International Journal of Scientific Research & Engineering Trends
Volume 6, Issue 4, July-Aug-2020, ISSN (Online): 2395-566X

Deep Convolutional Neural Network Based Knee Injury Classification Using Magnetic Resonance Imaging

Rishi Pandey , Soumya Mitra
Dept. of Electronics Engineering
Kalinga Institute of Industrial Technology (KIIT)
Bhubaneshwar, India.

Abstract:-Radiologists tend to possess human error during pathologies scans for any abnormalities, thus the introduction of automation shall have a great impact on accurately detecting injuries and more musculoskeletal examinations. Magnetic Resonance Imaging (MRI) scans are an effective method to detect injured sections but the process tends to be time-consuming and prone to human error. Therefore, our paper highlights the automation impact on knee MRI for abnormal, anterior cruciate ligament (ACL), meniscal damages using deep learning. Deep learning model such as Convolutional Neural Network (CNN) can infer the representation of images due to its properties: local connection and shared weights. We have explored two deep CNN models (VGG16 and VGG19) with transfer learning approach to predict knee injury on MRNet dataset collected by Stanford University. The classification accuracy obtained for abnormal, ACL tear and meniscal tear are 85.83%, 70% and 76.67% respectively using VGG16 whereas 83.33%, 67.50% and 68.33% respectively using VGG19 model.

Keywords- Knee Injury, MRI, Deep Learning, CNN, Transfer Learning.

I. INTRODUCTION

Knee injury is one of the most common injuries which is caused when an unwanted bending force applied at the knee joint from accidents or falls. Swelling and pain are the symptoms of knee injuries. The most common knee injuries include tear of anterior cruciate ligament (ACL) and meniscus. The ACL is a tissue that joins the femur to the large bone tibia of the lower leg at the knee joint. It is one of the major ligaments of the knee and can get ruptured due to sudden jerks while playing sports like basketball, volleyball, football etc. Diagnosis of an ACL tear is executed by Magnetic Resonance Imaging (MRI) scans to figure out the signs of injuries and damaged tissue in the knee, including cartilage.

The meniscus tear is one of the most conventional cartilage injuries. The role of the meniscus is to act as a shock absorber that predominantly maintains knee joint stability during weight-bearing activities. Initial diagnosis of meniscal tear involves physically examining the injury by palpating the joint to look for the tender areas and examining the motion of the knee joint. A surgical repair is usually recommended in the circumstance that it doesn't repair itself. MRI captures the images in three planes: sagittal, coronal and axial. Fig. 1 provides an illustration of knee MRI in these three planes: sagittal, coronal and axial. Here, the first row provides a black and white view of the knee MRI in the three planes views namely sagittal, coronal and axial, whereas the second row provides the same views in colored format. The images in Fig. 1 are taken from the very same MRNet dataset considered in this paper for experiment on which the models were trained. Diagnosis of these injuries is done either by an X-ray or MRI as per the medical requirements. An MRI primarily envisions components of the joint, this includes the articular cartilage, menisci and intra-articular ligaments.

However, diagnosis of injury using MRI is time-consuming and prone to human error. Therefore, the aim of this paper is to develop a predictive model capable of automatically determining whether an injury is abnormal, ACL tear or meniscal tear.

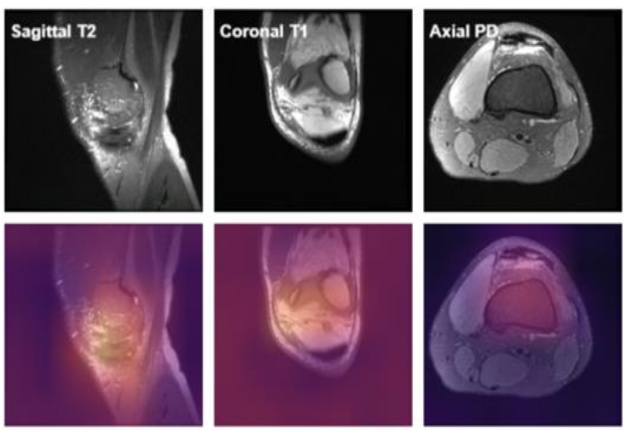


Fig. 1 Knee MRI in three planes: sagittal, coronal, axial.

II. METHODOLOGY

Deep learning is analogous to a function that precisely focuses on mimicking the human brain and how the brain processes data which drives the decisions taken by it. Deep learning has the capability to learn from raw unstructured data. The huge data is available now for example: the data present in the online media, social media, e-commerce which simply termed as big data altogether.

However, it might be time consuming for human comprehension but can be handled using deep learning. A class of deep learning is convolutional neural network (CNN) which finds its application in visual imagery. CNN is inspired by biological process between the neurons and the numerous connected layers. It mainly has three layers: convolution, pooling and fully connected layer. Fig. 2 represents the general CNN architecture where the input images of the dataset are convolved and pooled subsequently as they are processed. Transfer learning is vital in certain applications and contexts where obtaining large dataset for training neural networks is either costly or impossible. The limitation of CNN in its inability to store the partial results produced which can be further processed to update the weights in the subsequent iterations,

However, the limitation of CNN is its high computational cost and requirement of large dataset to train effectively. Hence, we have used transfer learning approach which helps to store the results of the initial weights so that they can be updated for the next iteration.Transfer learning that is vital in certain applications and contexts where obtaining large dataset for training neural networks is either costly or impossible. A brief description of transfer learning has been provided in next section.

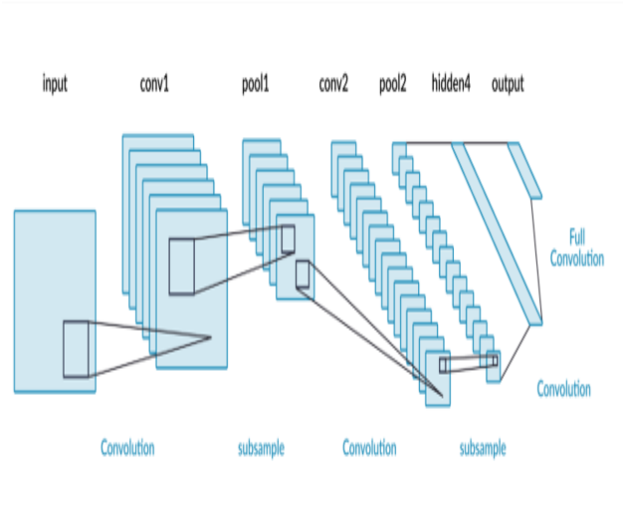


Fig. 2 A general CNN architecture.

1. Transfer Learning

It is an exploratory, analysis in the machine learning field which primarily stores the knowledge received while solving a particular problem so that it can be applied on another contrasting, but related problem. For example, the knowledge gained while recognizing cars, so that it can be further used for the identification of trucks. Here, we have used transfer learning approach for knee injury classification where which helps to store the results of the initial the initial weights used for the model are the weights obtained after training the model on ImageNet dataset .so that they can be updated for the next iteration. In the models VGG-16 and VGG-19 the results of the weights of the subsequent layers after every iteration is stored in memory for updation in the forthcoming iteration, by the use of transfer learning since CNN is not capable of storing results. Further, all the layers are frozen in transfer learning approach except last few fully connected layers, i.e., the weights of only unfrozen layers are updated while training. Fig. 3 shows the concept of transfer learning approach.

The detailed Experimental setup for this model is as (Fig 3): -

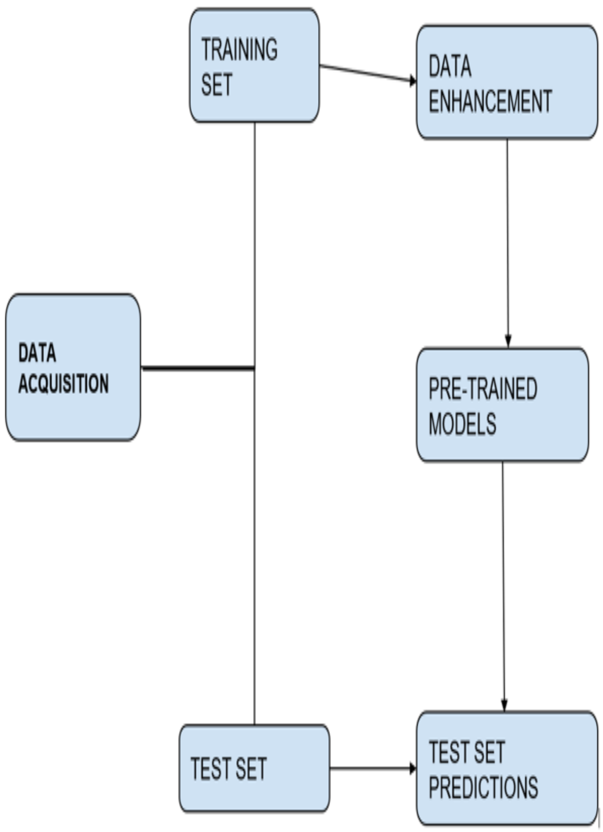


Fig. 3 Concept of transfer learning approach.

III. RESULTS AND DISCUSSION

1. Dataset Collection and Preparation

The dataset used in this paper is MRNet was that is acquired from the Stanford University Medical Center [ref]. MRNet website that It consists of 1370 knee MRI data categorizing into three classes abnormal, ACL tear and meniscal tear obtained from 1370 patients. Each data consists of all the three slices of images across each patient contains three types of planes namely sagittal, coronal and axial. The model is trained on each plane (sagittal, coronal and axial) separately.

2. Experimental Setup

In this paper, we have applied two pre-trained deep CNN models: viz. are VGG16 and VGG19. All the These models were pre-trained using imagenet dataset and trained weights were loaded initially for knee MRI classification. Based on the concept of transfer learning, all the layers of model are frozen except last layer while training. The dataset has been divided into training and test set with the ratio of 80:20, i.e., training set consists of 1096 images and test set has 274 images.

Due to large dataset and model complexity, we have further divided the training set into few parts and fed to model one part at a time. The trained weights are stored and loaded to the model for next part of training data. we have used Adam optimizer to update the weights. was used, which replaced the traditional stochastic gradient descent algorithm, since the Adam optimizer used to update the weights based on the training iterated data. Here the Adam optimizer was applied to the multi-layer perceptron's the two models presented here.

Further, 30 epochs were considered along with early stopping strategy to prohibit over-fitting of the data. Here, training is stopped if pre-defined criterion meets and model is trained till full epoch count if early stopping criterion does not meet. We have set the criterion as if validation loss does not decrease AA% till BB epochs, training should be stopped. Tensorflow and Keras open source neural network libraries have been used for implementation and all the experiments have been performed on open source google platform google-colaboratory. It supports up to 128 GB RAM and tensorflow TPU was used instead of the normal GPU for faster processing.

3. Performance Evaluation

3.1. VGG-16 and VGG-19

Validation Accuracy

After being trained with the test set the model is tested against the validation set to see how the trained model performs with unknown data, and accuracy of the same is stated as validation accuracy.

The main objective of this research is to develop a model for three types of knee injury: Abnormal, ACL tear and Meniscal tear. We have experimented with two pre-trained deep CNN models (VGG16 and VGG19) with transfer learning approach for each plane: sagittal, coronal and axial. In this way, each model is trained nine times individually with crisscross combination of three knee injuries (abnormal, ACL tear, meniscal tear) and three planes (saggital, coronal, axial).

Fig. 2 and Fig. 3 shows the performance while training using VGG16 and VGG19 respectively by depicting the plots between training and validation accuracy with respect to epoch. Table 1 presents the test accuracy obtained using two models corresponding to each knee injury and each plane and Table 2 shows the confusion matrix. Further, we have shown the receiving operating characteristic (ROC) curve in Fig. 4 and Fig. 5 for VGG16 and VGG19 respectively and area under the curve (AUC) in Table 4 and Table 5. Finally, we have found the best plane to detect the injury by taking the maximum accuracy and shown the final accuracy in Table 6.

3.2. Results

Table 1 Epoch Count (VGG-16).

Epoch_Counts	Sagittal	Axial	Coronal
Abnormal	9	28	37
ACL	40	29	28
Meniscus	28	30	28

Table 2 Validation accuracy at early stop Epochs (VGG-16).

Validation Accuracy (in %)	Sagittal	Axial	Coronal
Abnormal	80.53	83.19	81.42
ACL	84.96	80.53	84.96
Meniscus	67.26	70.8	66.37

International Journal of Scientific Research & Engineering Trends
Volume 6, Issue 4, July-Aug-2020, ISSN (Online): 2395-566X

Table 3 Epoch Count (VGG-19).

Epoch_Counts	Sagittal	Axial	Coronal
Abnormal	9	38	27
ACL	40	29	28
Meniscus	28	30	28

Table 4 Validation accuracy at early stop Epochs (VGG-19).

Validation Accuracy (in %)	Sagittal	Axial	Coronal
Abnormal	81.42	83.19	83.07
ACL	84.96	84.96	84.96
Meniscus	66.37	74.34	63.72

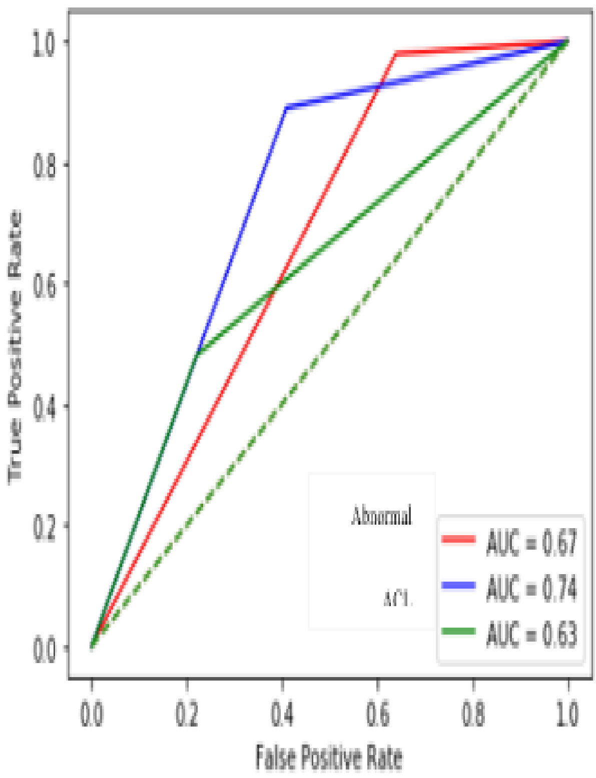


Fig. 5 ROC plot (VGG-16).

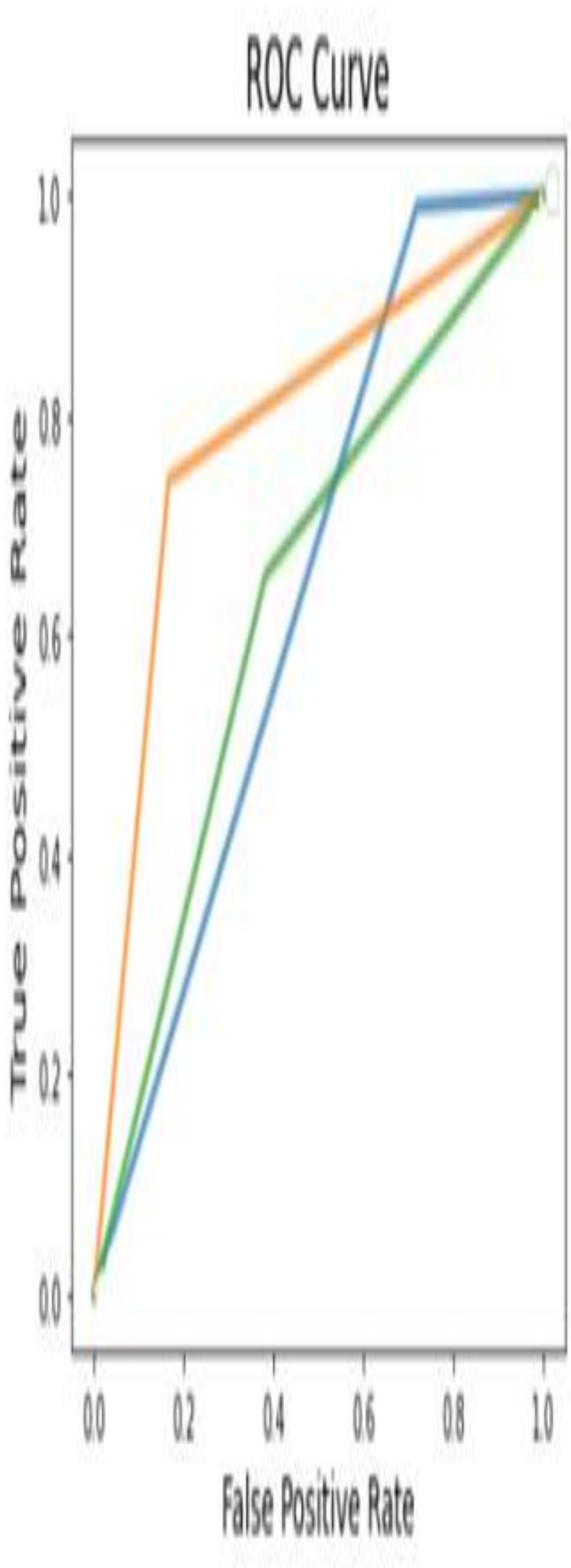


Fig. 6 ROC plot (VGG-19).

International Journal of Scientific Research & Engineering Trends
Volume 6, Issue 4, July-Aug-2020, ISSN (Online): 2395-566X

Table 5 Confusion matrix obtained using VGG-16 model.
Abnormal ACL Tear Meniscal Tear.

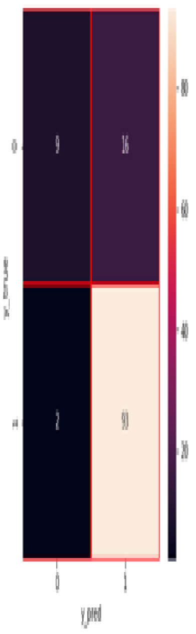
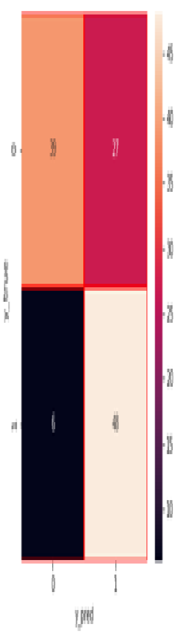
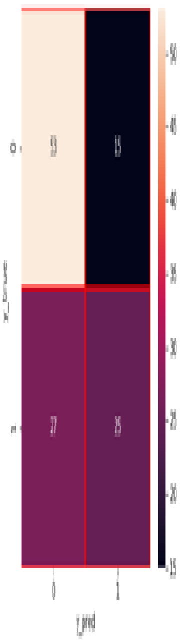
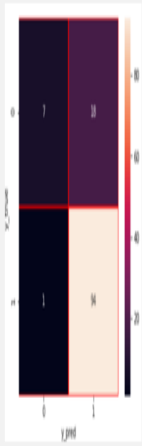
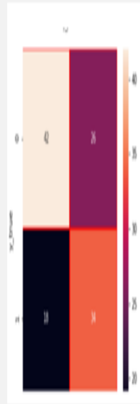
Abnormal	ACL Tear	Meniscal Tear
		

Table 6 Confusion matrix obtained using VGG-19 model.
Abnormal ACL Tear Meniscal Tear.

Abnormal	ACL Tear	Meniscal Tear
		

REFERENCES

[1] Qin, Ruoxi & Qiao, Kai & Wang, Linyuan & Zeng, Lei & Chen, Jian & Yan, Bin. (2018). Weighted Focal Loss: An Effective Loss Function to Overcome Unbalance Problem of Chest X-ray14. IOP Conference Series: Materials Science and Engineering. 428. 012022. 10.1088/1757-899X/428/1/012022.

[2] Ali Hooshmand and Ratnesh Sharma. 2019. Energy Predictive Models with Limited Data using Transfer Learning. In e-Energy '19: Proceedings of the Tenth ACM International Conference on Future Energy Systems, June 25–28, 2019, Phoenix, AZ, USA. ACM, New York, NY, USA, 5 pages. https://doi.org/ 10.1145/3307772.3328284

[3] Bien, Nicholas & Rajpurkar, Pranav & Ball, Robyn & Irvin, Jeremy & Park, Allison & Jones, Erik & Bereket, Michael & Patel, Bhavik & Yeom, Kristen & Shpanskaya, Katie & Halabi, Safwan & Zucker, Evan & Fanton, Gary & Amanatullah, Derek & Beaulieu, Christopher & Riley, Geoffrey & Stewart, Russell & Blankenberg, Francis & Larson, David & Lungren, Matthew. (2018). Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet. PLOS Medicine. 15. e1002699. 10.1371/journal.pmed.1002699.

[4] Francois Chollet; The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 1251-1258

[5] Very Deep Convolutional Networks for Large-Scale Image Recognition Karen Simonyan, Andrew Zisserman.