Report on Lumbar Spine Degenerative Classification Project

Objective

The primary goal of this project was to utilize **convolutional neural networks (CNNs)** for the classification of lumbar spine degenerative conditions, specifically focusing on detecting **"Subarticular Stenosis" at the L4-L5 spinal level**. This project not only aimed to tackle a critical medical imaging challenge but also served as a platform to apply and demonstrate advanced deep learning techniques learned during the course. By bridging theory and practical implementation, the project showcased the potential of deep learning in addressing complex real-world problems.

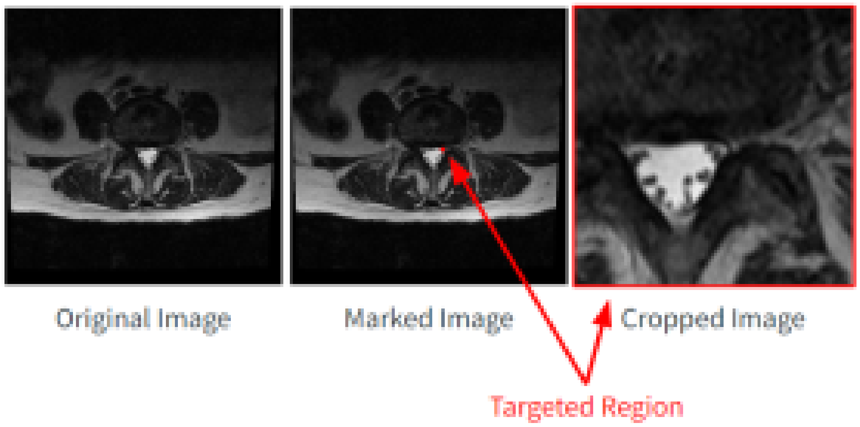
Methodology

1. **Data Acquisition**:

- The dataset was sourced from the [RSNA 2024 Lumbar Spine Degenerative](#) Classification competition on Kaggle, which provided comprehensive MRI scans.
- Given the size of the dataset (28.2 GB), a focused subset was extracted, targeting cases relevant to the evaluation of Subarticular Stenosis. This step was essential to streamline the analysis and ensure computational feasibility.

2. **Region of Interest (ROI) Extraction**:

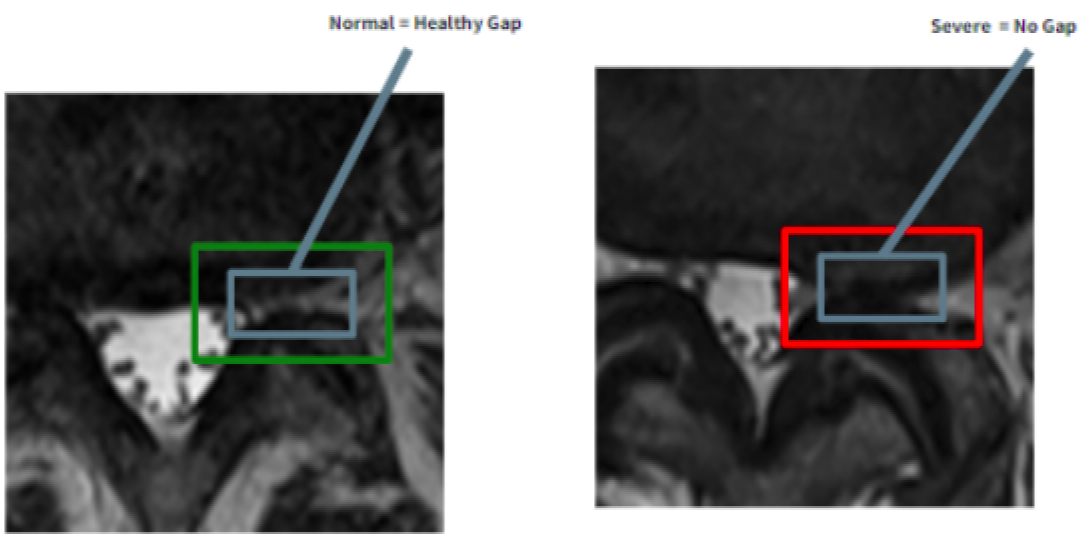
- To enhance model efficiency and accuracy, the **Region of Interest (ROI) was isolated from the MRI scans using the provided x-y coordinates.** This preprocessing step ensured that the model concentrated on the critical areas of the spine.
- The **ROI extraction involved cropping the targeted region, effectively reducing noise and irrelevant data in the input.** The following image illustrates the cropping process:



3. **Classification Tasks**:

Two classification tasks were undertaken:

- **Binary Classification**: Differentiating between Normal and Severe cases.
- **Multi-Class Classification**: Categorizing images into **Normal, Mild, and Severe** classes to provide a more granular understanding of condition severity.



4. **Model Implementation**:

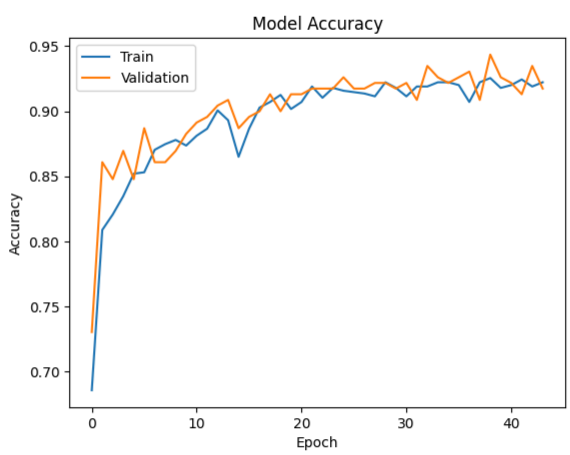
- A range of **CNN architectures were tested** to identify the optimal approach for this task. These included:
- **Dense CNN networks with fully connected layers** and dropout for overfitting prevention.

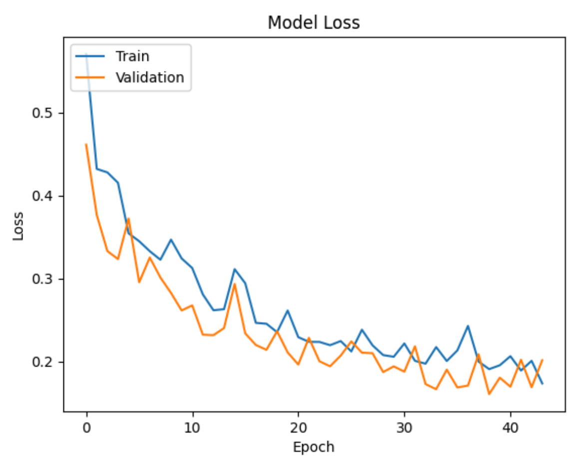
- **Residual block networks** that allowed deeper feature extraction while avoiding gradient vanishing issues.
- **Transfer learning using pre-trained ResNet-50 models** to leverage existing feature extraction capabilities.
- Custom dense convolutional models were also designed and evaluated for both binary and multi-class classification tasks.
- **Model performance was assessed through key metrics such as accuracy and loss,** providing insights into the effectiveness of each architecture.

Key Findings

1. Binary Classification:

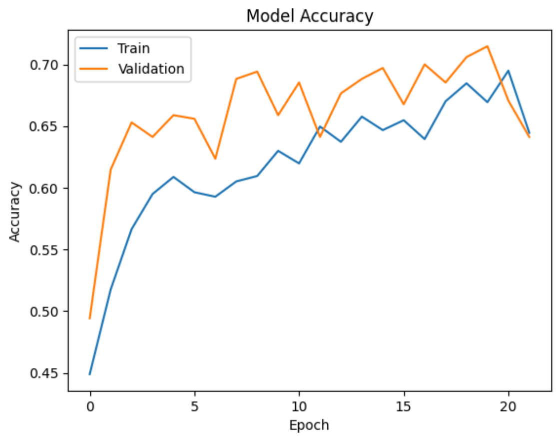
- The binary classification task yielded outstanding results, with a simple custom-built classifier achieving an accuracy of **91.7%**. This highlighted the model's ability to differentiate between Normal and Severe cases effectively.

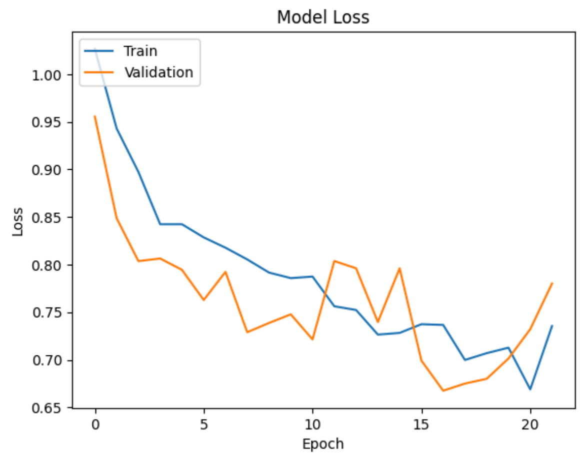




2. Multi-Class Classification:

- The **multi-class classification task, which included “Mild” cases,** presented additional challenges due to the subtle differences between categories.
- Despite this, the custom **Dense CNN** model achieved the highest accuracy of **73.24%**, showcasing its robustness even in the face of visually ambiguous data.





3. Observations and Future Work:

- The inclusion of **Mild class images,** which were often difficult to distinguish even to the human eye, posed significant challenges. Future work could focus on:
- Cleaning and refining Mild class images to reduce noise and inconsistencies.
- Splitting the **"Mild" class into two subcategories (Mild-Normal and Mild-Severe)** to improve classification granularity and accuracy.

Challenges

- **Dataset Management:** The large dataset required extensive preprocessing, including the extraction of a relevant subset and optimizing data loading pipelines.
- **Computational Constraints:** Training deep learning models on large datasets demanded efficient utilization of GPU resources, particularly in a Google Colab environment.
- **Mild Class Differentiation:** Differentiating Mild cases posed a unique challenge due to their visual similarity to both Normal and Severe cases, requiring advanced modeling techniques and preprocessing.

Conclusion

This project successfully demonstrated the application of convolutional neural networks in medical imaging, particularly for the classification of lumbar spine degenerative conditions. By focusing on Subarticular Stenosis, the study addressed a critical healthcare challenge and highlighted the potential of deep learning in medical diagnostics. The Dense CNN model emerged as the most effective architecture for both binary and multi-class classification tasks. Future directions for this work include refining Mild class differentiation, exploring more advanced architectures, and leveraging additional preprocessing techniques to further improve model performance.