Intelligent Magnetic Resonance Imaging Scan

I-MRI SCAN

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Table of Contents

Introduction

Why was this study done?

- We wanted to see if a deep learning model could succeed in the clinically important task of detecting disorders in knee magnetic resonance imaging (MRI) scans.
- We wanted to determine whether a deep learning model could improve the diagnostic accuracy, specificity, or sensitivity of clinical experts, including general radiologists and orthopedic surgeons.

Introduction

Why was this study done?

- Deep learning has the potential to provide rapid preliminary results following MRI exams and improve access to quality MRI diagnoses in the absence of specialist radiologists.

- Providing clinical experts with predictions from a deep learning model could improve the quality and consistency of MRI interpretation.

Background

Magnetic resonance imaging (MRI) of the knee is the preferred method for diagnosing knee injuries. . However, interpretation of knee MRI is time-intensive and subject to diagnostic error and variability.. An automated system for interpreting knee MRI could prioritize highrisk patients and assist clinicians in making diagnoses.

. Deep learning methods, in being able to automatically learn layers of features, are well suited for modeling the complex relationships between medical images and their interpretations. In this study we developed a deep learning model for detecting general abnormalities and specific diagnoses (anterior cruciate ligament [ACL] tears and meniscal tears) on knee MRI exams. We then measured the effect of providing the model's predictions to clinical experts during interpretation.

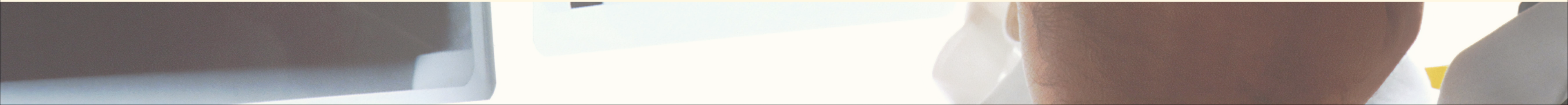
Knee Problems

- ***Anterior Cruciate Ligament (ACL) tear:***

  ACL tears happen when the anterior cruciate ligament is either extended, incompletely torn, or totally torn. The most widely recognized injury is a finished tear.

- ***Meniscus tear:***

  A torn meniscus is one of the most widely recognized knee wounds. Any action that makes you powerfully curve or turn your knee, particularly when putting your full weight on it, can prompt a torn meniscus.



MRI

- Magnetic resonance imaging (MRI) of the knee is the favored technique for diagnosing knee wounds. Be that as it may, translation of knee MRI is timeintensive and subject to diagnostic error and variability.

- MRI is a clinical imaging strategy utilized in radiology to shape an image of the anatomy and the physiological procedures of the body.

- MRI is utilized to analyze how well you reacted to treatment just as distinguishing tears and basic issues, for example, heart failure, brain injury, blood vessel disease, and so forth.

Deep Learning

- Deep Learning: Is a basic class of the meaning of Machine Learning. It is used in many AI applications in various fields. One of its most popular Architecture is the (DNNs) Deep Neural Networks, that is depend on the meaning of dividing big data into many stages and apply all of its components separately.

- Deep Neural Networks (DNNs): it has many architectures like convolution neural network (CNN) and recurrent neural network (RNN) and their architectures.

CNN

- Convolution neural network (CNN): it is layered model processing the depend on multi-layer perceptron (neuron which is building unit in neural network) and it consists of input layer, one or more hidden layers and output layer.

- CNN use a variation of multilayer perceptron's designed to require minimal preprocessing.

- CNN is used in many applications like image classification, image segmentation. it is used in computer vision and to train the models on three stages:
    1. Convolution layer
    2. Pooling layer
    3. Fully connected layers

Methodology

Why about dataset and model?

- Deep learning draws near, in having the option to naturally learn layers of highlights, are appropriate for displaying the intricate connections between clinical pictures and their understandings.
- such methodologies have beaten conventional picture examination techniques and empowered critical advancement in clinical imaging errands, including skin disease arrangement, diabetic retinopathy location, and lung knob discovery.

Dataset

- Our dataset consisted of 1,250 knee MRI exams.

- Divided into training set 1130 case and validation set 120 cases and, is composed as follows:
    - Train Folder.
    - Valid Folder.

Dataset

- Train Folder contain:
  1. Axial (folder contains train axial dataset).
  2. Coronal (folder contains train coronal dataset).
  3. Sagittal (folder contains train sagittal dataset).
  4. train-abnormal.csv (the file contains the result of abnormal cases if positive or negative).
  5. train-acl.csv (the file contains the result of ACL cases if positive or negative).
  6. train-meniscus.csv (the file contains the result of meniscus cases if positive or negative).

Dataset

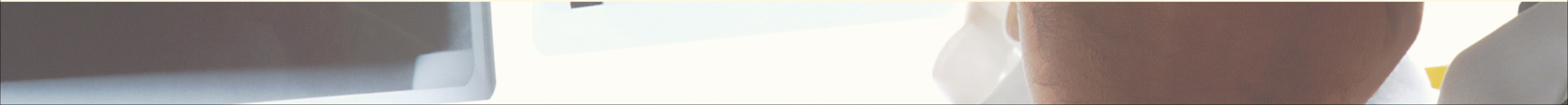
- Valid Folder contain:
  1. Axial (folder contains valid axial dataset).
  2. Coronal (folder contains validcoronal dataset).
  3. Sagittal (folder contains valid sagittal dataset).
  4. valid-abnormal.csv (the file contains the result of abnormal cases if positive or negative).
  5. valid-acl.csv (the file contains the result of ACL cases if positive or negative).
  6. valid-meniscus.csv (the file contains the result of meniscus cases if positive or negative).

Model

- Images were extracted from Digital Imaging and Communications in Medicine (DICOM) files, scaled to 256 × 256 pixels, and converted to Portable Network Graphics (PNG) format using the Python programming language and the pydicom library.

- To account for variable pixel intensity scales within the MRI series, a histogram-based intensity standardization algorithm was applied to the images.

- For each series, a representative intensity distribution was learned from the training set exams. Then, the parameters of this distribution were used to adjust the pixel intensities of exams in all datasets (training, tuning, and validation).

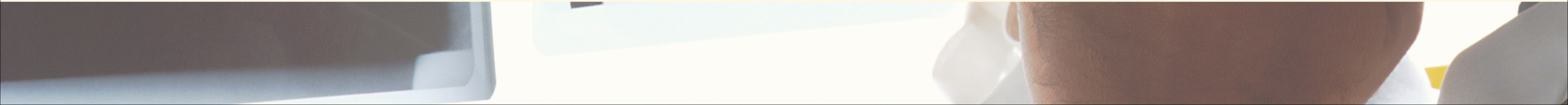


Model

- The primary building block of our prediction system is MRI_alex, a convolutional neural network (CNN) mapping a 3-dimensional MRI series to a probability.
- Training a CNN for image classification from scratch typically requires a dataset larger than 1,130 examples. For this reason, we initialized the weights of the AlexNet.
- We implemented the model in PyTorch to fully take advantage of the capabilities of this framework.

Model

- The training of the 3 models is done through the minimization of the crossentropy loss using Adam optimizer.
- During training the gradient of the loss is computed on each training example using the backpropagation algorithm and the network parameters are then adjusted in the opposite direction of the gradient.
- During training some geometric transformations are applied on the input MRI scans. These transformations are label-invariant. They are meant to bring diversity in the dataset and increase the stability of the model while decrease its tendency to overfitting. This procedure is called data augmentation.



Model

- We are organized the source code in three main classes:

1. Model class:
   a. Define the model architecture in the forward method.
   b. Performs transfer learning by loading pre-trained CNN model.
2. DataLoader class:
   a. Load the MRI dataset and applies data augmentation.
3. Training class:
   a. Instantiates the model, the dataloaders on train and validation sets, the optimizer (Adam), and the loss.
   b. Loops over train data to update model's weights.
   c. Loops over validation data to evaluate the model's performance.

All source code presented on: https://github.com/muhammadtarek98/Graduation-project

GUI

- The GUI consists of name, the blood type and age of patient, then adding the slices for each sagittal, coronal, axial planes then the results will appear for each injury and can transfer the slices to video with extension .mp4 with wanted number of slices per second.

- Future work:
  1. Make this application as a website and mobile application.
  2. Add new features like segmentation using deep learning approach and 3D reconstruction.
  3. Entering more parts are used in MRIs such as the shoulder, spine, etc.

GUI

- We have built our desktop application with PYQT5 where the application can be used easily with different types of users.

- We use OpenCV (open computer vision) library for some features.

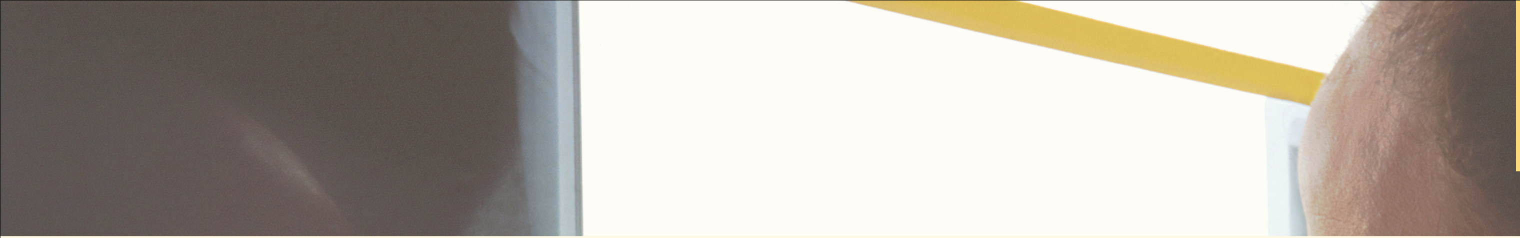
All source code presented on: https://github.com/muhammadtarek98/Graduation-project

Results

- Our deep learning model predicted 3 outcomes for knee MRI exams (meniscal tears, anterior cruciate ligament [ACL] tears, and general abnormalities) in a matter of seconds and with similar performance to that of general radiologists.

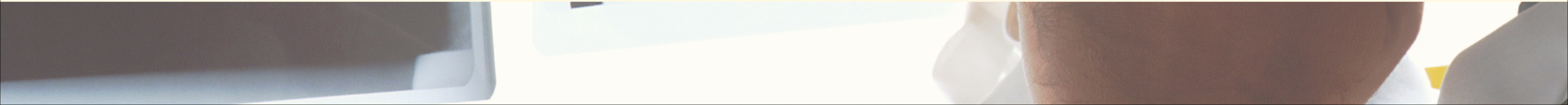
- In detecting abnormalities, there were no significant differences in the performance metrics of the model and general radiologists.

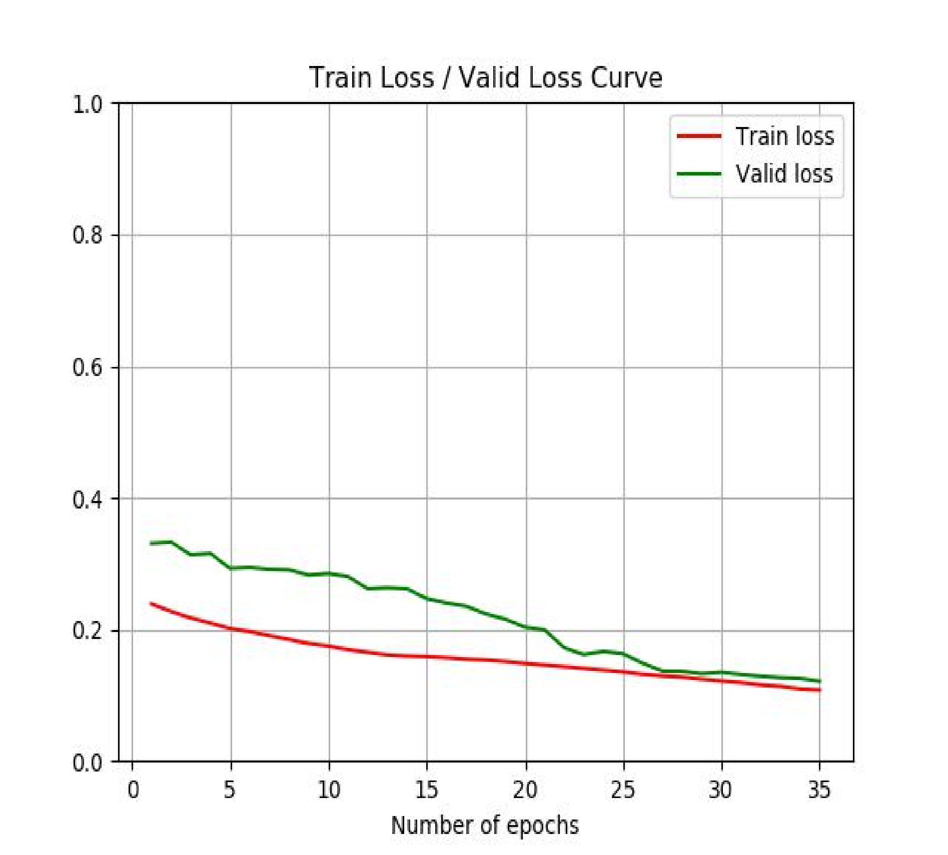
- Our results demonstrate that a deep learning approach can achieve high performance in clinical classification tasks on knee MRI.



Results

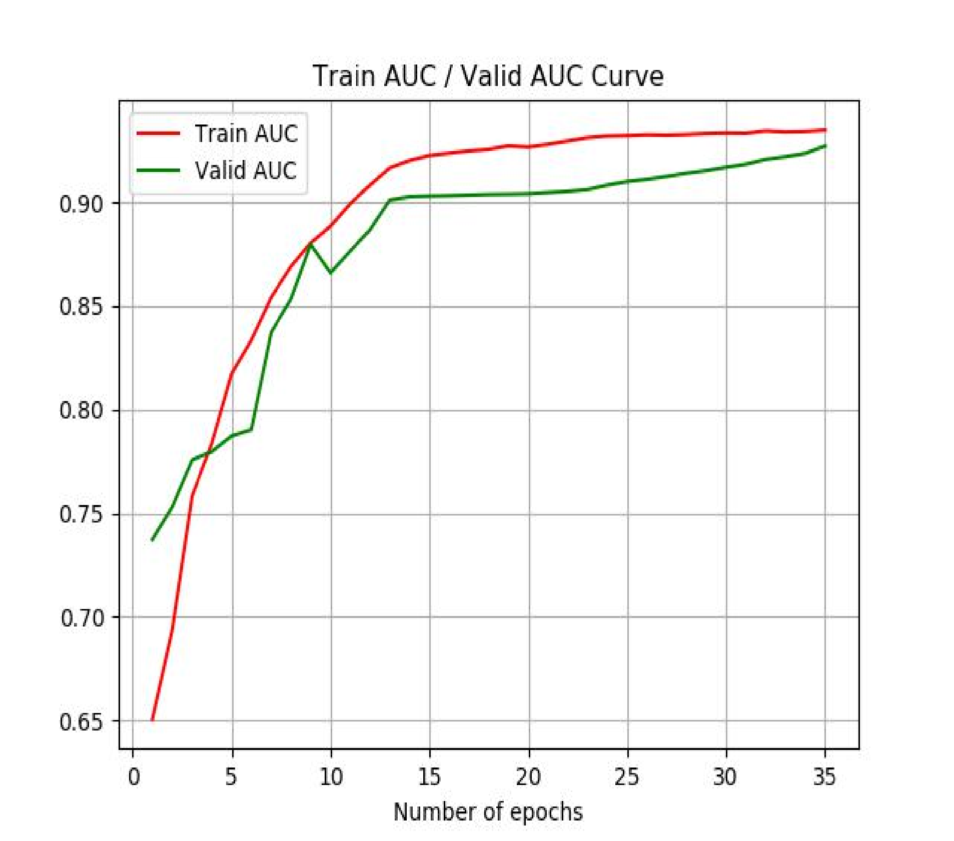
- The model achieved high specificity in detecting ACL tears on the internal validation set, which suggests that such a model, if used in the clinical workflow, may have the potential to effectively rule out ACL tears.
- The MRI model achieved state-of-the-art results on the external dataset, but only after retraining. It remains to be seen if the model would better generalize to an external dataset with more MRI series and a more similar MRI protocol.
- Deep learning has the potential to provide rapid preliminary results following MRI exams and improve access to quality MRI diagnoses in the absence ofspecialist radiologists.





ACL Results:

- Number of epochs = 35
- Time = 3:29:12.627334
- Learning rate=1e-06



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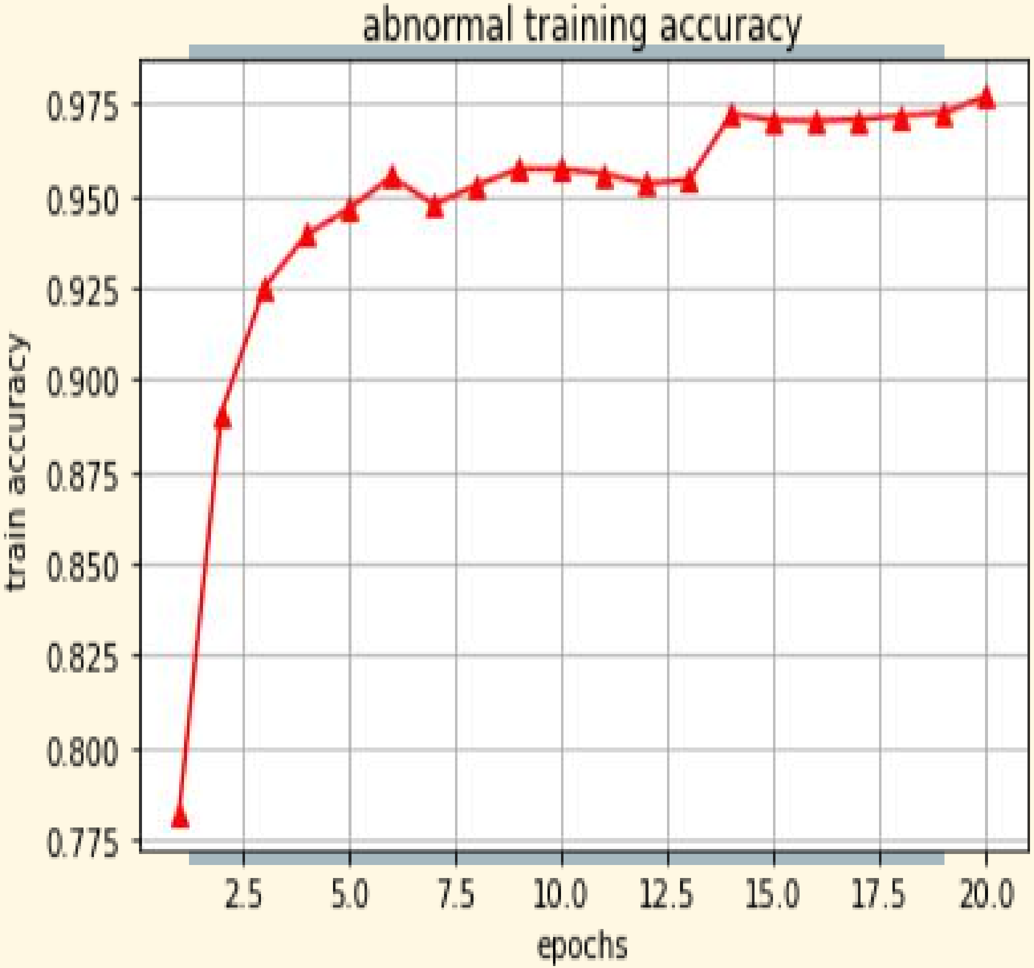
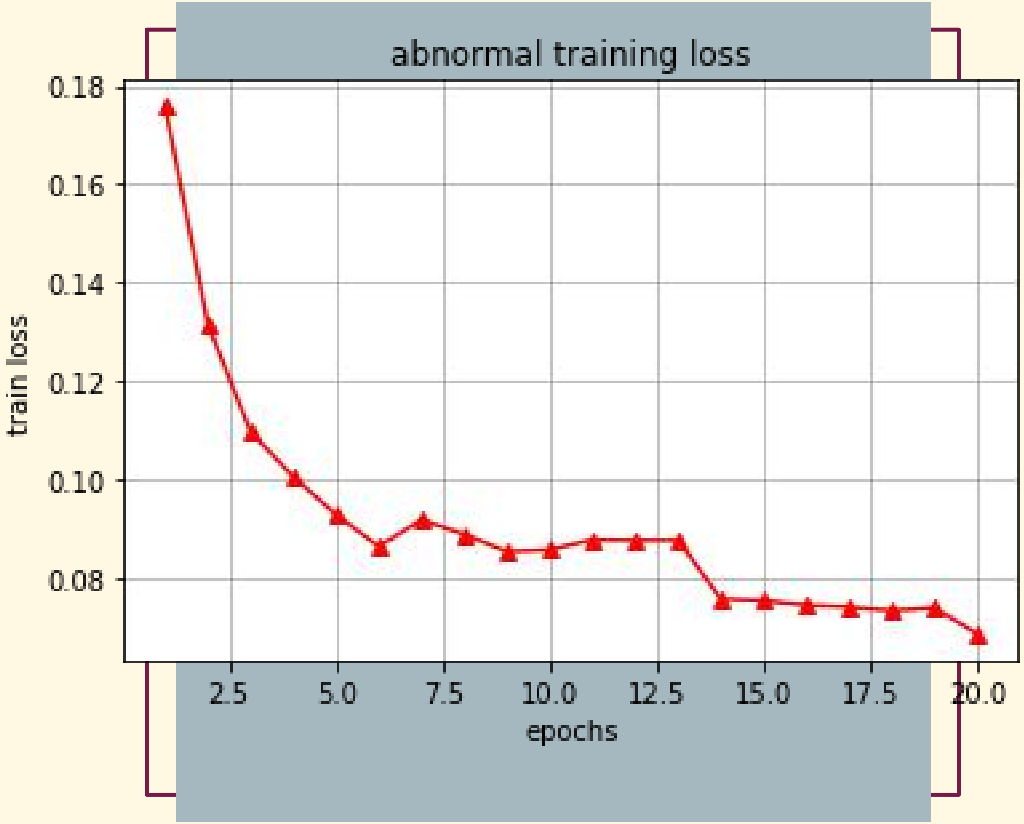


Abnormal Results:

- Number of epochs = 20
- Time = 2:04:11.717334
- Learning rate=1e-05

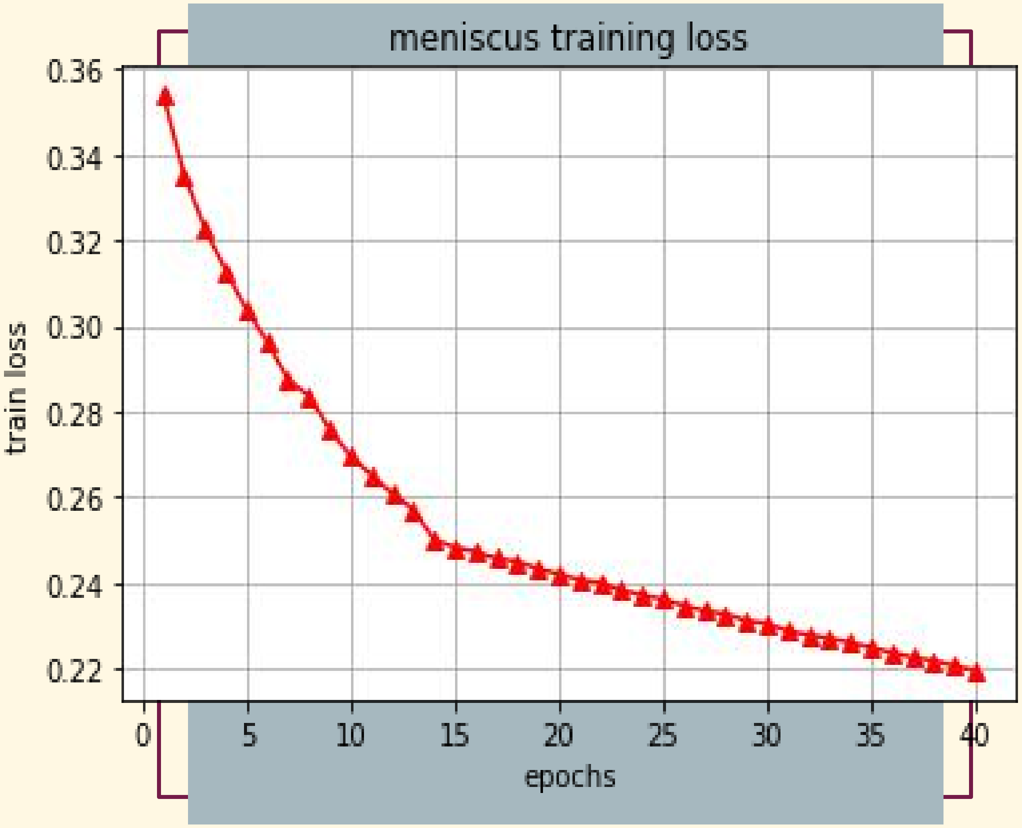


Abnormal Results:

- Number of epochs = 20
- Time = 2:04:11.717334
- Learning rate=1e-05

Meniscus Results:

- Number of epochs = 40
- Time=3:11:35.956819
- Learning rate=1e-06



Meniscus Results:

- Number of epochs = 40
- Time=3:11:35.956819
- Learning rate=1e-06

Results

	Abnormal	ACL	Meniscus
Training accuracy	0.9772	0.9398	0.9365
Training loss	0.0686	0.1085	0.2194
Validation accuracy	0.9478	0.9271	0.8182
Validation Loss	0.1229	0.1217	0.3013

Conclusion

- we classify our data into 3 type of injuries (abnormality, meniscal tear, ACL tear) each type is binary classified. we choose approach Multi-Input Convolutional Neural Network with the transfer learning where it was the best in both training time and results.

- We have written deep learning code in python using PyTorch framework for the build the model, train the model and save the training parameters of the model.

Conclusion

- We have built our desktop application with PYQT5 where the application can be used easily with different types of users.
- We use OpenCV (open computer vision) library for some features.
- The GUI consists of name, the blood type and age of patient, then adding the slices for each sagittal, coronal, axial planes then the results will appear for each injury and can transfer the slices to video with extension .mp4 with wanted number of slices per second.

Thanks

I MRI SCAN team