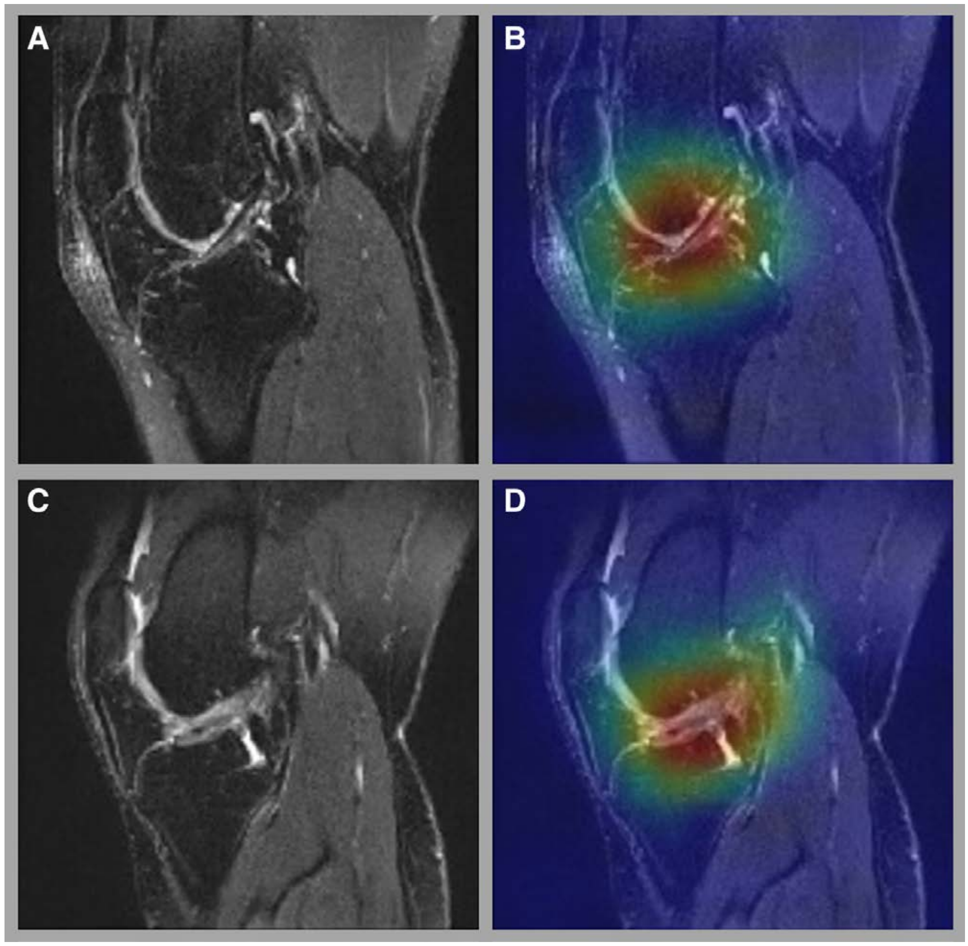

Figure 2. Visualizations of intact and torn anterior cruciate ligament (ACL) images using Grad-CAM on trained model. Red and yellow regions show regions of interest in model during prediction phase. (A) Original image of intact ACL; (B) class activation map of intact ACL; (C) original image of torn ACL; (D) class activation map of torn ACL. ACL = anterior cruciate ligament.

was calculated using the approach used by DeLong et al[19] The receiver operating characteristic curve analysis and AUC calculation were performed using scikit-learn.

3. Results

In the classification of intact and tears of the ACL with the test dataset using the VGGNet model, the accuracy was 94.12% (Table 2). Furthermore, the AUC was 0.941 (95% CI, 0.862–1.000) (Fig. 3).

4. Discussion

In the present study, we developed a CNN model for diagnosing ACL tears using only one MR image as the input data.

The AUC of the model that we developed, evaluated with the test dataset, was 0.941 with regard to the classification of the ACL state from MR images into "intact" and "tear." Considering that an AUC > 0.9 is generally considered outstanding, our CNN model trained using knee MRI input data can facilitate clinicians in diagnosing ACL tears.[20]

A deep neural network is characterized by a multilayer perceptron with multiple hidden layers or a feedforward neural network; it possesses greater ability than a traditional shallow neural network.[11] A CNN is a representative deep neural network model. It receives multiple channels of 2-dimensional data as input and transforms them repeatedly using convolution and pooling operations.[12] These processes allow valuable features to be extracted from the input data. Therefore, CNNs have been used to process image data and recognize image patterns.[12] Our model recognized the characteristics of MR images of intact and torn ACLs and demonstrated high diagnostic accuracy.

The efficacy of CNN for detecting ACL tears in knee MRI have been evaluated in 4 studies hitherto.[13–16] In 2018, Bien et al[13] included 266 patients with ACL tears and 319 subjects with no abnormalities based on knee MRI in their study. They used whole T2-weighted MR images (coronal, sagittal, and axial images) of each patient to develop a CNN model. The AUC of the model was 0.824. After Bien et al's study, the accuracies of the models were improved significantly. In 2019, Chang et al[14] used 4144 coronal MR images of 260 patients as input data. Among the 260 patients, 130 patients' ACLs were completely torn, whereas the other 130 patients' ACLs were intact. They used the CNN model to detect torn ACL, in which the accuracy reported was 96%. In 2019, Liu et al[16] used whole T2-weighted fat-suppressed MR images (coronal, sagittal, and axial images) of 175 subjects with complete ACL tear and 175 subjects with intact ACL. The CNN model showed an AUC of 0.98. In 2020, Germann et al[15] recruited 512 patients (ACL tear in 234 and intact ACL in 278) and used all sets of coronal and sagittal fat-suppressed MR images in each patient. Their developed CNN model showed an AUC of 0.935. In general, the CNN models used in previous studies demonstrated high diagnostic accuracy, and many MR images were used to develop a CNN model for detecting ACL tears. In contrast to the previous studies, we used only one oblique-sagittal MR image, on which the largest ACL was observed, as the input image data for

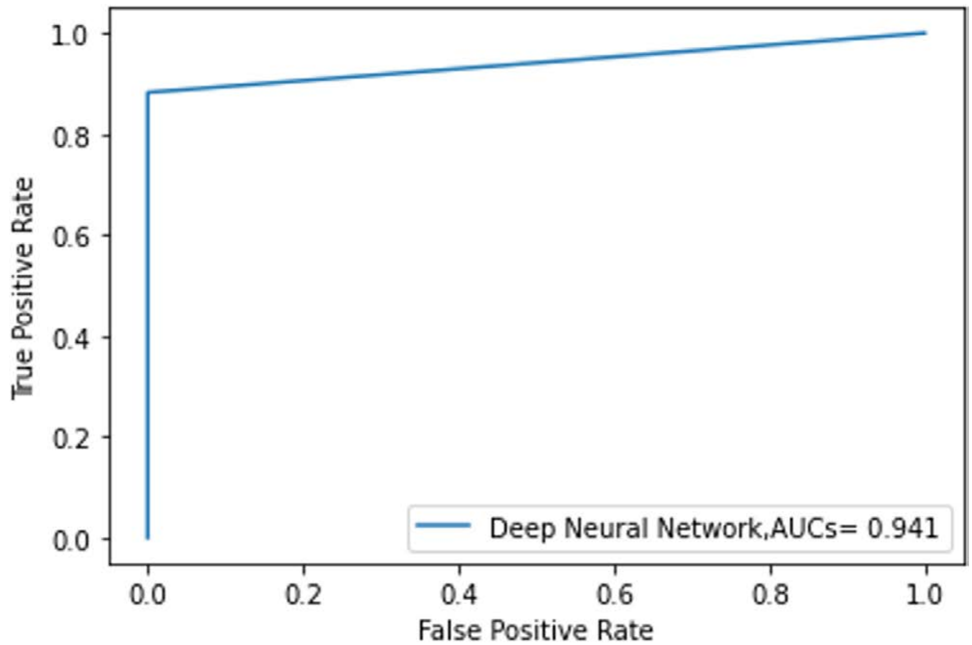

Figure 3. Receiver operating characteristic curve and area under the curve (AUC) for testing dataset. AUC = area under the curve.

each patient. The diagnostic accuracy was comparable to that reported in previous studies.

5. Conclusion

Using only one oblique sagittal knee image in the current study, we created a CNN model for diagnosing ACL tears, and its diagnostic accuracy was high. However, our study was restricted in that we used MR images of a small number of subjects. Also, we used image data obtained from a single center. Therefore, the generalizability of our study may be limited. We believe that further studies with a larger number of subjects and with image data obtained from external centers are necessary in the future.

Authors contributions

HS, WL, GSC and MCC designed the study, collected data, analyzed data, and wrote the manuscript. MCC supervised the study. All authors read and approved the final manuscript.
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