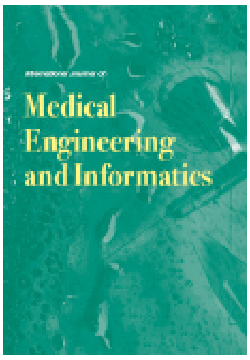

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Automatic knee anterior cruciate ligament torn diagnosis using CNN-XGBoost

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Automatic knee anterior cruciate ligament torn diagnosis using CNN-XGBoost

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Abstract: The knee joint is very important for everyone as it helps us in movements, which is essential for everyone. One of the most diseases that injure the knee is the anterior cruciate ligament (ACL). This work has developed a computer aided diagnosis (CAD) system for examining the given knee magnetic resonance imaging (MRI) image and automatically determining if there is a torn in ACL or not. The region growing based segmentation algorithm is used to get the region of interest (ROI) from MRI image, e.g., extract ACL region from knee image then CNN-XGBoost model is used for knee ACL classification. The model is divided into two main parts: the first part extract the feature uses CNN and the second part using XGBoost for feature classification. The designed model gives us an accuracy of 91%.

Keywords: deep learning; CNN; XGBoost; knee ACL.

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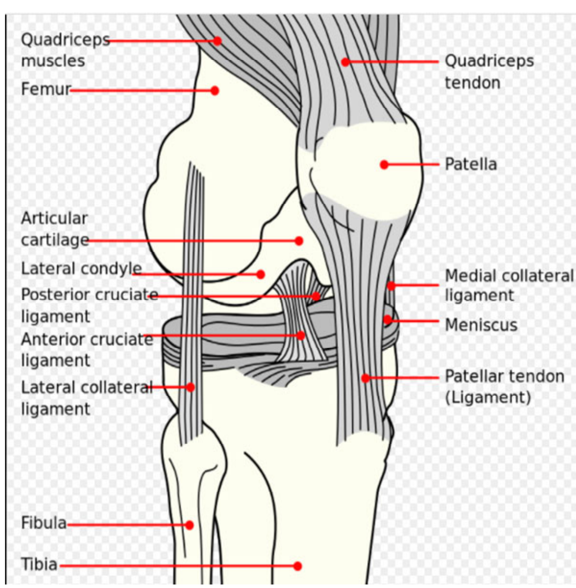
1 Introduction

The knee joint is an important joint in the body as it helps us in our daily activities such as moving, sitting and standing (Taylor, 2019). The knee joint is weak by nature because it carries the majority weight of the body and takes the brunt of the impact from walking, running, and jumping. Also, it does not have much protection from trauma or stress. This makes the knee to be more vulnerable to inquire with diseases. The anatomy of the knee is illustrated in Figure 1 (Wikipedia, 2021).

Figure 1 Knee anatomy (see online version for colours)



In recent past years, magnetic resonance imaging (MRI) images are used to diagnose knee diseases. MRI (Wradiology, 2005) is an imaging technology that uses magnetic fields and radio waves to produce more clarify images. The MRI knee images help us to easily distinguish the knee joint main parts such as bones, cartilage, tendons, and ligaments. The MRI images also produce a sequence of images from different three planes; axial, sagittal, and coronal as shown (BESBES, 2019).

The knee joint contains of four ligaments, one of them is anterior cruciate ligament (ACL), which provides stabilisation for the knee joint. ACL is the most common disease that inquires the knee especially among the people that practice sports such as football. The ACL is connective tissues, which course from the femur to the tibia. The ACL occurs when ACL is either stretched, partially torn, or completely torn (Blood-Smyth, 2015).

The goal of this work is to automatically diagnose the knee ACL torn. The used dataset is obtained from Clinical Hospital Centre Rijeka, Croatia (Štajduhar et al., 2017). This dataset contains a set of MRI images in the sagittal plane. The dataset is divided into two classes; images containing ACL torn and normal knee images.

The automatic diagnosis is done through two main stages. The first stage concerns extracting the region of interest (ROI), e.g., extract ACL part from the knee image, and the second stage is done to determine if the ACL contains torn or not. The first stage is based on a regional growing-based segmentation algorithm which was first introduced by Adams and Bischof (1994) and Shrivastava and Bharti (2020). The main idea of region growing-based segmentation is to start with a starting pixel called the initial seed. Then, the movement grows out through an iterative process to merge pixels with similar properties to the initial seed. These pixels represent the region to be segmented, e.g., ROI. The second stage is the stage of classification, which accepts the produced ACL images and divides the data into two parts: a training part and a testing part. In this work, we use CNN which consider the most robust and essential model for feature extraction mechanism, and then replace the final classification layer with the XGBoost model. The big advantage of XGBoost is that it uses ensemble learning which combines more than one random forest classifier, then applies different hypotheses to build a better hypothesis which helps us to obtain more precise predictions (Kohavi and Wolpert, 1996).

The dataset used in this work is knee MRI images in sagittal plane obtained from Clinical Hospital Centre Rijeka, Croatia. The total number of images used in this work is 230 images, 121 images for norm ACL, and the rest 109 images containing ACL torn (Group, https://stanfordmlgroup.github.io/competitions/mrnet/).

The remainder of the paper is laid out as follows. Section 2 briefly mentions some related work for ACL segmentation. Section 3 will discuss the methods used in this work. Section 4 describes the proposed model methodology and algorithm steps. Section 5 shows the proposed model result. Finally, Section 6 presents the work conclusion.

2 A literature review

Methods for performing knee segmentations are varied widely depending on the knee part, which we want to segment. Furthermore, each imaging modality has its own idiosyncrasies with which to content (Tortora and Derrickson, 2018). There is currently no single segmentation method that yields acceptable results for every medical image.

We will briefly discuss some of the most relevant related work to our approach, e.g., ACL segmentation. For ACL segmentation, there are many articles that discuss ACL segmentation, but most of them use semi-segmentation or manual segmentation.

The work of Štajduhar et al. (2017) in the paper 'Semi-automated detection of anterior cruciate ligament injury from MRI' tries to build a semi-automated model to diagnose ACL model. The oriented gradient histogram descriptors and gist descriptors are extracted from manually selected rectangular zones of interest encircling the broader anterior cruciate area.

The work of Vinay et al. (2014) in the paper 'An active contour method for MR image segmentation of anterior cruciate ligament (ACL)' attempt to create a semi-automated ACL segmentation system using an active contour algorithm. In this work, we will introduce a fully automatic model that can diagnose ACL torn. The regional base segmentation is used to extract the ACL part from MRI knee images while the SVM algorithm for classification.

3 Materials and methods

3.1 Dataset description

MRI images were collected by Clinical Hospital Centre Rijeka, Croatia, from 2006 until 2014 (Štajduhar et al., 2017). This dataset stores knee MR images in volumes and each volume is saved in Python pickle objects format (P.3.10. Documentation, 2021). The dataset helps scientists and students interesting in machine vision and/or machine learning to explore and the diagnose the knee ACL torn.

3.2 Regional-based segmentation algorithm

In this section, we will discuss the regional-based segmentation algorithm (Verma et al., 2011). Image segmentation's main purpose is to divide an image into non-intersecting or independent sections. The algorithm is divided into four main steps:

The first step is to define the criteria that describe the target of the segmented areas, e.g., mean, variance, bimodality of histogram, texture, etc. The second step, select the starting points or initial seed points. The initial seed selection is very important as it determines the overall segmentation parts by region growing technique. There are many techniques used for initial seed selection depending on the images. The work of Tang uses the watershed algorithm to select an initial seed (Raja et al., 2018). The work of Fan et al. (2001) first applies the edge-based segmentation and then uses centroid as the starting initial seeds. The third step, examines all neighbouring pixels which match the initial seeds features, e.g., grey level, texture, colour, etc. and add these pixels to the region.

The final step continues by grouping the similar pixels to each other and producing a region corresponding to each seed.

3.3 Convolutional neural network

CNN is the most well-known deep learning architecture which used in image classification problems and always achieved good accuracy since 2012 (Rawat and

Wang, 2017). The big advantage of CNN compared to other architecture come from its ability to automatically extract the features in a well efficient manner (Dertat, 2017).

CNN is a feed-forward neural network (NN) that consists of many layers stacked together in sequential manner (Krizhevsky et al., 2012). One can the CNN main basic structure layers to the input layer, the convolution or feature extraction layer, the feature reduction or pooling layers, the flatten layer, and finally the output layer.

The input layer takes the image data and converts it to an array of pixels to be handled by the next layer. A convolution layer (E. at F.U.C. '19, 2016) consists of a set of convolution kernels that can compute different feature maps.

The filters' hyper-parameters values are calculated during the training. All of these features combined together to build image feature map (Jin et al., 2014).

The pooling layer is usually added after the convolution layer to reduce the feature map dimension and thus the computation time. The most commonly used operations in the pooling layer are maximum and minimum (Boureau et al., 2010).

The flatten layer converts the image features to a single row vector that can be used as an input to the last layer (Jin et al., 2014). The final layer usually uses a fully connected NN, which receives one dimension row vector features from flatten layer, determine the NN weights. This layer is connected with the activation function in order to predict the right label (Marchesi et al., 1990).

3.4 XGBoost

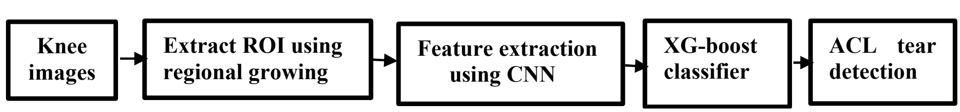
XGBoost is a robust methodology used for prediction and classification that was developed by Chen and Guestrin as a research project at the University of Washington (Chang et al., 2018).

XGBoost is an ensemble machine learning algorithm based on decision trees that employs a gradient boosting framework. The XGBoost is described below (Jiao et al., 2021; Chen and Guestrin, 2016).

3.5 The proposed system

The main idea of this work is based on the region growing technique. This technique divides the image into non-overlapping regions. In this work, we use a region-growing technique with a single seed to extract the ACL part from knee images. Firstly, a region-based segmentation algorithm is used to detect the knee femur location. After allocating the femur location, we can select the maximum deep point from the femur location. Then, we create a fixed size rectangle' mask that nearly has the same size as ACL. Then, we move the created mask centroid to be aligned with a certain margin down to the selected deep point. Finally, we segment the ACL area according to the mask.

Figure 2 Proposed system



First, we select the initial seed point to be located on the femur bone. This is the most important step in the region's development technique. The selected seed should have similar characteristics to its neighbours in the femur. We select the initial seed to lay between the lowest and the highest intensity for femur bone that will be considered as the boundary for growing.

Second, we start growing from the initial seed location, e.g., $X_{intialSeed}$ and $Y_{intialSeed}$, and continue add neighbouring pixels, e.g., $X + 1_{intialSeed}$ and $Y + 1_{intialSeed}$ to the femur region in all directions, e.g., up, down, right, and left. The growing process stops in a certain direction when the neighbouring pixel does not lie between the lower and highest intensity boundary. The growth is completely stopped in all directions after allocating the knee femur.

Third, we calculate the maximum deep point from the femur then create a rectangle a window mask with a fixed size that can match nearly the ACL size then coincide with the created masked centroid with the maximum seed point.

Finally, after cropping the ACL part, we build pre-trained VGG-16 – CNN for feature extraction. We replace the last fully connected layer and the soft-max layer (classifier layer) in VGG-16 by XGBoost. The XGBoost is an ensemble classification, which uses more than one classifier and then combines their predictions for the classification of unseen instances using some form of voting.

Algorithm 1 Automatically locate initial seed point

Step 1	Divide each image to square blocks, and then calculate the pixels intensity for each block.
Step 2	Determine the block that match femur bone intensity.
Step 3	Select initial seed point to be in the centre of the selected block.

Algorithm 2 Building regional area

Step 1	Check if all neighbouring pixel match femur bone intensity; add this pixel to region else, stop growing in this direction.
Step 2	By the end of this step, one can determine the bottom of femur bone.

Algorithm 3 Extract ACL region

Step 1	Determine the centroid of the created region.
Step 2	Create fixed mask for ACL region with left top corner equal to the calculated centroid.
Step 3	Multiply original image with the created mask to extract ACL region.

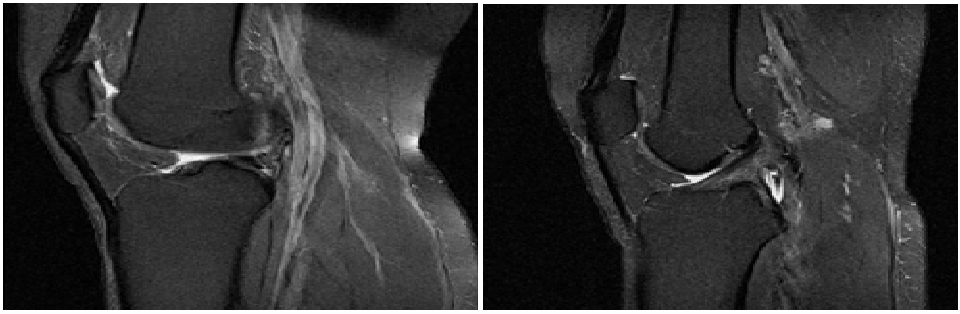
Algorithm 4 Classification using CNN-XGBoost

Step 1	Extract image feature vector using CNN; pre-trained VGG-16.
Step 2	Determine no. of trees in XGBoost.
Step 3	For each tree; use a GradienBosstingClassifier to compute the optimal weights.
Step 4	Using ensemble classifier to detect if image contains ACL torn.

4 Results

The total number of images used in this work is 130 images, 121 images for normal ACL and the rest 109 images contain ACL torn. Each image size is 240 × 240, Figure 3 shows two data samples.

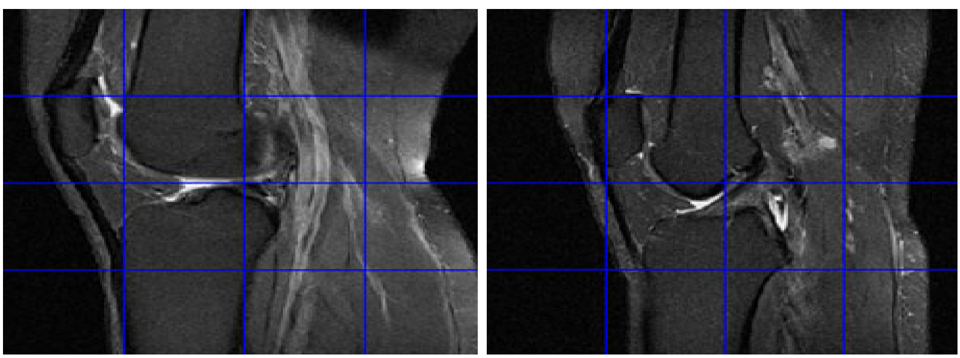
Figure 3 Dataset samples, (a) sample 1: norm ACL (a) sample 2: norm ACL



(a) (b)

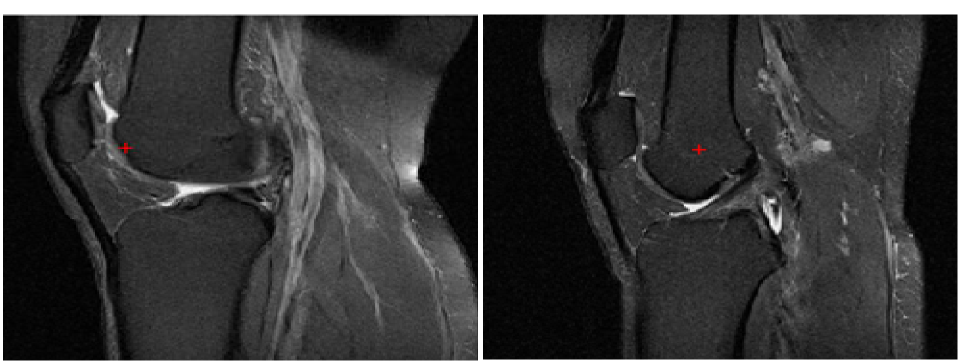
Divide each image to 4 × 4 equal regions (block); each region contains 60 * 60 pixels in order to detect femur bone according to intensity as shown in Figure 4.

Figure 4 Divide images to 4 × 4 block, (a) sample 1: norm ACL (b) sample 2: norm ACL (see online version for colours)



(a) (b)

Figure 5 Initial seed for four samples, (a) sample 1: norm ACL (b) sample 2: norm ACL (see online version for colours)

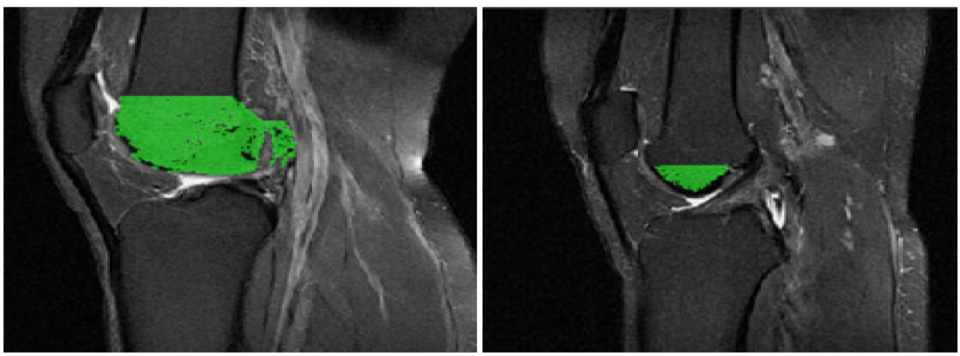


(a) (b)

To automatically select the initial seed point; calculate the pixels intensity in each region to be lies between lower and higher boundaries for the femur bone; lay between pixel intensity from 25 to 26. Set the centroid of the region that has max sum to be the initial seed point, Figure 5 shows the initial seed points for the four samples.

In order to detect the femur bone; starting from the initial seed point, merge all the pixels those have the same intensity for femur bone, e.g., the intensity between 25 and 60 intensity. The merging process is done in three directions only; left, right and bottom. The merging process stops in any direction if the intensity does not match with the femur bone intensity. The aim of this process is to mark the bottom of the femur bone. Figure 6 shows the bottom of the created region after the merging process ends.

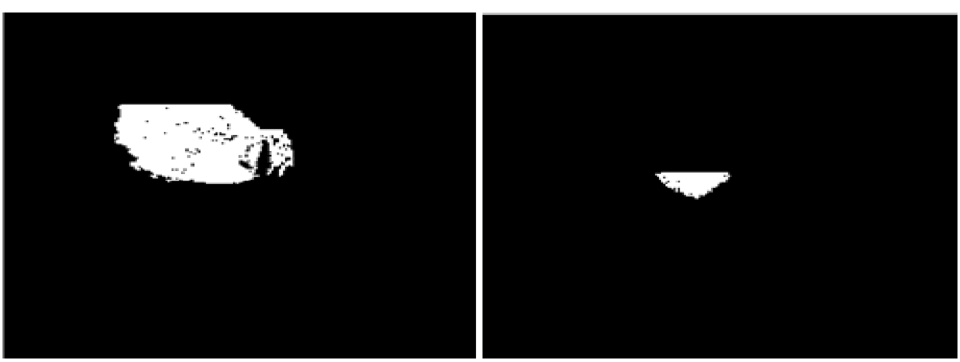
Figure 6 Segment the bottom part of femur, (a) sample 1: norm ACL (b) sample 2: norm ACL (see online version for colours)



(a) (b)

To extract femur bone; create a mask from the bottom part of the femur as shown in Figure 7.

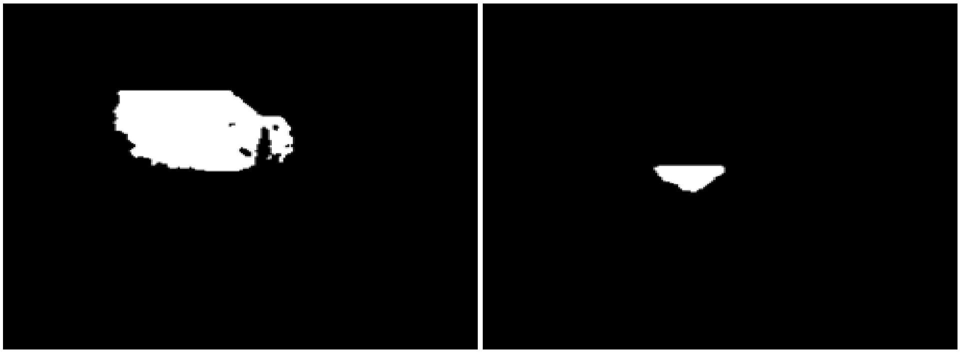
Figure 7 Mask the bottom part of femur, (a) sample 1: norm ACL (b) sample 2: norm ACL



(a) (b)

Perform a median filtering of the masked image to remove the salt and pepper noise as shown in Figure 8.

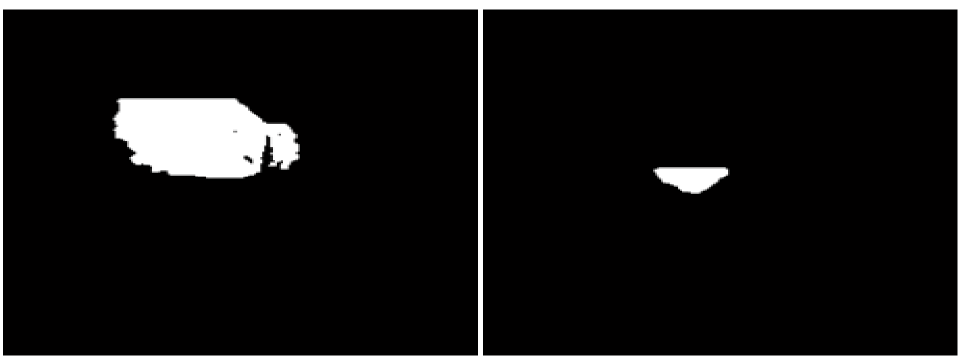
Figure 8 Remove salt and pepper noise, (a) sample 1: norm ACL (b) sample 2: norm ACL



(a) (b)

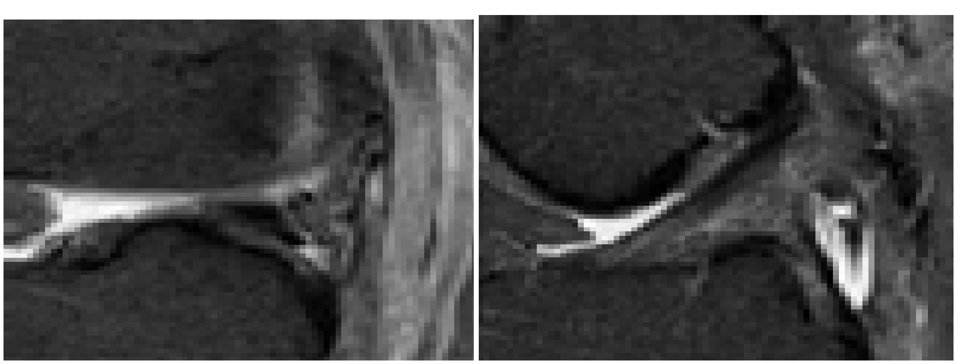
Apply dilation to expand or to thicken the foreground for the knee femur as shown in Figure 9.

Figure 9 Apply dilation, (a) sample 1: norm ACL (b) sample 2: norm ACL



(a) (b)

Figure 10 ACL part segmentation, (a) sample 1: norm ACL (b) sample 2: norm ACL



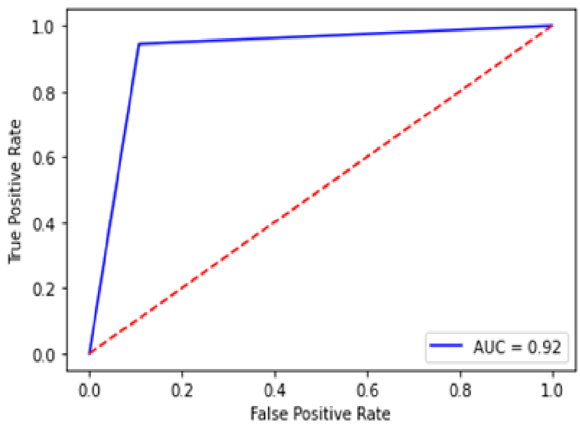
(a) (b)

Determine the max bottom point in the femur mask as a reference point and cut the image part from –40 pixel left, +40 pixel right, –20 pixel right and +60 pixel right to extract ACL part from the knee image as shown in Figure 10.

The segmented ACL images are classified by using CNN-XGBoost. In this study, we use 121 images for normal ACL and 109 images containing ACL torn. So the total number of images used in this study is 230 images. We use 184 images for training and the rest 46 images are used for testing. The proposed gives total accuracy 91%.

Figure 11 shows the ROC curve (Thomas and Tape, http://gim.unmc.edu/dxtests/ROC1.htm). From Figure 11, one can notice that, at certain threshold and at cost of false positive rate 0.15, we can get true positive nearly 0.96–0.99.

Figure 11 Area under the curve (AUC) (see online version for colours)



5 Conclusions

In this work, we introduce a model for knee ACL torn detection. The proposed model automatically extracts the ACL part regionally. This can automatically detect ACL torn. After extracting the ACL, we can classify the segment taken from the MRI knee image. The proposed model is based on a regional growing segmentation algorithm with a single seed to segment ACL. Then the model is classified using CNN-XGBoost. The system classifier showed good performance with an accuracy of 91%.

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