KNEE INJURY CLASSIFICATION

Project Report
DS5220: Supervised Machine Learning and Learning Theory
Krishnan Narayanan
Neha Reddy Palnati
Vinisha Sunkara
GitHub

Contents

1 ABSTRACT **1**

2 OVERVIEW **2**
2.1 What is the Problem? 2
2.2 Why is this Problem Interesting? 2
2.3 What is the approach you propose to tackle the problem? 2
2.4 What is the rationale behind the proposed approach? 3
2.5 What are the key components of the approach and results? 3

3 Experiment Setup **4**
3.1 Dataset 4
3.2 Implementation and Model Architecture 4

4 Results and Discussions **5**

5 Conclusion **5**

1 ABSTRACT

The project focuses on predicting knee injuries using MRI images from the Stanford MRNet dataset. The dataset includes MRI scans categorized by three distinct planes: axial, coronal, and sagittal, each corresponding to specific types of knee injuries such as abnormalities, anterior cruciate ligament (ACL) tears, and meniscus damage. A deep learning approach is employed, where a separate ResNet-18 model is trained for each MRI plane to extract relevant features from the scans. The features from all three models are then combined into a comprehensive feature vector, which is used to train a logistic regression classifier for final injury prediction. To enhance user interaction and accessibility, a Streamlit dashboard is integrated, allowing users to upload MRI images and receive real-time predictions of knee injuries. The performance of the model is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and AUC. The results demonstrate the potential of using multi-plane MRI scans, deep learning techniques, and user-friendly interfaces to improve knee injury diagnosis, providing a framework for further development of automated medical image analysis tools.

2 OVERVIEW

2.1 What is the Problem?

The problem addressed by this project is the automated diagnosis and classification of knee injuries using MRI scans. Knee injuries, including common conditions such as ligament tears (e.g., ACL injuries), meniscus tears, and various other abnormalities, are prevalent in both athletic and non-athletic populations. These injuries require accurate and timely diagnosis for effective treatment, as delayed or incorrect diagnoses can lead to worsened outcomes. Currently, the diagnosis process largely depends on the manual review of MRI scans by trained radiologists, which is not only time-consuming but also prone to human error. Given the increasing demand for radiological expertise and the limitations in healthcare resources, the need for an automated system that can assist in knee injury diagnosis becomes critical.

The primary challenge is that knee injuries can vary in severity and location, with subtle differences that require careful inspection. Accurately, interpreting these images requires significant expertise, and some injuries might be overlooked if a thorough review is not conducted. Furthermore, variations in image quality due to factors such as the MRI machine used or patient positioning can make it more difficult.

2.2 Why is this Problem Interesting?

This problem is of significant interest due to its potential to address key challenges in the assessment of knee injuries. Knee injuries, such as ligament tears and meniscus damage, are common, especially among athletes and active individuals. Traditional diagnosis of these injuries involves manual interpretation of MRI scans by radiologists, a process that can be time-consuming, subjective, and prone to human error. Automating this process through deep learning models can significantly improve diagnostic efficiency, reduce the workload on healthcare professionals, and provide faster, more consistent results. This is particularly valuable in regions with limited access to trained radiologists, where an automated system could help bridge the gap and ensure timely and accurate diagnoses.

The use of deep learning, in analyzing medical images presents an exciting opportunity to enhance the capabilities of healthcare systems. MRI images offer detailed anatomical information, but interpreting these images manually can be challenging due to the complexity and subtlety of some injuries. By leveraging deep learning models, this project seeks to extract meaningful features from multi-planar MRI images, improving the ability to detect and classify injuries. The challenge of integrating features from multiple planes of MRI data highlights the innovative nature of this work, aiming to create a more comprehensive diagnostic tool. Beyond improving diagnostic accuracy, this project holds promise for broader applications in the field of medical imaging.

2.3 What is the approach you propose to tackle the problem?

The proposed approach to tackle the problem of knee injury diagnosis from MRI scans involves a combination of deep learning for feature extraction and machine learning for classification. Initially, MRI images are preprocessed to select the middle slice from each scan, resize the images, and normalize them to ensure consistency across the dataset. This preprocessing step focuses the model on the most informative slice while ensuring that all images are of the same size, which is crucial for effective model training. Data augmentation techniques are also applied to increase the robustness of the model and improve its ability to generalize to new, unseen data.

For feature extraction, the ResNet-18 model, a convolutional neural network (CNN), is fine-tuned for single-channel MRI images. ResNet-18 is chosen for its deep architecture, which allows it to capture complex patterns in images through residual connections. Separate ResNet-18 models are trained for each MRI plane—axial, coronal, and sagittal—allowing the model to focus on the unique features present in each plane and provide a more comprehensive understanding of the knee injury. These models are trained on the respective images to extract the most relevant features for classification.

Once the features are extracted from each of the three MRI planes, they are combined into a single feature vector. A logistic regression model is then trained on this combined feature set to classify the type of knee injury, such as ACL tears, meniscus damage, or abnormalities. Logistic regression is chosen for this fusion step because it is a simple yet powerful model that can handle high-dimensional feature spaces effectively.

It also allows for easy interpretation of results, which is important in clinical settings where transparency is critical.

The final model is evaluated using a set of standard classification metrics, including accuracy, precision, recall, F1 score, and AUC (Area Under the ROC Curve). These metrics provide a comprehensive view of the model's performance on a validation set, helping to assess how well it generalizes to new data. Additionally, the approach is supplemented with a Streamlit dashboard, providing an interactive interface for healthcare professionals to upload MRI scans and receive real-time injury predictions. This feature aims to make the model accessible for practical use in clinical environments, offering fast and accurate decision support for medical professionals.

2.4 What is the rationale behind the proposed approach?

The rationale behind the proposed approach is based on the success of deep learning in image classification tasks, particularly for medical images. ResNet-18 is chosen for its ability to handle complex image patterns due to its deep architecture and residual connections. This approach is also motivated by the idea of combining features from multiple planes to capture the full spectrum of knee injuries. Previous studies have used deep learning for MRI image classification, but our approach differentiates itself by focusing on three distinct MRI planes, using a fusion model (logistic regression) to combine the extracted features, and implementing a Streamlit dashboard for practical deployment. This user-friendly interface allows healthcare professionals to interact with the model, making it more accessible in clinical settings.

2.5 What are the key components of the approach and results?

The key components of the approach involve a combination of deep learning for feature extraction and machine learning for classification. Here is a breakdown of the key components:

Key Components of the Approaches

- Preprocessing: Prepared MRI scans by selecting the middle slice, resizing, normalizing, and augmenting data to ensure consistency and enhance model performance.
- ResNet-18 Models: Trained separate ResNet-18 models for axial, coronal, and sagittal planes to extract unique features from each view.
- Feature Fusion: Combined features from all planes using logistic regression for accurate injury classification.
- Interactive Dashboard: Built a Streamlit dashboard for real-time predictions and easy accessibility for healthcare professionals.
- Streamlit Dashboard: The model is integrated with a Streamlit dashboard, offering an interactive interface for healthcare professionals. This allows medical practitioners to upload MRI scans, visualize predictions, and gain insights into potential knee injuries, making the system more practical for real-world applications.

Key Components of the Results

- Achieved accurate predictions for knee injuries based on MRI scans, validated using metrics like accuracy, F1 score, and AUC.
- Demonstrated the feasibility of combining CNN-based feature extraction with logistic regression for robust multi-plane MRI analysis.
- Limited by dataset diversity and computational requirements, suggesting areas for future improvement.

3 Experiment Setup

3.1 Dataset

The dataset that we used in the project is the Stanford MRNet dataset, which contains MRI scans of knees captured in three views: axial, coronal, and sagittal. These different perspectives provide valuable insights into the knee's structure and help identify specific injuries or conditions. The dataset is designed to assist in diagnosing abnormalities, ACL tears, and meniscus tears.

- MRI Views: Each knee scan includes three views—axial, coronal, and sagittal—ensuring comprehensive coverage of the knee anatomy.
- Data Format: The images are stored as NumPy arrays, allowing for efficient processing and analysis.
- Labels: Each scan is labeled for three potential issues:
  Abnormality: Detects any unusual features in the scan.
  ACL Tear: Identifies injuries to the anterior cruciate ligament.
  Meniscus Tear: Highlights damage to the knee meniscus.
- Dataset Insights: The dataset includes 1,200 training scans and 300 validation scans, offering a solid foundation for model training and evaluation.
- Each scan contains multiple slices, typically with dimensions like 254x254 pixels per slice.
- The dataset has an imbalanced label distribution, with certain conditions being less common, which poses challenges for classification and evaluation.
- This dataset provides a rich resource for building models to predict knee injuries while highlighting the need for thoughtful handling of imbalanced data and multi-view analysis.

3.2 Implementation and Model Architecture

This project leverages deep learning to predict knee injuries by analyzing MRI scans from three anatomical planes: axial, coronal, and sagittal. Each plane offers a unique perspective, providing critical insights into the knee's structure. The pipeline begins with preprocessing, where the middle slice of each 3D MRI volume is selected for analysis. These slices are resized to 224x224 pixels, converted to tensors, and normalized with a mean of 0.485 and a standard deviation of 0.229 to standardize input data for model training. Augmentations, such as resizing and tensor conversion, ensure the robustness and consistency of the input data.

For feature extraction, ResNet-18 models pre-trained on ImageNet are fine-tuned for each plane. The network architecture is adjusted to accept single-channel grayscale images, and the final fully connected layer is modified to output predictions for one class, focusing on binary classification tasks for abnormalities, ACL tears, and meniscus injuries. The models are trained using the Binary cross entropy with Logit Loss function, optimized with Adam at a learning rate of 1e-4, for 10 epochs. This fine-tuning process enables the models to extract plane-specific features critical for injury detection.

Once the ResNet-18 models are trained, feature embeddings are extracted from each plane for the validation set. These embeddings, representing the learned spatial patterns from the MRI scans, are concatenated to form a combined feature vector. This comprehensive feature representation, encompassing insights from axial, coronal, and sagittal planes, is used to train a logistic regression model. The logistic regression classifier aggregates the extracted features and predicts the final injury type, leveraging the complementary information from all three planes.

The models and their outputs are validated using metrics such as accuracy, precision, recall, F1 score, and AUC. The trained ResNet-18 models are saved as .pth files, while the logistic regression model's coefficients and intercepts are stored as .npy files for later use. This streamlined pipeline showcases an effective integration of advanced preprocessing, model fine-tuning, and feature fusion, offering a robust framework for knee injury prediction and paving the way for scalable applications in medical imaging diagnostics.

4 Results and Discussions

The model demonstrated impressive results on the validation dataset, achieving an accuracy of 87.50, precision of 86.83, recall of 87.50, and an F1-score of 86.70. Its ability to distinguish between different knee injuries, such as abnormalities, ACL tears, and meniscus damage, is further highlighted by an AUC score of 0.9023. These metrics confirm the effectiveness of the approach, which uses ResNet-18 models for feature extraction and logistic regression for final classification. By analyzing MRI scans from three anatomical planes—axial, coronal, and sagittal—the model successfully captures complementary information from multiple perspectives, significantly improving its ability to classify injuries.
However, these results come with certain limitations. The dataset used for training and validation was relatively small and curated from a specific clinical setting at Stanford, which may limit the model's performance in broader, real-world scenarios. Additionally, the dataset's class imbalance poses challenges for consistent classification across all injury types. The model's generalizability to different MRI machines, imaging protocols, and patient populations has yet to be fully tested. Expanding the evaluation to include larger, more diverse datasets and conducting trials in clinical settings would provide a better understanding of the model's robustness and practical utility.

5 Conclusion

his project presents an effective solution for automating knee injury diagnosis using MRI scans. By combining ResNet-18 models for detailed feature extraction from three key anatomical planes and a logistic regression classifier for final decision-making, the pipeline delivers accurate and reliable predictions. The strong performance metrics, combined with the user-friendly Streamlit dashboard, make this system a promising tool for supporting healthcare professionals. The dashboard enables real-time predictions, offering a fast and accessible way to assist in clinical decision-making.
While the system has shown strong potential, there is room for further improvement. Testing the model on larger, more diverse datasets and ensuring its adaptability across various clinical environments are essential next steps. Enhancements to the dashboard, such as batch processing and support for multiple file formats, could also improve its practicality. Despite these challenges, this project represents a significant step forward in using AI for medical imaging, paving the way for scalable, efficient, and accessible tools to aid in knee injury diagnosis.

References

[1] Ori Gershon-Coneal, *:Living in Large Urban Developments: A Critical Understanding of the Housing Experience*, 2024.

[2] EAthanasios Siouras, *:Knee Injury Detection Using Deep Learning on MRI Studies: A Systematic Review*, 2022.

[3] Carl Petter Skaar Kulseng, *:Automatic segmentation of human knee anatomy by a convolutional neural network applying a 3D MRI protocol*, 2023.

[4] Kowshik Deb Nath, *:An Attention-Based Deep Learning Approach to Knee Injury Classification from MRI Images*, 2023.

[5] Matteo Dunnhofer, *:Deep convolutional feature details for better knee disorder diagnoses in magnetic resonance images*, 2022.

[6] Chen Liang, *:Effective automatic detection of anterior cruciate ligament injury using convolutional neural network with two attention mechanism modules*, 2023.

[7] Gary H Chang, *:Assessment of knee pain from MR imaging using a convolutional Siamese network*, 2021.

[8] Chen-Han Tsai, *:Knee Injury Detection using MRI with Efficiently-Layered Network (ELNet)*, 2020.

[9] Matteo Dunnhofer, *:Improving MRI-based Knee Disorder Diagnosis with Pyramidal Feature Details*, 2021.

[10] S. Sridhar, *:A Torn ACL Mapping in Knee MRI Images Using Deep Convolution Neural Network with Inception-v3*, 2022.

[11] Hyunkwang, *:Development of convolutional neural network model for diagnosing tear of anterior cruciate ligament using only one knee magnetic resonance image*, 2022.

[12] Stanford ML Group, *:MRNet: Deep-learning-assisted diagnosis for knee magnetic resonance imaging.*