Pre-Screening for Spine Red Flags in the Emergency Room

A Radiologist’s Assistant

Josh Cyphers, Heaven Klair, Fengshou Liang, Joe Schwab, Brian Tung
Fewer than 14% of EDs achieve 90% Threshold of seeing patients triaged for immediate Care (< 1 Hr)

Overcrowding in the ER leads to Adverse Outcomes and Increased Overall Mortality

2.6 million Emergency Room visits per year (3% of all ER visits)
Second most common reason for missing work (after common cold)

Yet, Back Pain is Almost Always Self Limiting and Does not Require ER or Hospital Care. Unless.....
Spine Red Flags

Infection  Fracture  Tumor

Paralysis, Death, Disability Unless Treated
Spine Red Flags must be confirmed via an MRI

However, Radiologists often have little effective means to prioritize their workload in the Emergency Department

All cases are emergencies by definition
Assist the Overworked Radiologist

Pre-Review the Spinal MRIs ordered in the ER

Screen for “Red Flags” & Place “Red Flag” Cases at the top of the Queue

Decrease Wait Times in EDs efficiency
Problem Statement

This project focuses on the critical "Red Flag" symptoms in lumbar spine MRI images: Tumors, Infections, and Fractures. With emergency departments facing overcrowding issues, our goal is to develop and implement a Convolutional Neural Network (CNN) capable of detecting these "Red Flag" indicators.

By incorporating this model into clinical workflows, we aim to enable radiologists to receive immediate alerts for cases requiring urgent attention. We seek to streamline this diagnosis process, ensuring timely intervention for patients with serious health conditions.
Data Collection

- **Dataset Overview**: Comprises 1372 hand-picked MRI images from 88 different patients categorized into 4 labels: Tumor, Fracture, Infection, and No Red Flag.
  - Total Images: 1372
  - Patients Represented: 88 unique patients
  - Categorization: Tumor, Fracture, Infection, and No Red Flag

- **Data Source**
  - [https://radiopaedia.org/?lang=us]: “Radiopaedia.org is a rapidly growing, peer-reviewed open-edit radiology resource, compiled by radiologists and other health professionals from across the globe”

- **Data Quality**
  - Expert Validation: Radiologists/Medical professionals reviewed the images to confirm the accuracy of the categorization and the clarity of the images.

  Total cases: 88
  Training files: 924, Cases: 61
  Validation files: 335, Cases: 13
  Testing files: 100, Cases: 14
Exploratory Data Analysis

- **Varying Image Dimensions**: Dataset contains MRI images of different sizes, impacting uniformity and model training efficiency.
- **Standardization Approach**:
  - **Dimension Standardization**: To achieve uniformity, applied black padding to resize all images to 255x255 pixels without distorting aspect ratios.
  - **Grayscale Normalization**: Standardized image intensity by converting all images to grayscale and normalizing pixel values for improved model consistency.
- **Label Distribution**:
  - [Insert the counts for each label]
Data and ML Pipelines

**Modeling Phase 1:**
RadImageNet Dataset
25,570 Images

- **Orientation Classification Task** (Binary)

**Modeling Phase 2:**
Red Flags
1372 Flags Images

- **Red Flags Classification Task** (Binary and Multiclass)
Spine Image Binary Classification

Distribution of Axial vs Sagittal Images:
Axial: 572
Sagittal: 585

26/26 [---------------------------------] - 133s 5s/step - loss: 0.1363 - accuracy: 0.9543 - val_loss: 0.0035 - val_accuracy: 1.0000
Epoch 2/10
26/26 [---------------------------------] - 129s 5s/step - loss: 0.0523 - accuracy: 0.9928 - val_loss: 0.0997 - val_accuracy: 0.9844
Epoch 3/10
26/26 [---------------------------------] - 126s 5s/step - loss: 0.0580 - accuracy: 0.9904 - val_loss: 0.1611 - val_accuracy: 0.9844
Epoch 4/10
26/26 [---------------------------------] - 130s 5s/step - loss: 0.0322 - accuracy: 0.9940 - val_loss: 0.0071 - val_accuracy: 1.0000
Epoch 5/10
26/26 [---------------------------------] - 129s 5s/step - loss: 0.0182 - accuracy: 0.9952 - val_loss: 0.1184 - val_accuracy: 0.9844
Epoch 6/10
26/26 [---------------------------------] - 129s 5s/step - loss: 0.0058 - accuracy: 0.9976 - val_loss: 0.1188 - val_accuracy: 0.9844
Epoch 7/10
26/26 [---------------------------------] - 129s 5s/step - loss: 0.0041 - accuracy: 0.9988 - val_loss: 0.1279 - val_accuracy: 0.9844
Epoch 8/10
26/26 [---------------------------------] - 129s 5s/step - loss: 0.0037 - accuracy: 0.9988 - val_loss: 0.2075 - val_accuracy: 0.9844
Epoch 9/10
26/26 [---------------------------------] - 127s 5s/step - loss: 9.0466e-04 - accuracy: 1.0000 - val_loss: 0.1128 - val_accuracy: 0.9844
Epoch 10/10
26/26 [---------------------------------] - 128s 5s/step - loss: 7.5549e-05 - accuracy: 1.0000 - val_loss: 0.1607 - val_accuracy: 0.9844
7/7 [---------------------------------] - 10s 1s/step - loss: 0.0375 - accuracy: 0.9911
Test accuracy: 0.9910714030265888
Pipeline Results

There are 721 files in the RIN_MRI_SPINE_CORD_Pathology folder.
There are 8320 files in the RIN_MRI_SPINE_Disc_Pathology folder.
There are 1580 files in the RIN_MRI_SPINE_Foraminal Pathology folder.
There are 10647 files in the RIN_MRI_SPINE_NORMAL/normal folder.
There are 2291 files in the RIN_MRI_SPINE_OSSaceous_ABN folder.
There are 1991 files in the RIN_MRI_SPINE_SCOLIOSIS folder.
Multiclass Classification Setup

- **Input**: 224x224
- **Conv1 + MaxPool**: 16 filters of size 5x5 with stride 1 and padding 2
- **Conv2 + MaxPool**: 32 filters of size 5x5, stride 1, and padding 2
- **FC1**: $32 \times 56 \times 56 = 100352$
- **FC2**: 512d
- **Output**: 4 classes

Options:
- No Red Flag
- Fracture
- Infection
- Tumor
CAM Activation and ROI Labeling
## Exploring Alternatives: Model Experimentation

All Models evaluated via K-Fold cross validation

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>SimpleCNN</td>
<td>0.89</td>
<td>0.92</td>
<td>0.92</td>
<td>0.92</td>
<td>Best Model</td>
</tr>
<tr>
<td>DenseNet</td>
<td>0.75</td>
<td>0.76</td>
<td>0.75</td>
<td>0.74</td>
<td>Overfitting</td>
</tr>
<tr>
<td>SimpleCNN + ROI</td>
<td>0.78</td>
<td>0.88</td>
<td>0.78</td>
<td>0.81</td>
<td></td>
</tr>
<tr>
<td>Dual PathWay</td>
<td>0.84</td>
<td>0.87</td>
<td>0.84</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>SimpleCNN + ROI</td>
<td>0.84</td>
<td>0.87</td>
<td>0.84</td>
<td>0.84</td>
<td></td>
</tr>
</tbody>
</table>
Minimum Viable Product (MVP)

- Desktop/Mobile application: a classifier that identifies MRI images which present a red flag vs those that do not
- Values:
  - Less wait time for the patient obtaining the MRI
  - Less wait time for the patients waiting to enter the ED but cannot due to the bed being occupied by the patient waiting for the MRI
  - Improved overall throughput for the ED which translates to more money for the institution which can be reinvested into the ED providing better care
Client Application

- Client application developed as a fast and efficient way to utilize the algorithm for inference.
- Two usage modes:
  - Personal: A user can upload an image and observe an inferred pathology (or lack thereof) from their uploaded image
  - Professional: Radiologists can view MRIs in their queue prioritized by pathology type
- Designed for simplicity
- Mobile application in the near future
Application Demo
Ethics and Privacy

- As a “successor” to RadImageNet, we follow the same ethics guidance as that original work. For that study, the institutional review boards waived the requirement for written informed consent for this retrospective, Health Insurance Portability and Accountability Act–compliant study.
- All images de-identified before classification and processing.
- No link between the patients, data provider, and data receiver(s) was made available.
- Privacy concerns regarding the client application will need to be analyzed in a different light – radiologists may need to access patient data.
Conclusion:

- Our project uses ML to detect 'red flag' indicators in lumbar spine MRIs.
- Achieving over 90% accuracy, it could speed up emergency care.
- Next steps involve refining, integrating, and ensuring ethical use.
- Ultimately, our goal is to improve care by alerting radiologists promptly.