Machine Learning Models for Interpretation of Knee MRI

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I. Introduction

N. Bien et al. [1] used transfer learning to develop a fully automated convolutional neural network (CNN) for classifying MRI series. They aggregated predictions from three series per exam using logistic regression, resulting in an accuracy of 86.7% and an area under the curve (AUC) of 0.965 for detecting anterior cruciate ligament (ACL) tears. When compared to evaluations by three radiologists on a test set of 120 knee MRI images, the AI model's performance was found to be significantly lower in sensitivity for tear diagnosis, with the radiologists achieving an AUC of 0.91 compared to the model's AUC of 0.76. The radiologists also had a higher accuracy of 92%, surpassing the AI model's accuracy of 86.7%.

J. Li et al. [2] used a mask regional convolutional neural network (R–CNN) to identify and diagnose meniscal injuries in knee MRI images from a total of 924 patients. The backbone of the deep learning architecture was built using ResNet50, with the model trained on datasets of 504 patients for training and 220 patients for validation. The results indicated that the model effectively distinguished between healthy and injured menisci, with diagnostic accuracy reported as 87.50%, 86.96%, and 84.78% for these categories, respectively.

M. Mangone et al. [3] proposed a model named KNet, that utilizes CNNs to extract features from knee MRIs. It processes individual MRI slices using AlexNet, generating feature vectors that are then pooled to create a global representation. A classification head determined whether the knee was intact or injured based on the output, achieving a maximum accuracy of 83.7%, sensitivity of 82.2%, and specificity of 87.99% for meniscus tears.

J-C. Fu et al. [4] compared two SVM models to detect meniscus tears. One utilized a selection of 180 spatial and textural features, and the second model employed the SVM without any feature selection. The results showed that the SVM model without feature selection achieved an AUC of 0.73, whereas the model that incorporated feature selection resulted in a significantly higher AUC of 0.91.

H. Shin et al. [5] developed a CNN model to detect meniscal tears and classify tear types in knee MRIs. For tear type classification, the dataset included tear cases categorized as horizontal, complex, radial, or longitudinal. The model achieved AUC scores of 0.889, 0.817, and 0.924 for medial, lateral, and combined meniscal tears, respectively, and AUCs of 0.761, 0.850, 0.601, and 0.858 for horizontal, complex, radial, and longitudinal tear types.

D. Azcona et al. [6] explored four distinct architectures for ACL detection: a deep residual network utilizing transfer learning, a custom deep residual network with a fixed number of slices, a multi-plane deep residual network and a multi-plane multi-objective deep residual network. Their findings indicated that the combination of transfer learning and data augmentation was essential for achieving optimal performance as well as utilizing pre-trained weights from ImageNet for transfer learning. Through the application of these deep learning architectures and data augmentation techniques, they attained an AUC of 0.96 on the validation dataset for ACL detection.

I. Štajduhar et al. [7] implemented two feature extraction methods: histogram oriented gradient (HOG) and generalized search tree (GIST), which they combined with two machine learning (ML) models: support vector machines (SVM) and random forests. The optimal performance was achieved by the HOG feature extraction combined with a linear-kernel SVM, yielding an AUC of 0.89 for distinguishing between ACL-injured and healthy individuals, and an AUC of 0.94 for detecting completely ruptured ACLs.

F. Liu et al. [8] developed a model using two CNNs to isolate the ACL on MRIs, followed by a classification CNN to detect structural abnormalities. The study analyzed MR images from 175 subjects with full-thickness ACL tears and 175 subjects with intact ACLs. The ACL detection system achieved a sensitivity and specificity of 0.96, comparable to clinical radiologists whose sensitivity ranged from 0.96 to 0.98 and specificity from 0.90 to 0.98.

Y. Dai et al. [9] used the TransMed model to detect meniscus tears, implementing transformer blocks with attention mechanisms, achieving an accuracy of 94.9% and an AUC of 0.98, outperforming the MRNet method.

G. Sezen et al. [10] utilizes a combination of CNN and sequential network deep learning models for detecting general anomalies, ACL tears, and meniscal tears on knee MRI, then combines information from multiple MRI views with transformer blocks for final diagnosis, achieving an average performance of 0.905 AUC for the three injury cases of the MRNet dataset.

C. Germann et al [11] built a CNN that includes extra preprocessing steps: selects, resizes, and crops are applied to coronal and sagittal fluid-sensitive, fat-suppressed MRI scans. Next, these scans are processed independently in parallel and then merged before passing through a dense layer. Finally, a softmax layer outputs the confidence level for an ACL tear.

P. D. Chang et al. [12] tested three CNN models to detect complete ACL tears, varying by field of view (full slice, cropped slice, dynamic patch-based sampling) and number (single, three, or five slices). The study found out that limiting the field of view, as well as including adjacent slices, significantly improved algorithm performance, achieving a 96.7% accuracy and an AUC of 0.97.

V. Roblot et al. [13] divided the problem into three subtasks: detecting the position of both meniscal horns, identifying the presence of a tear, and determining the tear's orientation. A classification algorithm was developed using fast region-based and faster region-based CNNs to address each sub-task, yielding a final weighted AUC of 0.90.

MHF Zarandi et al. [14] segmented MR images and applied a perceptron neural network (PNN) to classify meniscal tears, achieving 90% accuracy in distinguishing between meniscus tears and non-tears on a small test set of 50 MRI scans.

William Burton II [15] and his colleagues used semi-supervised learning for automatic segmentation. A dice similarity coefficient (DSC) of 0.989 and an intersection-over-union (IoU) of 0.978 were attained by 3D CNNs that used Monte Carlo patch sampling during inference. The range of the median surface error between the ground truth and anticipated geometries was 0.56 to 0.98 mm.

A deep learning model created by Mazhar Javed Awan and his associates [16] performed well for prospective classification and showed promise for osteoarthritis patients. The suggested CNN model achieved an accuracy, precision, specificity, and sensitivity above 98% and includes numerous hidden layers, dropout layers, the RMSprop optimizer, and a learning rate of 0.001. The findings showed that, in terms of AUC as well, the deep learning-based CNN model significantly enhanced the categorization of knee ACL tears.

Bruno Astuto and his colleagues [17] analyzed 1435 knee MRI studies in order to grade abnormalities of the cartilage, bone marrow, menisci, and ACL. For every tissue, the reported binary lesion sensitivity ranged from 70% to 88% and the range of specificity was 85% to 89%. All tissues had an area under the receiver operating characteristic curve between 0.83 and 0.93.

Ali Can Kara and Fırat Hardalaç [18] created a progressive deep learning model to diagnose knee injuries (ACL, meniscus and abnormalities) using MRI images from three planes—sagittal, coronal, and axial. Using a modified ResNet50 model, the model achieved high accuracy and ROC-AUC scores - around 79% accuracy and 0.87 ROC-AUC for ACL, around 73% accuracy and 0.75 ROC-AUC for meniscus, around 89% accuracy and 0.87 ROC-AUC for abnormalities.

Chen-Han Tsai et al.'s [19] study used axial axis images to detect ACL injuries and coronal axis images to diagnose meniscus tears, along with abnormalities. They used an architecture known as an optimized efficiently layered network (ELNet). For meniscus, ACL, and abnormalities diagnosis, the study's ROC-AUC values were 0.904, 0.960, and 0.941, respectively.

Jiunn Horng Kang and Nguyen Quoc Khanh et al. [20] conduncted 584 knee MRI studies for detection of meniscus tears. On the internal testing, internal validation, and external validation data sets, our model's overall accuracies for identifying meniscus tears were 95.4%, 95.8%, and 78.8%, respectively. This model outperformed one radiologist in identifying meniscus tears (accuracy: 0.9025 ± 0.093 vs. 0.9580 ± 0.025).

According to a study conducted by M. I. A. Sharifah [21] in identifying meniscus tears in individuals who have tears in their anterior cruciate ligament (ACL), 65 patients were included in this. The MRI diagnosis of lateral meniscal tears in our patients had sensitivity, specificity, accuracy, PPV, and NPV of 83, 97, 92, 96, and 90%, respectively, while the corresponding values for medial meniscus tears were 82, 92, 88, 82, and 88%.

A. Tack, A. Mukhopadhyay and S. Zachow [22] used a combination of 2D U-Net, SSM and 3D U-Net for the segmentation of knee meniscus from the MRIs. Medial menisci (MM) and lateral menisci (LM) segmentation accuracy, as determined by dice similarity coefficient, was 83.8% and 88.9% at baseline, respectively, and 83.1% and 88.3% at the 12-month follow-up.

Pedoia et al. [23] used 1481 knee MRI tests to assess 2D U-NET's capacity to identify and categorize meniscus and patellofemoral cartilage abnormalities. They classified the severity of meniscus tears using the WORMS system. For the identification of meniscus tears, the CNN demonstrated 81.9% sensitivity, 89.9% specificity, and an 89% AUC. Additionally, it obtained an accuracy of 78.02% for mild-to-moderate tears, 75% for severe tears, and 80.74% for intact meniscus.

Benjamin Fritz et al. [24] created a DCNN to validate this network for detection of meniscus tears. Images used in this DCNN are cropped around the meniscus and scaled to a standard pixel size, slice distance, and slice numbers using spline 3rd order interpolation. The DCNN's AUC-ROC for detecting medial, lateral, and total meniscus tears was 0.882, 0.781, and 0.961, respectively.

B. Rizk et al. [25] used a 3D CNN, trained with sagittal and coronal MRIs of the knee. 3D convolutional neural networks with a combined architecture of meniscal localization and lesion classification achieved AUC values of 0.91 (95% CI 0.87, 0.94) for medial and 0.95 (95% CI 0.92, 0.97) for lateral meniscal tear migration detection, and 0.93 (95% CI 0.82, 0.95) for medial and 0.84 (95% CI 0.78, 0.89) for lateral meniscal tear detection.

II. Gaps and Improvement

Despite high performance metrics in some models, several research gaps remain, such as the trade-off between specificity and sensitivity, especially with models focused on single-plane MRIs or specific injuries. For instance, ACL detection models (e.g., [1], [3], [7]) often achieve high AUCs but still fall short compared to radiologists in sensitivity for nuanced tear detection. Additionally, many models focus on either ACL or meniscus pathologies, lacking comprehensive approaches that simultaneously analyze multiple structures and tear types within the knee.

While CNNs remain popular, there is limited exploration of hybrid or transformer-based models, which may better capture complex spatial and contextual information in 3D MRIs (e.g., [10]). Future work could focus on multi-task learning frameworks that assess multiple knee structures or the application of transformers for enhanced spatial awareness.

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