3D Convolutional Neural Network for Meniscus and ACL Injury Detection

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Abstract. Anterior cruciate ligament (ACL) and meniscus tears are among the most common knee injuries, often occurring simultaneously, especially among athletes. They both play a critical role in ensuring adequate stability and controlling movement in the knee, so the accurate diagnosis of any abnormality is crucial. In this paper, we propose the implementation of a 3D Convolutional Neural Network (CNN) model to analyze MRI data obtained from knee scans across the axial, sagittal, and coronal planes. The main objective of the model is to detect any abnormalities associated with the meniscus and/or the ACL. To do so, we developed a multi-label classification model integrating a *sigmoid* activation function within the output layer and employing compiled binary cross-entropy. Using a dataset of 1130 knee scans, the 3D CNN model achieved an accuracy of 69.68% and AUC score of 0.8221, which was then compared against the average AUC values obtained by the 2019 finalists of the Stanford MRNet challenge, a competition aimed to develop models for automated interpretation of knee MRI's. In addition, we explored as a side project the possibility of reformatting the 3D data images into an extended 2D image collage framework to determine if it was possible to achieve a better training time and overall model performance.

Keywords: Knee injury classification · 3D MRI · 3D convolutional neural network.

1 Introduction

The anterior cruciate ligament (ACL), positioned centrally within the knee joint, is one of the four major knee ligaments and it facilitates rotational as well as forward movements of the shin bone by connecting the femur to the tibia.

Composed of dense connective tissue, it resists anterior tibial translation and rotational forces within the knee joint [1]. ACL injuries result primarily from excessive stretching or complete tearing and are the most common type of knee ligament injuries, specifically among athletes [2].

The meniscus, on the other hand, is a cartilaginous structure in the knee responsible for shock absorption, as well support against tension and torsion [3]. Meniscus injuries are often diagnosed alongside ACL injuries and they are typically caused by abrupt movements, or twisting motions, hence very common among athletes as well. Meniscus injuries can result from trauma or age-related degeneration [4].

Machine learning can assist with diagnosis for effective treatment and Convolutional Neural Networks (CNNs) are particularly adept in image processing compared to other neural networks. In this course project, we built a 3D CNN to predict, classify, and diagnose ACL tears, meniscus tears, knee abnormalities, and any combinations of the above diagnoses. Our 3D CNN model was implemented in TensorFlow, and takes inputs of 3D knee MRI GIFs as training dataset. The dataset was split into training, validation, and testing sets. As a side project, we also attempted a 2D "collage" CNN approach [5], which has much lower computational resource requirements, which is further discussed in the Accomplishments section.

1.1 Report Map

The remaining of the report is structured for clarity as follows:

1. **Materials:** Description of our dataset used for training, validation, and testing.
2. **Methods:** An overview of our 3D Convolutional Neural Network, and various techniques utilized to optimize fitting.
3. **Results:** Here we present our model plots and metrics to demonstrate our model's performance.
4. **Accomplishments:** A summary of further attempts with 2D collaging CNN to improve model performance.
5. **Contributions:** A list of individual contributions toward the course project.
6. **Conclusion and Discussions:** A review and analysis of our experimental results as well as final remarks regarding our project.
7. **Future Work:** An outline of suggested future improvements and research of the model.
8. **Acknowledgements:** Here we acknowledge the important resources and individuals that contributed to our course project.
9. **References:** A list of all the articles, journals, websites, and any additional sources we consulted.

2 Materials

2.1 Dataset

The dataset used for the study was accessed from the Stanford Machine Learning Group, which contains 1370 knee MRI exam results gathered at the Stanford University Medical Centre.

The data contains 1104 (80.6%) abnormal exams with 319 (23.3%) ACL tears, 508 (37.1%) meniscal tears, and 194 (38.2%) with ACL tears coincidental with meniscal. Due to the large proportion of abnormal exams, the dataset is imbalanced with respect to healthy knees, which in the context of our study refers to knees showing no abnormalities, a point which will be mentioned later in the Results section. Each knee MR exam contains three GIFs in the NumPy file format, each along three planes: coronal, axial, and sagittal. The exams were separated into training set (1130), and validation set (120) by Stanford. In addition to the GIFs, the data also contained CSV files for each exam, storing a binary value indicating the existence of injuries (ACL, meniscal, abnormal) as corresponding labels, where labels are 1 if injuries are diagnosed, 0 otherwise.

Moreover, we partitioned the Stanford training dataset and labels into our own training set (70%), validation set (20%), and testing set (10%), as listed in Table 1. The Stanford dataset distribution can be seen in Table 2. The deep learning model is trained using the training set and its performance during training is assessed with the validation in order to adjust specific parameters. Upon completion of training and validation, the testing set is employed to evaluate the model's performance.

Table 1: Partitioned dataset distribution.

Partition	Percentage	Size
Training	*70*	791 exams
Validation	*20*	226 exams
Testing	*10*	113 exams
Total	*100*	1130 exams

Table 2: Stanford dataset distribution.

Pathology	Percentage	Size
Abnormality	*80.8*	913 exams
ACL tear	*18.4*	208 exams
Meniscal tear	*35.1*	397 exams
ACL and meniscal tear	*11.1*	125 exams
Total	*100*	1130 exams

3 Methods

3.1 Overview

Utilizing a series of 2D images across different planes like axial, sagittal, and coronal, knee MRI's can provide a detailed 3D view of the knee structure.

By implementing a 3D Convolutional Neural Network (CNN) we can leverage the spatial dimensionality in MRI's to analyze the entire image sequence, especially through the use of 3D kernels [6]. In fact, unlike in 2D CNN, the use of 3D kernels allows the linking of information from neighbouring slices (ie. scans) [7] across the various planes, enabling the detection of more complex 3D patterns and characteristics within the knee.

In our research, we developed an ML model to analyze sequences of 3D MRI knee scans to identify injuries in the ACL and/or meniscus, as well as general knee irregularities. More specifically, the model predicts three categories: ACL injuries, meniscus injuries, and overall knee abnormalities. Through the use of the *sigmoid* activation function for binary cross-entropy in the final layer, the model is able to detect and categorize ACL and meniscus anomalies, providing valuable insights into the patient's knee structure.

3.2 Preprocessing

To ensure a consistent slice count across the axial, sagittal, and coronal scans we applied padding, which involves adding extra slices to have a uniform size across the data. More specifically, we determined that 30 slices yielded the best results, as well as a manageable computation time, therefore we padded the data containing fewer than 30 slices and cropped those over 30 to achieve a uniform 30-slice count across all three planes.

In addition, given that the objective of the model was to recognize patterns within the subregion of the knee containing the ACL and meniscus, we cropped the input scans to 160 × 160, in order to focus on the knee subregions of interest. To do so, we used the *crop_center* function, which extracted the central region of each scan and was implemented on the slides in batches of 10, for memory handling purposes.

3.3 Data Augmentation

The augmentation process for the MRI scan slices included two main transformations: random rotation and horizontal flipping.

Random rotation reorients the slices by multiples of 90 degrees, ensuring that the model is exposed to various image orientations of the knee scans and, as a result, improving the model's robustness.

Horizontal flipping, on the other hand, mirrors scan slices along the width axis, further improving the model's adaptability to different spatial orientations of the scans. Given that ACL and meniscus tears are identified by specific characteristics, the augmentation process did not include shearing, to avoid distorting the scans and negatively affect the integrity of the data.

3.4 3D CNN Model

To conduct the model's training, we used a computer with an NVIDIA GeForce RTX 2060 GPU. The data was analyzed in batches of 10 by implementing the model with the library TensorFlow using Python (version 3.8.6). Early stopping criteria based on validation loss were implemented to prevent the model from overfitting and set to a limit of 15 epochs.

The architectural design of the 3D Convolutional Neural Network (CNN) in this study was largely influenced by Guida et al. [7]. Initially, a convolutional block was created, incorporating 32 kernels of size 7 × 7 × 7 and implementing batch normalization to streamline data, alongside Rectified Linear Unit (ReLU) activation for better data interpretation. Later steps included applying a MaxPooling layer for data compression and integrating two sets of residual blocks using 3D convolutions. Additionally, a dropout layer set at a 50% rate was used to prevent the model from fixating on specific details.

The model ended with a GlobalMaxPooling3D layer to extract relevant data features, transitioning into a densely connected layer with 1024 units for further data combination, reinforced by an extra dropout layer. Its output layer included three nodes using the *sigmoid* activation function to calculate probabilities of the three categories: ACL injury, meniscus injury, knee abnormality. Moreover, the model's training used the Adam optimizer with a value of 0.001 to minimize binary cross-entropy loss.

4 Results

We fitted our model with 15 epochs, which is the number of times the model iterates through the entire training dataset. We also passed in our validation dataset, and saved our training records inside an object declared "history". To gauge our model's performance, we evaluated it with four TensorFlow metrics: Precision, Recall, Accuracy, and AUC.

In the context of our project, Precision is a measure of the model's accuracy in correctly identifying meniscus tears, ACL tears, and abnormal knees among the predicted positive scans, and it is calculated as follows:

$$Precision = \frac{TP}{TP + FP}. \tag{1}$$

where TP = True Positives, FP = False Positives.

Recall, on the other hand, measures the model's effectiveness in detecting meniscus tears, ACL tears, and abnormal knees correctly, hence the fraction of actual injuries correctly diagnosed and it is measured as:

$$Recall = \frac{TP}{TP + FN}, \tag{2}$$

where FN = False Negatives. It is worth mentioning that for medical diagnoses, Recall is a more important metric than Precision and there is trade-off between the two metrics. The reason for this consideration is that detecting (and potentially curing) false positives is usually less detrimental than not correctly identifying true positives.

Accuracy is the ratio between the total number of correct predictions and the total number of predictions, measured as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{3}$$

which is the fraction of how many diagnoses our model correctly predicted, including "healthy".

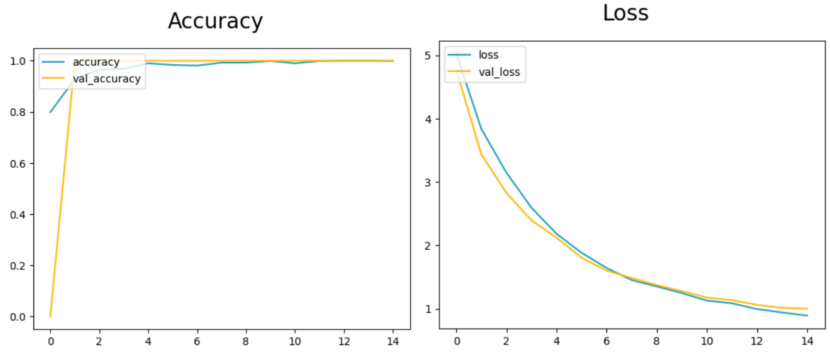
Lastly, AUC (Area Under Curve) measures the model's ability to distinguish healthy knees and those with a meniscus injury, ACL injury or general abnormalities across varying threshold values. A higher AUC value indicates that our model can successfully distinguish between a healthy knee and an injured one, within the three classes: ACL, meniscus, or abnormal.

The summary of our metric values are included in the Table 3 below.

Table 3: Evaluation results.

Precision	Recall	Accuracy	AUC
0.6968	0.7397	0.7493	0.8221

From the classification metrics, the model's overall predictions were 74.93% (Accuracy) correct, with 69.68% (Precision) of the model's positive predictions correct. In the figures below, we also plotted our overall training loss and validation loss, as well as our training and validation accuracy saved in our model history.



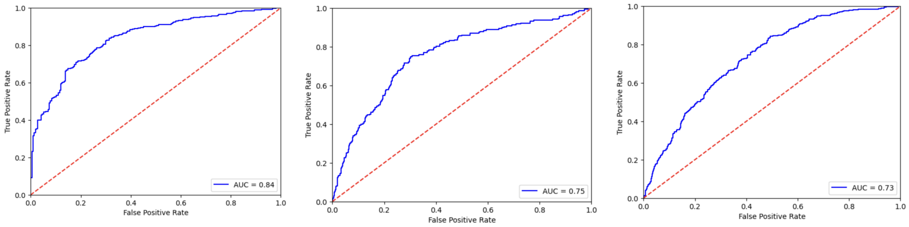
(a) Accuracy vs. Epoch.

(b) Loss vs Epoch.

Fig. 1: Accuracy increase and Loss decrease over 15 epochs.

As Fig.1 shows, both the training and validation loss decreased over time, indicating that our efforts with Regularisation and Dropout were successful in rectifying overfitting.

For a more detailed illustration of our model's classification performance, we plotted the individual ROC curves of our three pathologies, as shown in Fig.2, with their respective optimal thresholds in Table 4 below.



(a) ROC curve for abnormal classification.

(b) ROC curve for ACL injury classification.

(c) ROC curve for meniscus injury classification.

Fig. 2

Table 4: Optimal threshold for maximum AUC.

	Abnormal	ACL	Meniscus
Threshold	0.6363	0.4486	0.5028

4.1 Negative Results

Despite our efforts to develop a reliable model, there were some negative results that should be considered. In fact, the model's evaluation scores (74.93% accuracy, 69.68% precision, and a recall rate of 0.739) indicate that there are certain shortcomings worth addressing.

False Positives. The precision score of 69.68% indicates that approximately 30% of the positive predictions made by the model were incorrect. These false positives, where the model incorrectly classified instances as ACL injuries, meniscus injuries, or general knee abnormalities when they were not present, is an important factor to consider should the model be used for actual patients' diagnoses.

False Negatives. An arguably more critical factor to consider within the context of medical diagnoses is False Negatives, where our model failed to detect actual instances of knee injuries. Despite achieving a Recall rate of 0.739, indicating the model's ability to detect 73.9% of true positive cases, the 26.1% of undetected knee injuries could potentially lead to more serious medical consequences. In fact, an undiagnosed condition gone untreated could be potentially more severe than an incorrectly diagnosed condition (False Positive).

5 Accomplishments

5.1 3D CNN

Throughout our project of developing a 3D CNN model to detect knee injuries, our team encountered a multitude of challenges to overcome.

One of the main components of our project involved creating a user-friendly website to interact with the knee injury detection model and obtain a diagnosis. Since none of the team members had any experience building a website, we had to learn to use CSS, HTML, and JavaScript, which allowed us to create a website that we eventually hosted on Heroku.

The most challenging task involved in the website development was being able to run Python scripts from JavaScript, in order to connect the website to the model, which after many trials and errors we were able to accomplish. The heart of our project was undoubtedly the 3D CNN model, which was also completely new to all of us.

Firstly, before even being able to work on the model, we had to learn how to properly load data, comprising three distinct NumPy files, each with scans across various planes and with varying slice counts. The preprocessing stage required us to think about how to handle these different data structures.

After succeeding in loading and preprocessing, we had a chance to learn how to properly use hyperparameters and layer architectures to build our model, which was a rather challenging task we eventually overcame with extensive backgrounf research on 3D CNN models and tips from the TA's and Professor.

5.2 2D Collage Model

Inspired by a research paper co-authored by our professor, Dr. Ghassan Hamarneh [5], we attempted, as a side project, to develop an image collage based deep convolutional neural network (CNN) approach to detect knee injuries. In the paper [5], it demonstrated that the 2D collaging CNN outperforms a 3D CNN, therefore we wanted to explore whether it would perform better than our model.

The approach involved transforming 3D GIF's volumes into 2D 4 × 4 grids of 16 slices, which was selected based on the GIF with the smallest number of slices (17) and rounded down to the nearest perfect square. These 16 slices were specifically chosen from the middle of the GIFs in an attempt to preserve the integrity of the data while reducing computational complexity. However, for future work, larger grids could be considered, as our limited grid size might have resulted in the loss of important information regarding the knee structure GIFs with more slices.

To focus on the knee subregions of interest and reduce computational load, the slices were cropped to 128 × 128 around the center of the images. The collages were systematically arranged into a 1 × 3 array across all three axes, or into a single 512×512×3 RGB image (RGB stack), with each channel being composed of a single grid from one of the three axes (axial, coronal, sagittal) corresponding to the same sample, laying the groundwork for subsequent model developments.

For model creation, TensorFlow Keras facilitated the stacking of labels (ACL, meniscus, abnormal) into a tuple, serving as the image data's labels. We tested various models, more specifically binary, multi-class and multi-label.

The binary model was an initial trial in which we tried to only distinguish meniscus tears from non-meniscus tears. However, this model suffered from over fitting and poor generalization, achieving a best validation accuracy of approximately 70% during training with some over fitting seen in the binary cross-entropy loss curves, using a perfectly balanced training dataset. This result might be due to the relatively small tear sizes in comparison to the entire image within the 4 × 4 grids and a insufficiently deep model architecture.

Two other approaches involved multi-class and multi-label models, where we divided the labels into seven classes covering all the possible diagnoses combinations, as shown in Table 5 or stacking the labels into a 1×3 tuple of labels as done in our 3D CNN model respectively.

Table 5: Labels used for the 2D multi-class collaging model.

Label Number	Label Type
1	healthy
2	ACL tear
3	Meniscus tear
4	Abnormal
5	ACL and Meniscus tear
6	Meniscus tear and abnormal
7	ACL tear and abnormal
8	ACL tear, meniscus tear and abnormal

Despite efforts to balance the dataset, overfitting persisted, leading to poor performance on the validation dataset. For the multi-class as well as the multi-label model, we think that just like the binary model, further investigation into automated hyper-parameter tuning and architecture construction might mitigate overfitting and improve the model's performance. Despite an inability to create a functional model to compare to the 3D CNN, we have compiled the tools into an open source GitHub repository, making them easy to apply to another dataset to continue this work in the future.

6 Contributions

- **Jack Weatherbe**: Researched potentially viable 3D CNN models to analyze our data with the rest of the team. Did extensive background research on the model we ultimately chose. Preprocessed and augmented the data to adequately train the model and implemented the key components of the model whose functions and parameters were later adjusted with the help of the team. Overviewed the drafting of the report to ensure that the model architecture and findings were accurately reported.
- **Yvonne Wang**: Developed from scratch a website to ulpoad MRI scans detectable by our model. Connected the backend to the front end so the uploaded images could be connected and analyzed by our ML model. Helped Jack train his model by suggesting a few changes (ie. change validation loss

parameter). Reviewed the final report to ensure it accurately reported our findings. Routinely participated in group meetings to ensure other team members were aware of the progress in building the website.

- **Daniel Sloseris**: Extensively researched viable 2D CNN models as an alternative solution to the 3D CNN model. Developed and tested a 2D collaging model as suggested by the Professor to determine if it would yield a better performance than the 3D model. Routinely briefed teammates on his progress and technical issues related to the 2D collaging project, so that they were aware of the results and they could faithfully document them. Overviewed and participated in writing of the 2D collaging mode sections in the report.
- **Edoardo Rinaldi**: Did extensive research on potential project topics and found the dataset we eventually used for the project. Contacted various research groups to ask for their datasets and information regarding their project. Worked alongside Yvonne in the website development, cleaning up the code and adjusting a few UI features. Routinely participated in group meetings to document the technical progress of every member in order to accurately document it in the final report. Worked alongside Thomas to do background research on 2D and 3D models, as well as ours specifically in order to draft the final report.
- **Thomas Lin**: Did background research alongside Edoardo on various studies in knee-related issues to determine a viable 3D CNN model to implement in our project. Routinely documented Daniel's findings, technical issues and progress to adequately report them in our final paper. Participated in group meetings to take notes on other members' progress, in order to document it in the final report.

7 Conclusion and Discussions

Our project aimed to detect knee injuries, more specifically ACL tear, meniscus tears and general knee abnormalities. The 3D CNN model we built yielded a 0.8221 AUC value, which falls slightly short of the AUC value (0.837) obtained by the sixth ranked team from the Stanford MRI Competition [8].

One main challenge that is crucial to take into consideration is our skewed data. More than 80% of our data had some sort of knee abnormality, whether in the form of an ACL injury, meniscus injury or general knee abnormality, which resulted in our data being unbalanced. Since the model was trained on a dataset containing primarily abnormalities, it is not unreasonable to conclude that it might have learnt to generalize knee irregularities even among healthy patients, leading to a higher number of False Positives.

Similarly, given the limited percentage of healthy knee scans, the model is likely to not have learnt in depth the characteristics of a healthy knee, leading to a higher number of undetected cases (False Negatives). This was partially rectified by implementing dropout, regularisation, and data augmentation. Through trial and error, we found that the *sigmoid* activation function and binary cross-entropy function lead to the best results.

In conclusion, we built a convolution neural network that performs classification on MRI 3D images to detect ACL and meniscus abnormalities with a 74.93% Accuracy. Although these results are not consistent enough yet for safe diagnoses of knee injuries, we anticipate that future improvements to the model can greatly increase the efficiency of the procedural work of diagnosing knee injuries.

8 Future Work

8.1 3D CNN

Future work should be focussed on improving the performance of our 3D CNN model for knee injury detection.

More specifically, the model architecture could potentially include more convolutional layers and perhaps deeper convolutional blocks with varying kernel sizes. In doing so, the model might be able to detect more subtle details within the GIF's that our current model was not able to.

Moreover, the dataset to train our model should ideally include more variety of knee scans, more specifically a larger percentage of healthy knee images. We think that by having a larger dataset, coupled with introducing more healthy knee data, could help the model better recognize the traits of a healthy knee structure and reduce the number of false positive and false negative detections.

8.2 2D Collage

Although the 2D Collage model was a side project, we would still like to mention some improvements that can be done to refine the model.

More specifically, despite tuning some automated hyper-parameters (for learning rate), future work should involve more extensive investigation of automated hyper-parameter tuning and automated architecture construction to optimize validation accuracy and improve the model's ability to generalise.

As the soft tissue abnormalities make up a small portion of each slice, and sometimes only a few slices of an entire GIF, collaging the images presented a challenge for the CNN. This is due to the fact that abnormalities made up an even smaller portion of the entire collaged image, furthering the need for improved model architecture and grid size experimentation to pick up more intricate details.

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We would like to sincerely thank our professor, Dr. Ghassan Hamarneh, for his guidance and valuable insights. His paper served as the foundational inspiration for our attempt to construct a 2D collaging model.

Our sincere appreciation extends to our teaching assistants, Ben Cardoen and Kumar Abhishek, who patiently assisted us during the model implementation by providing resources and insights on how to resolve technical issues.

We are also indebted to the Stanford MRnet group for their generosity in providing the data which formed the basis of our project.

The support and assistance from these individuals and groups have been instrumental in the completion of our project, and we are immensely grateful for their contributions.

Appendix

For more details on how to execute our code, please refer to the README.md on GitHub.

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