LUMBAR SPINE DEGENERATION DISEASE CLASSIFICATION

Report submitted to

Spring & River

in partial fulfillment of the project requirements

Submitted by

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Sprinriver Technology Private Limited

Kolkata, West Bengal

Declaration

I declare that the report titled "**Lumbar Spine Degeneration Disease Classification**" submitted by me is an original work done by me under the guidance of **Dr. Prabir Aditya**, CEO at Spring & River, **Mr. Soomit Banerjee**, Director at PastelShade Software Technology & Partner at Eternis Services, and **Mr. Ehtesham Nehal**, Data Scientist at Spring & River, during the project period at **Spring & River** in June-July 2024. The work is original, and wherever I have used materials from other sources, I have given due credit and cited them in the text of the report. This report has not formed the basis for the award of any degree, diploma, associateship, fellowship, or other similar title to any candidate of any institution.

Signature of the candidate:

Name of the candidate: T. Sri Prasad
Date:

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Abstract

This abstract provides a concise overview of a machine learning project aimed at automating the classification of lumbar spine degenerative diseases using MRI scans, specifically focusing on foraminal narrowing, subarticular stenosis, and canal stenosis in Sagittal T1, Sagittal T2, and Axial T2 images. The project utilizes advanced image processing techniques and deep learning methodologies to achieve accurate disease detection and severity classification.

Project overview:

Degenerative spine conditions significantly impact individuals' quality of life, necessitating prompt and accurate detection to formulate effective therapeutic plans. This project aims to develop automated methods for detecting and assessing the severity of degenerative spine conditions using MRI imaging. Specifically, the focus is on identifying and grading three types of conditions in the lumbar region: foraminal narrowing, subarticular stenosis, and canal stenosis. These conditions are assessed at various vertebral levels (L1/L2, L2/L3, L3/L4, L4/L5, and L5/S1), with the severity graded as normal/mild, moderate, or severe.

The project involves the use of machine learning models to automate the detection and severity assessment of these conditions. MRI images in axial and sagittal planes, both T1 and T2 weighted, are used for training the models. The expected output is a probability score representing the likelihood of a specific grade of compression at each spinal level for each condition.

The project leverages the FastAI framework alongside essential Python libraries such as pandas, matplotlib, scikit-learn, and OpenCV for robust data handling, visualization, and model development. It encompasses a detailed pipeline from DICOM image extraction to pixel conversion and model training, ensuring comprehensive coverage of preprocessing steps crucial for training convolutional neural networks (CNNs).

Data Structure:

Data for this project is structured into training and testing sets, with images stored in DICOM format. The training set includes labeled data indicating the presence and severity of each condition, while the test set is used to validate the model's performance. Data augmentation and transformations were applied to enhance model generalization.

Methodology:

The methodology involved processing the RSNA 2024 Lumbar Spine Degenerative Classification dataset, which includes detailed MRI images and diagnostic labels. Each MRI series was converted from DICOM format to 8-bit images, focusing on the middle slice of the sagittal plane.

These 8-bit DICOM images are converted to PNG format and preprocessed to standardize pixel intensities, crucial for consistent model training across diverse datasets. Data augmentation techniques are applied to mitigate overfitting and enhance model generalization. Upsampling strategies are employed to address class imbalance, optimizing the model's ability to discern between disease severity levels.

Model Development and Training:

Each lumbar spine condition—such as spinal canal stenosis, neural foraminal narrowing, and subarticular stenosis—is trained separately using transfer learning with ResNet34 architecture. Model performance is evaluated using metrics like accuracy, training time per epoch, and convergence rates. Iterative fine-tuning and adjustment of epochs based on accuracy thresholds ensure optimal model performance and robustness.

Results and Inference

Comprehensive results from a full model run are detailed, showcasing accuracy rates, optimal training epochs, and GPU resource utilization constraints. The project's inference capabilities are validated through detailed analysis, highlighting areas for model refinement and future enhancements. Visual representations including confusion matrices and performance graphs offer intuitive insights into disease classification efficacy.

The project underscores the significance of AI in enhancing diagnostic accuracy and efficiency, paving the way for potential clinical applications in healthcare settings. Future directions include expanding dataset diversity, refining model architectures, and exploring real-time diagnostic integration to further advance medical imaging capabilities.

This report outlines the clinical significance of the project, the anatomical basis of the conditions, and the methodology for data processing and model training. The ultimate goal is to provide a tool that assists radiologists in diagnosing degenerative spine conditions more efficiently and accurately, thereby improving patient outcomes and reducing the burden on healthcare providers.

Introduction

Lumbar spine degenerative diseases pose significant challenges in clinical diagnosis and management, impacting millions worldwide with varying degrees of severity and symptoms. Manual assessment of conditions such as foraminal narrowing, subarticular stenosis, and canal stenosis from MRI scans is labor-intensive, subjective, and prone to inter-observer variability. To address these challenges, this project endeavors to harness the power of machine learning and medical imaging to automate and enhance the accuracy of lumbar spine disease classification.

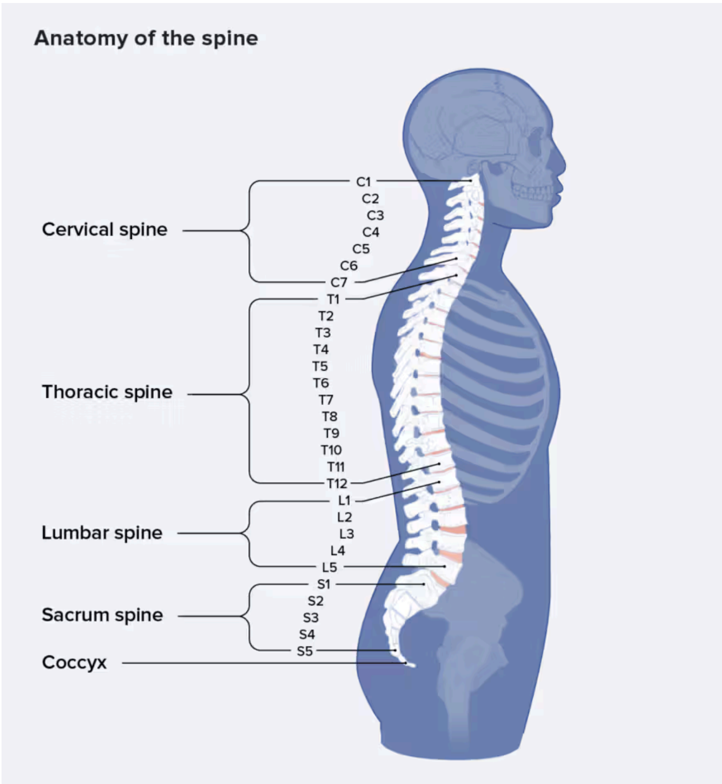
Background

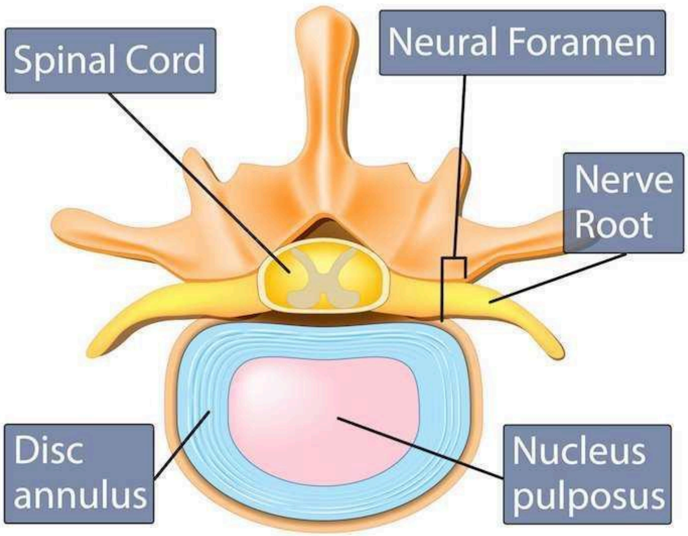
Degenerative diseases of the lumbar spine, including stenosis and narrowing, are common causes of chronic lower back pain and neurological deficits in adults. These conditions are typically diagnosed through imaging modalities such as Magnetic Resonance Imaging (MRI), which provides detailed anatomical information crucial for precise diagnosis and treatment planning. However, interpreting MRI scans requires specialized medical expertise and is time-consuming, limiting scalability and consistency in diagnostic accuracy.

The motivation behind this project stems from the pressing need to improve the efficiency and reliability of lumbar spine disease diagnosis. By developing automated tools that can accurately classify degenerative conditions from MRI scans, healthcare providers can streamline workflows, reduce diagnostic errors, and expedite treatment initiation. Moreover, automating these processes can potentially alleviate the burden on radiologists and clinicians, allowing them to focus on more complex cases and patient care.

Anatomical Overview

The spine is divided into four regions: the cervical region (with 7 vertebral bodies), the thoracic region (with 12 vertebral bodies), the lumbar region (with 5 vertebral bodies), and the sacral region (with 3-5 fused vertebral bodies).



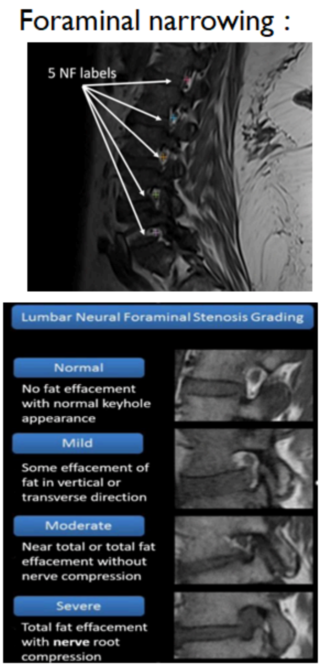


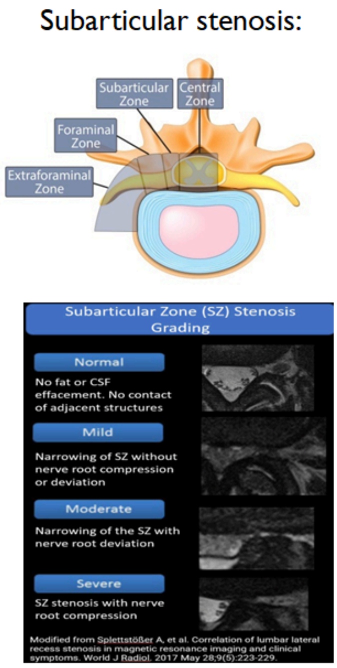
Between each vertebral body in all of the regions (except the sacrum) is a vertebral disc. Furthermore, along the posterior aspect of each vertebral body lies the spinal cord. At each vertebral body, spinal nerves leave the spinal cord through openings between vertebral bodies called foramina.

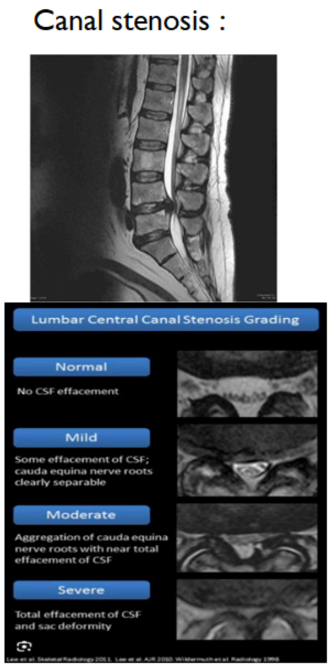
Compression of the spinal cord or any of the nerves can cause pain to patients. Things that can cause compression of these nerves/the spinal cord include a bulging vertebral disc, degenerative changes in the bones itself (leading them to grow protrusions/become compressed), trauma, or thickening of the ligaments surrounding the spinal cord.

The spine degeneration gives rise to three major conditions:

1. Foraminal narrowing (on either the left or right foramen at a specified level).
2. Subarticular stenosis (on either the left or right side at a specified level).
3. Canal stenosis (only at a specified level).







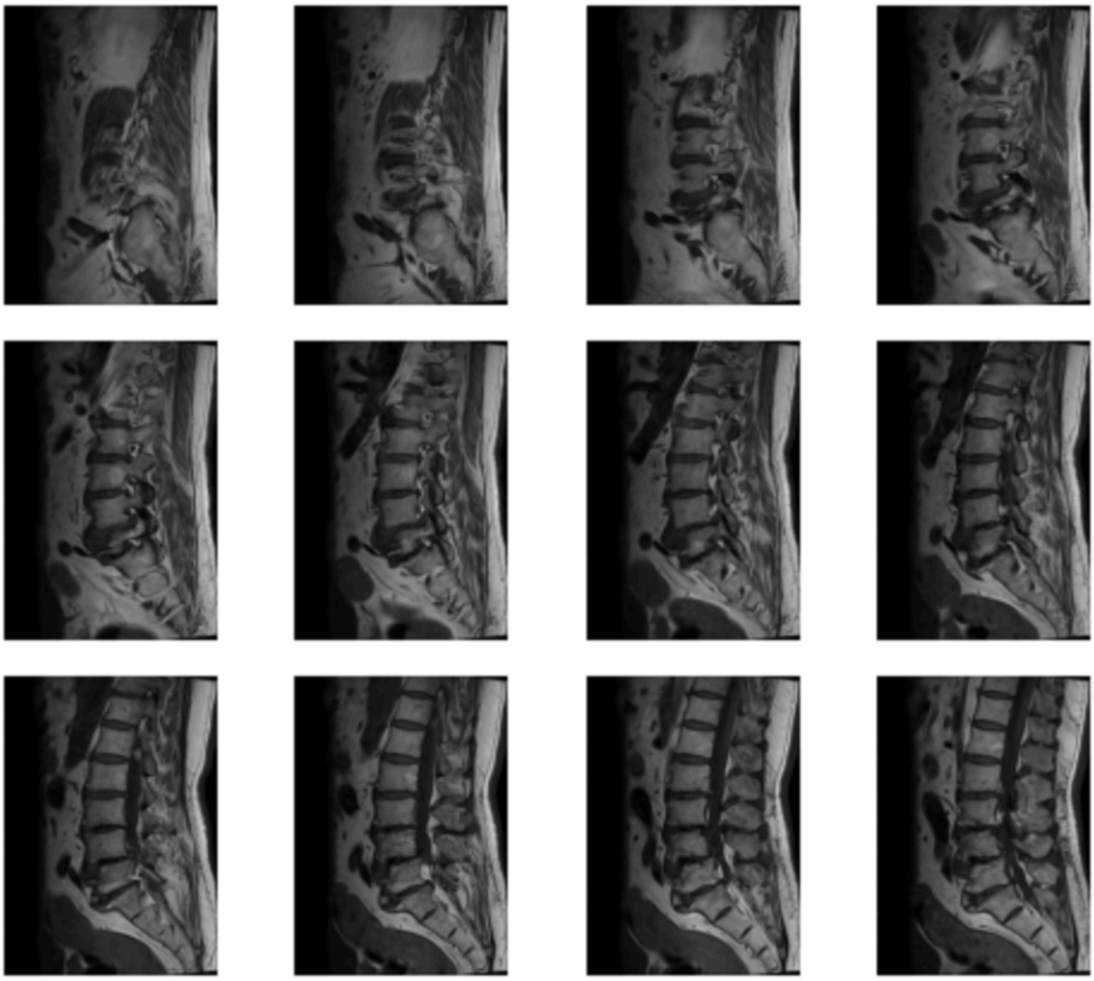
<u>Classes of MRI Images:</u>

MRI images come in multiple variants. They can generally be classified as either being T1 weighted or T2 weighted. T1 weighted images show fat as being brighter. The inner part of bones would appear brighter on T1 images. T2 images show water as brighter.

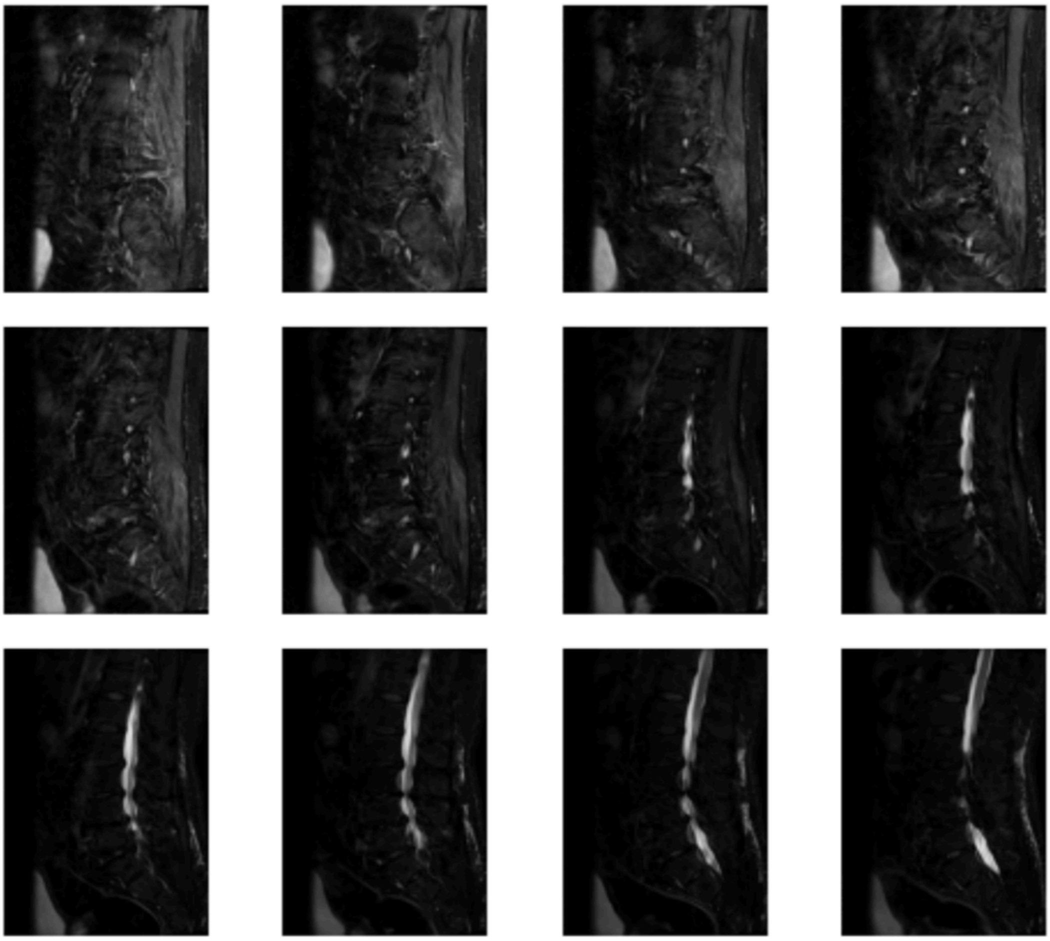
In this project, three major types of MRI Images are used: Sagittal T1, Sagittal T2, Axial T2

Below is an example of how these three classes of MRI Images look like:

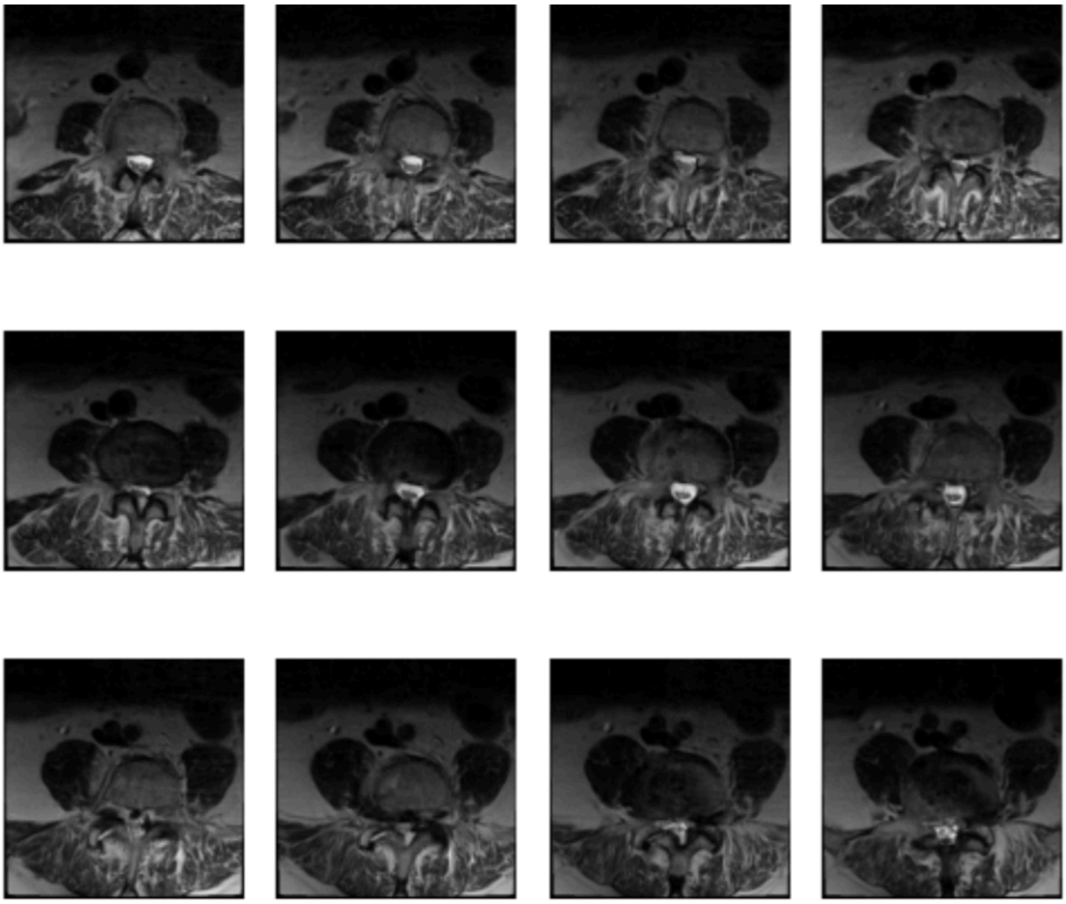
<u>Sagittal T1</u>



Sagittal T2



Axial T2



1) Foraminal Narrowing Overview

The spinal cord has spinal nerves that exit the spinal canal through openings called foramina. The foramina are best viewed in the sagittal plane. Sometimes these openings can become compressed, resulting in foraminal narrowing. This compression results in pain for patients along the nerve distribution that is downstream of the compression. This condition can be clearly identified with a lateral view especially Sagittal T2 images and it can be identified with some uncertainty with Sagittal T1 images.

2)Subarticular Stenosis Overview

Subarticular stenosis is due to compression of the spinal cord in the subarticular zone. This compression can be best visualized in the axial plane, i.e. Axial T2 images. It is harder to notice this condition in a lateral view because the subarticular zone is hidden between the Foraminal and Central zone.

3)Canal Stenosis Overview

Canal stenosis is impingement on the spinal canal (where the spinal cord travels). Impingement can be due to a bulging vertebral disc, trauma, bony osteophytes (outgrowths of the vertebral bodies due to degenerative changes), or ligamental thickening (of the ligaments that run along the length of the spinal canal). The degree of compression is best assessed in the axial plane as well as in lateral Sagittal plane, especially through Axial T2 and Sagittal T1 images.

***This project and its analysis is done based on the results from training models on Sagittal T1 images only* Further improvements can be done in finding conditions like Subarticular Stenosis and Foraminal Narrowing through Axial T2 and Sagittal T2 images.**

Objectives

The primary objective of this project is to develop and evaluate a machine learning-based system capable of classifying lumbar spine degenerative diseases using MRI images. Specifically, the system aims to:

1. **Automate Classification:** Implement a robust pipeline for preprocessing MRI images, extracting relevant features, and training convolutional neural networks (CNNs) for disease classification.
2. **Enhance Accuracy:** Achieve high levels of accuracy in distinguishing between different severity levels of foraminal narrowing, subarticular stenosis, and canal stenosis, surpassing manual assessment capabilities.
3. **Improve Efficiency:** Reduce the time required for diagnosis by providing rapid and reliable automated assessments, potentially improving patient outcomes through earlier intervention and treatment.

Subsequent sections will delve into each aspect of the project, providing insights into data acquisition, model development, performance evaluation, and the broader impact on healthcare delivery and patient outcomes.

Methodology

This section elaborates on the steps taken to develop and implement the machine learning system for classifying lumbar spine degenerative diseases from Sagittal T1 MRI scans. It encompasses data acquisition, preprocessing, model development, training, evaluation, and post-processing. The methods adopted ensure robustness, accuracy, and efficiency in the classification tasks.

Data Acquisition:

The project utilizes a comprehensive dataset of Sagittal T1 MRI scans, sourced from the RSNA 2024 Lumbar Spine Degenerative Classification dataset. This dataset is organized in a structured directory format, ensuring ease of access and efficient processing. The directory structure is as follows:

```
.
├── ExploreData.ipynb **This notebook
└── /kaggle/input/rsna-2024-lumbar-spine-degenerative-classification/
    ├── test_images/
    │   ├── 1005139/   (study id)
    │   │   └── 609308237/    (series id)
    │   │       ├── 1.dcm    (dcm image)
    │   │       └── ...
    │   └── ...
    ├── test_series_descriptions.csv
    ├── train_images/
    │   ├── 4003253/  (study id)
    │   │   └── 702807833/ (series id)
    │   │       ├── 1.dcm   (dcm image)
    │   │       └── ...
    │   └── ...
    ├── train_label_coordinates.csv
    ├── train_series_descriptions.csv
    └── train.csv
```

train.csv:

- Labels for each patient study.
- Columns represent degenerative conditions at various spinal levels (e.g., normal, mild, moderate, severe).
- Used as ground truth for training the classification model.

train_label_coordinates.csv:

- Pathology annotations for identified images.
- Includes study_id, series_id, instance_number (linking to images), condition type, level (spinal segment), and x,y coordinates of the pathology.
- Used for visualization, segmentation training (optional), or enriching classification data (optional).

train_series_descriptions.csv:

- Descriptions of MRI series within each study.
- Includes study_id, series_id, and series_description (modality, orientation).
- Used for selecting appropriate images and understanding image context.

DICOM image files:

- Actual medical images in DICOM format.
- Organized by study_id folders with subfolders for different series (series_id).
- Each image has a unique identifier (a natural number).
- Used to train the model on visual characteristics of degenerative conditions.

Image Preprocessing:

Preprocessing steps are crucial for enhancing image quality and standardizing inputs for the machine learning models. The preprocessing pipeline includes:

- Resizing:
  - All images are resized to a consistent resolution to ensure uniformity and compatibility with the convolutional neural network (CNN) architectures.
  - the cv2.resize function is used to resize each DICOM image to the target shape specified by target_shape (256, 256). Images are resized again while defining Datablock.

```
if img.shape != target_shape:
    img = cv2.resize(img, target_shape, interpolation=cv2.INTER_AREA)
```

```
item_tfms=Resize(256)
```

- Normalization:
  - Pixel values are normalized to a range of numbers, improving the convergence of training algorithms.
  - The normalization is handled in the convert_to_8bit function, which scales the pixel values to the 8-bit range (0-255).

```
def convert_to_8bit(x):
    lower, upper = np.percentile(x, (1, 99))
    x = np.clip(x, lower, upper)
    x = x - np.min(x)
    x = x / np.max(x)
    return (x * 255).astype("uint8")
```

- Augmentation:
  - Data augmentation techniques, such as rotation, flipping, and zooming, are applied to increase the diversity of the training set and prevent overfitting.
  - The batch_tfms=aug_transforms() method is used when defining the DataBlock.

<u>Data Cleaning:</u>

- Handle missing values in CSVs using pandas .
- Verify data type consistency (ensure severity levels are categorical).

Data Splitting:

- Split data into training and testing sets (80%/20% using FastAI's RandomSplitter() method). This helps evaluate model generalizability on unseen data.
- cross validate with test data and draw confusion matrix

Model Architecture:

FastAI Framework:

FastAI, an advanced deep learning library, is utilized to streamline the development and training process. Key FastAI functions and modules used include:

- ImageDataLoaders: This class is used to load and preprocess the images, including applying transformations and creating batches for training.
- cnn_learner: This function simplifies the creation of a CNN model with a pre trained backbone, optimizing it for the specific classification task.
- Data Augmentation: FastAI provides built-in support for data augmentation, enabling techniques like random rotations, flips, and zooms to be easily applied.

Transfer Learning:

To expedite model development and enhance performance, transfer learning is employed. Pretrained models, such as ResNet, are fine-tuned on the MRI dataset. This approach leverages the knowledge acquired from training on large-scale image datasets, providing a solid foundation for medical image analysis.

Training Strategy:

The training process involves optimizing the model parameters using backpropagation and gradient descent. The following strategies are implemented:

- Learning Rate Finder: FastAI's lr_find() function is used to identify the optimal learning rate, ensuring efficient training.
- Learning Rate Scheduling: A dynamic learning rate schedule adjusts the learning rate during training, starting with a higher rate and gradually decreasing it to refine the model weights.

- Early Stopping: To prevent overfitting, early stopping monitors the validation loss and halts training if performance plateaus or deteriorates.
- Cross-Validation: K-fold cross-validation is used to assess model performance and ensure robustness. The dataset is divided into K subsets, and the model is trained and validated K times, each time using a different subset as the validation set and the remaining subsets for training.

Progress Tracking with tqdm:

The tqdm library is employed to provide real-time progress bars during training, giving visual feedback on the training process and epoch completion. This helps in monitoring the training status and detecting any potential issues early.

Computational Resources:

Training is conducted on GPU-accelerated environments, utilizing high-performance computing resources to expedite the process. Specifically, Kaggle's GPU infrastructure is leveraged, allowing for efficient training within a 12-hour runtime limit.

Evaluation Metrics:

The model's performance is evaluated using a suite of metrics, ensuring comprehensive assessment across various dimensions:

- Accuracy: The proportion of correctly classified instances among the total instances.
- Precision: The ratio of true positive predictions to the total positive predictions.
- Confusion Matrix: A detailed breakdown of true positives, true negatives, false positives, and false negatives for each class.

Prediction Interpretation & Visualization:

Post-processing involves interpreting the model's predictions and translating them into clinically relevant insights. The predicted labels are mapped back to the corresponding severity levels, providing a clear diagnostic output for medical professionals.

To enhance interpretability, heatmaps and Grad-CAM visualizations are generated. These visualizations highlight the regions of the MRI scans that contributed most significantly to the model's predictions, offering transparency into the decision-making process.

The methodology outlined above combines advanced machine learning techniques with domain-specific knowledge in medical imaging to develop a robust, accurate, and efficient system for classifying lumbar spine degenerative diseases. By automating the diagnostic process, the project aims to enhance clinical workflows, reduce diagnostic errors, and ultimately improve patient outcomes.

Discussion

Challenges Faced And How it is Overcome

Data Acquisition and Preparation

Sagittal T1 Images (in dcm format) of 1980 people were available as raw data. The first challenge of this project was to convert the images into proper PNG image by taking the middle slice out of the continuous dcm images.

The resulting MRI images needed a normalization to standard resolution (256 x 256).

Model Training and Validation

Challenges in Model Training

1. Overfitting
    - Challenge: Overfitting occurs when the model learns the training data too well, capturing noise and details that do not generalize to new data. This results in high training accuracy but low validation accuracy.
    - Methods to Overcome**:**
        - Data Augmentation: Applied augmentation transforms to the training data to increase its variability and help the model generalize better.
        - Balanced DataBlock: Ensured that the data block configuration was set up to handle the balanced data properly.

```python
dblock = DataBlock(
    blocks=(ImageBlock, CategoryBlock),
    get_x=ColReader('image'),
    get_y=ColReader('label'),
    splitter=RandomSplitter(valid_pct=0.2, seed=42),
    item_tfms=Resize(256),
    batch_tfms=aug_transforms()
)
```

- <u>Early Stopping:</u> Used an early stopping callback to halt training when the validation loss (the errors on unseen data) stops improving, preventing the model from overfitting.

```python
learn = cnn_learner(
    dls, resnet34,
    metrics=accuracy,
    cbs=[EarlyStoppingCallback(monitor='valid_loss', patience=3)])
```

2. <u>Class Imbalance</u>

  - Challenge: Class imbalance can lead to a model that is biased towards the majority class, resulting in poor performance on minority classes.
  - Method used to Overcome:
    - <u>Upsampling</u>: Resampled the minority classes to match the size of the majority class, ensuring that the model sees a balanced number of samples from each class during training.

```python
df = train[['study_id', 'series_id', column]].dropna(subset=[column])
df.columns = ['study_id', 'series_id', 'label']

normal_df = df[df.label == 'Normal/Mild']
moderate_df = df[df.label == 'Moderate']
severe_df = df[df.label == 'Severe']

moderate_upsampled = resample(moderate_df, replace=True, n_samples=len(normal_df), random_state=42)
severe_upsampled = resample(severe_df, replace=True, n_samples=len(normal_df), random_state=42)

upsampled_df = pd.concat([normal_df, moderate_upsampled, severe_upsampled])
```

3.Selecting the Right Hyperparameters

- Challenge: Choosing optimal hyperparameters such as learning rate, batch size, and number of epochs is crucial for achieving good performance and convergence.
- Methods to Overcome:
  - Learning Rate Finder**:** Used FastAI's learning rate finder to identify the optimal learning rate. It determines how fast or slow we move towards optimal weights.

```
learn = cnn_learner(dls, resnet34, metrics=accuracy)
lr_min, lr_steep, lr_valley, lr_slide = learn.lr_find(suggest_funcs=(minimum, steep, valley, slide))
print(f"Suggested learning rates - min: {lr_min}, steep: {lr_steep}, valley: {lr_valley}, slide: {lr_slide}")

learn.fine_tune(max_epochs, base_lr=lr_valley)
```

  - Experimentation with Epochs: Adjusted the number of epochs based on initial results and further trained models with more epochs if accuracy was below a certain threshold. This reduces the total run time of the program by a drastic amount.

```
learn,accuracy = cross_validate_model(data, column)
accuracy_threshold = 0.91
if accuracy <= 0.95:
    epochs = 5 if accuracy >= accuracy_threshold else 10
    learn, accuracy_value = train_model_for_column(column, data, max_epochs=epochs)
    results[column] = learn
else:
    learn, accuracy_value = train_model_for_column(column, data)
    results[column] = learn
```

4.Training Stability and Convergence

- Challenge: Ensuring that the model training is stable and converges to a good solution without oscillating or diverging.
- Methods to Overcome:
  - Consistent Validation Split**:** Maintained a consistent validation split to monitor performance reliably.

```python
def cross_validate_model(data, column, max_epochs=4):
    from sklearn.model_selection import train_test_split
    train_data, val_data = train_test_split(data, test_size=0.2, random_state=42)
    dblock = DataBlock(
        blocks=(ImageBlock, CategoryBlock),
        get_x=ColReader('image'),
        get_y=ColReader('label'),
        splitter=IndexSplitter(val_data.index),
        item_tfms=Resize(256),
        batch_tfms=aug_transforms()
    )
```

- Monitoring Loss and Accuracy**:** Closely monitored training and validation loss/accuracy to ensure convergence and adjust hyperparameters accordingly.

Computational Resources

Efficient Data Processing Using Multi-threading and processing images in Batch:

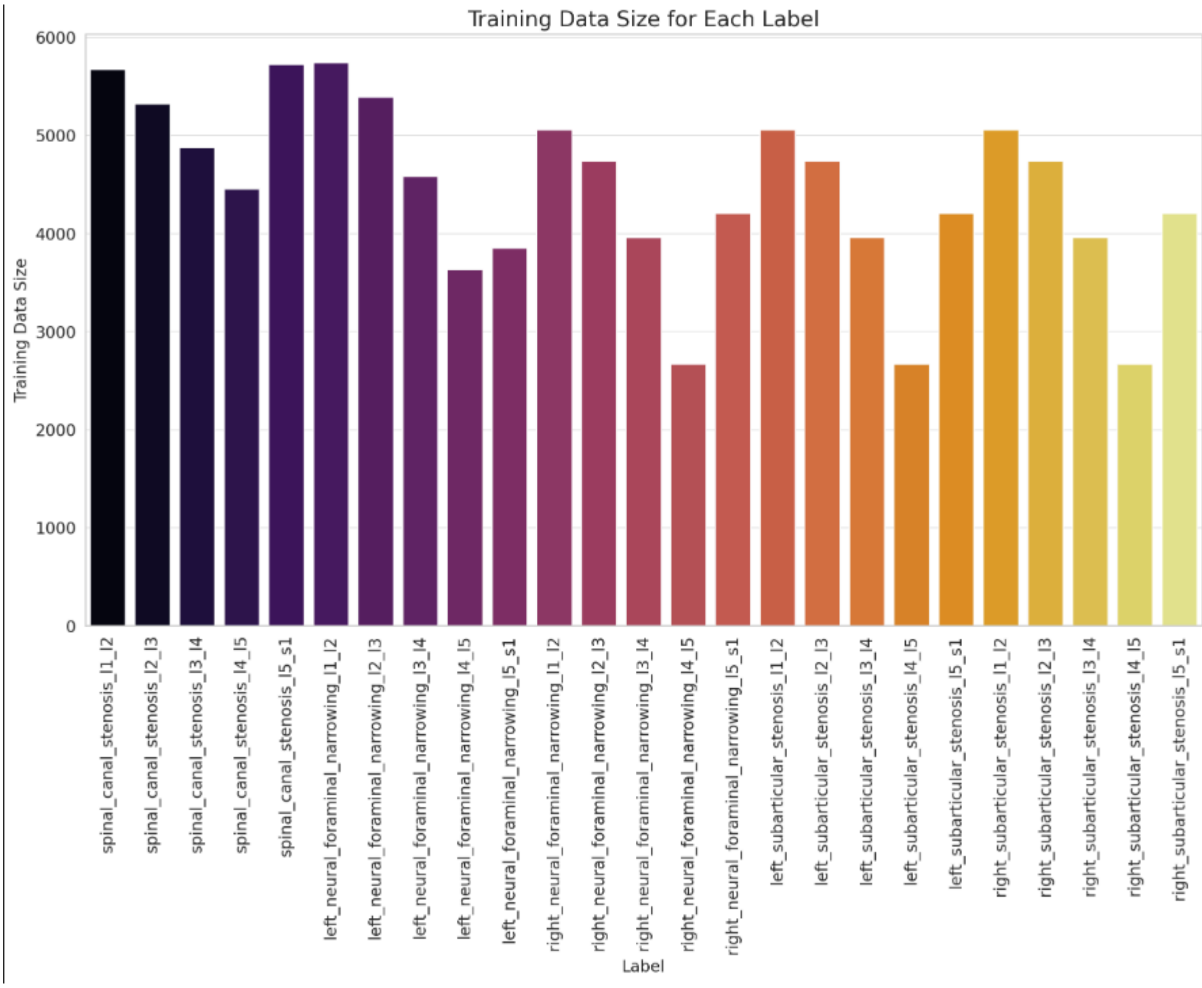
Multi-threading allows concurrent execution of image processing tasks, significantly speeding up the data preparation phase. Batch processing breaks the dataset into manageable chunks, ensuring that memory usage remains within limits and facilitating the handling of large volumes of data efficiently.

```python
total_batches = (len(upsampled_train) // batch_size) + 1

for batch_num in range(start_batch, total_batches):
    batch_save_path = f"{save_path}_batch_{batch_num}.csv"
    image_paths = []
    labels = []

    if os.path.exists(batch_save_path):
        print(f"Batch {batch_num} already processed. Skipping...")
        continue

    batch_start = batch_num * batch_size
    batch_end = min((batch_num + 1) * batch_size, len(upsampled_train))
    batch_df = upsampled_train.iloc[batch_start:batch_end]

    with ThreadPoolExecutor(max_workers=8) as executor:
        futures = []
        for count, row in enumerate(tqdm(batch_df.itertuples(), total=len(batch_df)), start=1):
            futures.append(executor.submit(process_row, row, count))

        for future in tqdm(futures, total=len(futures)):
            image_path, label = future.result()
            image_paths.append(image_path)
            labels.append(label)
```

Results at Each Stage

- Data Preprocessing and Augmentation
  - The Train data contained 1983 Study_id's each representing a person's MRI scan images.
  - Out of 1983, 1980 Sagittal T1 images were available.
  - The Sagittal T1 images were upsampled to equalize the data between the three types of values: Normal/Mild, Moderate, Severe; and an average of 4500 training images were obtained.

The training data size for each condition is depicted in the bar graph below:



- Model Training and Validation

The model Resnet34 was used for this project and the following results were obtained from the training and validation phases.

An example validation-loss curve and the confusion matrix:

>>>

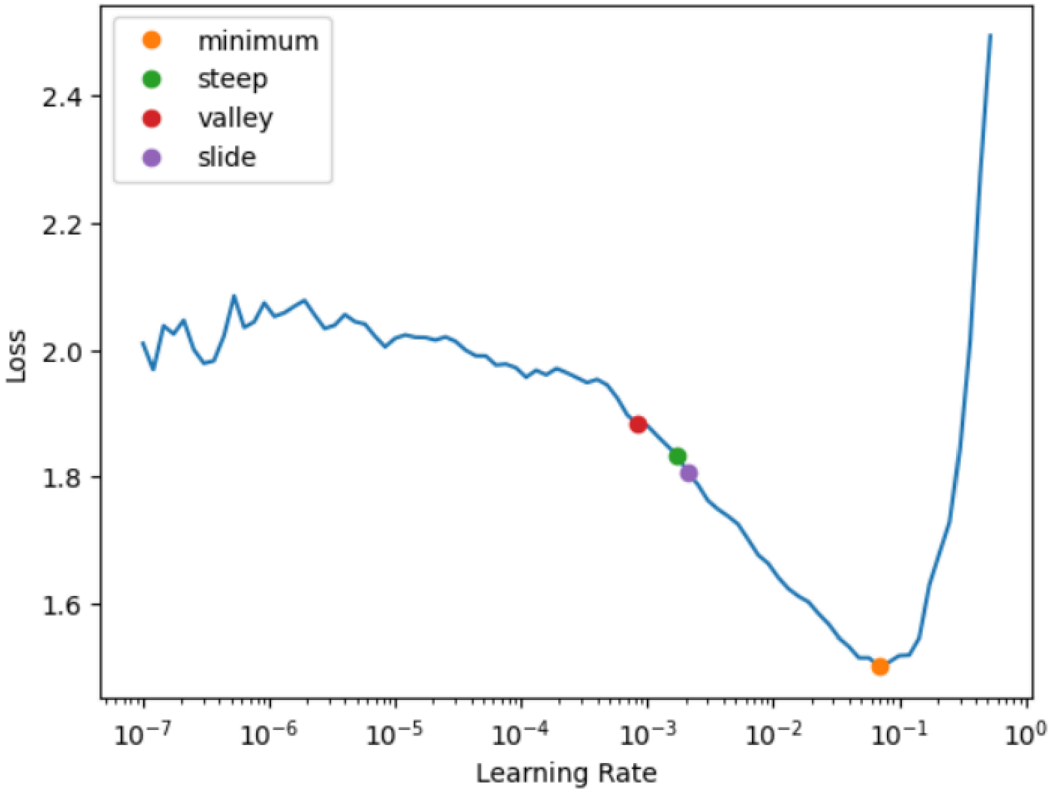
Training model for the column spinal_canal_stenosis_l1_l2

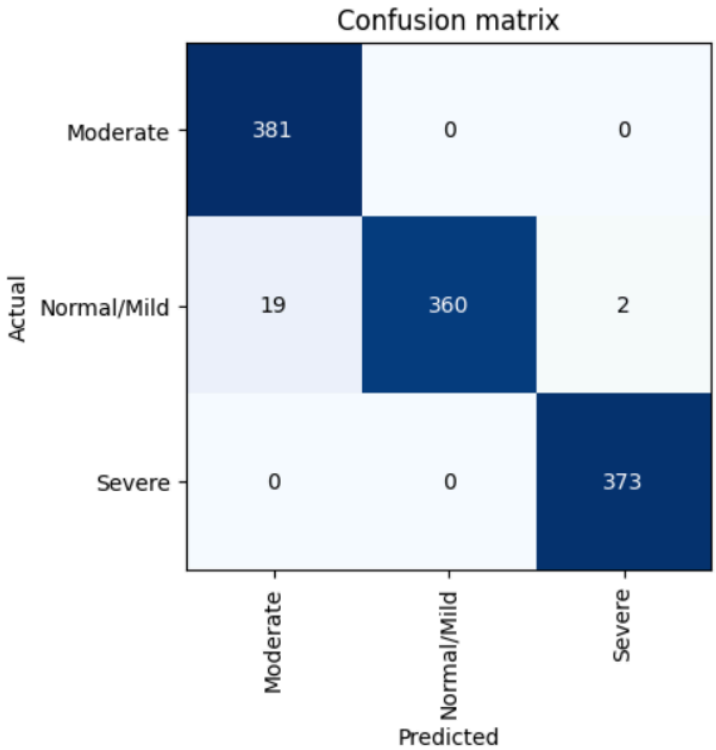
Length of data training: 5676

Training: Suggested learning rates - min: 0.006918309628963471, steep: 0.001737800776027143, valley: 0.0008317637839354575, slide: 0.0020892962347716093

epoch	train_loss	valid_loss	accuracy	time
0	1.271879	0.535032	0.792071	00:15

epoch	train_loss	valid_loss	accuracy	time
0	0.659350	0.199119	0.920705	00:19
1	0.356322	0.126064	0.949780	00:19
2	0.219469	0.090559	0.975330	00:19
3	0.152058	0.071977	0.981498	00:18


minimum
steep
valley
slide
Loss
Learning Rate
2.4
2.2
2.0
1.8
1.6
10^{-7}
10^{-6}
10^{-5}
10^{-4}
10^{-3}
10^{-2}
10^{-1}
10^{0}


Confusion matrix
Actual
Moderate
Normal/Mild
Severe
381
0
0
19
360
2
0
0
373
Predicted

Final Model Performance

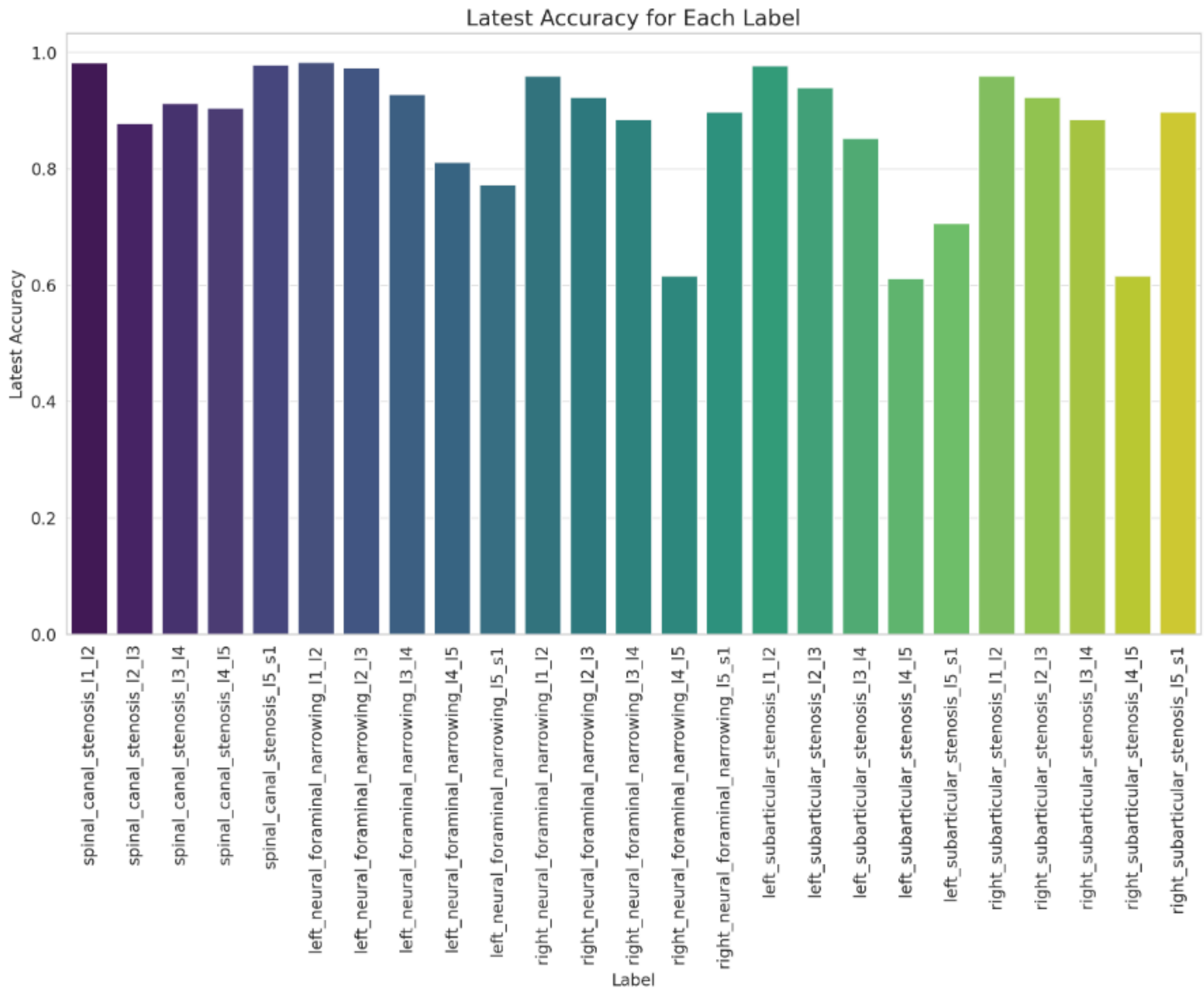
The model was trained on various labels and its final epoch accuracy (latest accuracy), the maximum accuracy obtained so far, the rate at which the model learned to predict (convergence rate) were noted and calculated along with other statistics.

	Label	Latest Accuracy	Max Accuracy	Avg Training Time/Epoch (s)	Optimal Epochs Needed	Training Data Size	Convergence Rate	Description	Suggested LR
1	spinal_canal_stenosis_l1_l2	0.982379	0.982379	18	3-4	5676	Fast	Fine	0.002511886414
2	spinal_canal_stenosis_l2_l3	0.878873	0.878873	17	3-4	5325	Moderate	Needs more fine tuning	0.004365158267
3	spinal_canal_stenosis_l3_l4	0.912821	0.915897	16	8-9	4878	Slow	Needs more fine tuning	0.002511886414
4	spinal_canal_stenosis_l4_l5	0.904602	0.904602	14	9-10	4458	Slow	Needs more fine tuning	0.00301995175
5	spinal_canal_stenosis_l5_s1	0.979039	0.9869	19	3-4	5727	Fast	Fine	0.002511886414
6	left_neural_foraminal_narrowing_l1_l2	0.983464	0.987815	19	3-4	5745	Fast	Fine	0.0005754399463
7	left_neural_foraminal_narrowing_l2_l3	0.974026	0.975881	18	4-5	5394	Fast	Fine	0.002089296235
8	left_neural_foraminal_narrowing_l3_l4	0.928026	0.928026	15	9-10	4587	Moderate	Needs more fine tuning	0.003630780615
9	left_neural_foraminal_narrowing_l4_l5	0.811554	0.811554	12	9-10	3636	Slow	Needs more train data & fine tuning	0.00301995175
10	left_neural_foraminal_narrowing_l5_s1	0.773022	0.775616	13	8-9	3858	Slow	Needs more train data	0.00301995175
11	right_neural_foraminal_narrowing_l1_l2	0.960435	0.960435	17	3-4	5058	Fast	Fine	0.002089296235
12	right_neural_foraminal_narrowing_l2_l3	0.922996	0.924051	16	8-9	4743	Moderate	Fine	0.002511886414
13	right_neural_foraminal_narrowing_l3_l4	0.885101	0.893939	13	8-9	3963	Moderate	Needs more train data	0.00301995175
14	right_neural_foraminal_narrowing_l4_l5	0.616105	0.631086	9	9-10	2670	Slow	Needs more train data	0.00301995175
15	right_neural_foraminal_narrowing_l5_s1	0.897741	0.897741	14	9-10	4206	Moderate	Needs more fine tuning	0.003630780615
16	left_subarticular_stenosis_l1_l2	0.977384	0.977384	17	3-4	5058	Fast	Fine	0.00301995175
17	left_subarticular_stenosis_l2_l3	0.940171	0.949786	15	8-9	4743	Moderate	Fine	0.002511886414
18	left_subarticular_stenosis_l3_l4	0.853015	0.853015	13	8-9	3963	Moderate	Needs more train data & fine tuning	0.0004786300997
19	left_subarticular_stenosis_l4_l5	0.61236	0.61985	9	9-10	2670	Slow	Needs more train data	0.00301995175
20	left_subarticular_stenosis_l5_s1	0.707202	0.707202	14	9-10	4206	Slow	Needs more fine tuning	0.002089296235
21	right_subarticular_stenosis_l1_l2	0.960435	0.960435	17	3-4	5058	Fast	Fine	0.002089296235
22	right_subarticular_stenosis_l2_l3	0.922996	0.924051	16	8-9	4743	Moderate	Fine	0.002511886414
23	right_subarticular_stenosis_l3_l4	0.885101	0.893939	13	8-9	3963	Moderate	Needs more train data	0.00301995175
24	right_subarticular_stenosis_l4_l5	0.616105	0.631086	9	9-10	2670	Slow	Needs more train data	0.00301995175
25	right_subarticular_stenosis_l5_s1	0.897741	0.897741	14	9-10	4206	Moderate	Needs more fine tuning	0.003630780615
	AVERAGE	0.87130776	0.87477136						

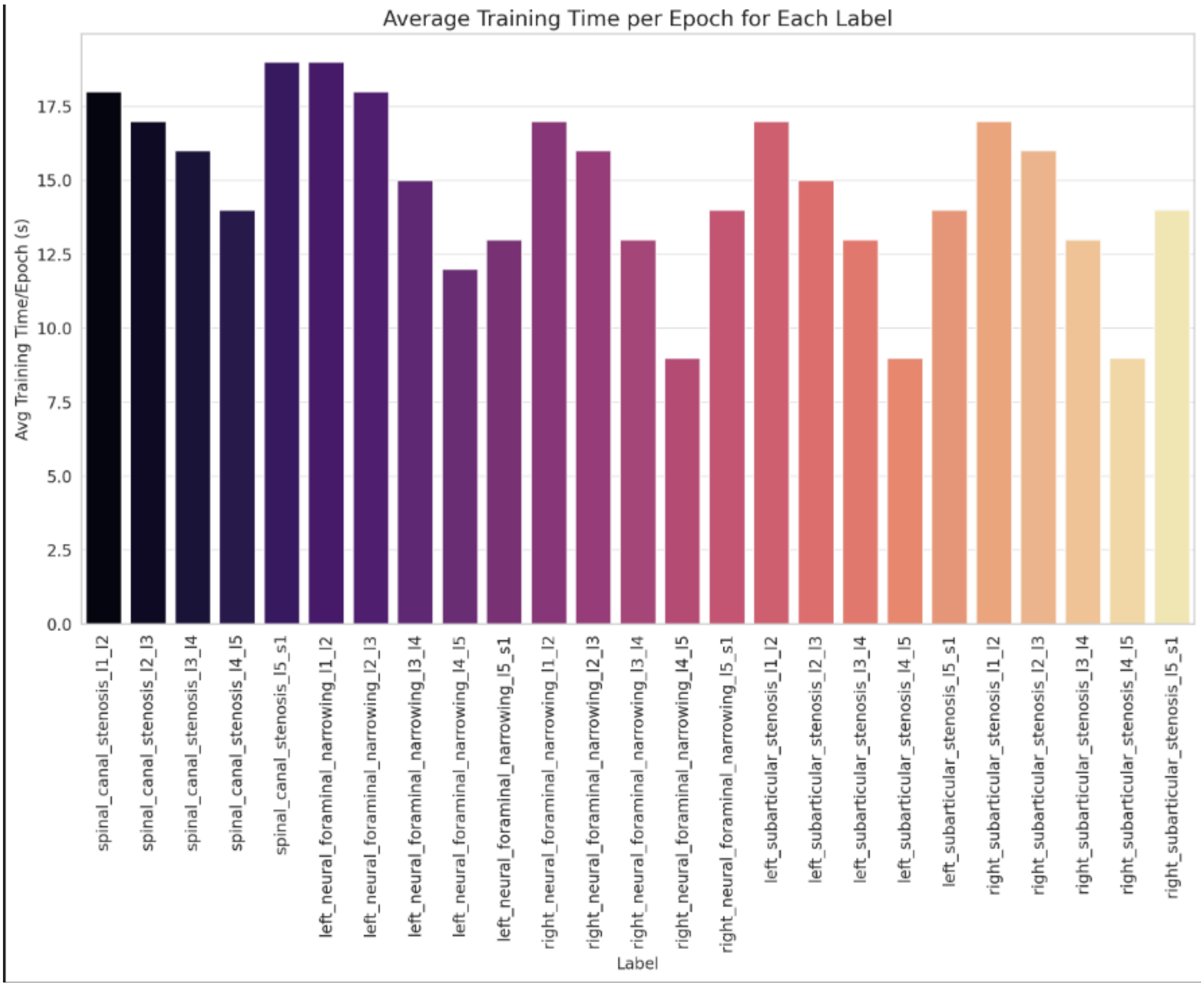
Inference and Detailed Analysis

- Key Findings:
  - Latest Accuracy for Each Label:
    - Observation: Most labels have high accuracy rates, with some labels like spinal_canal_stenosis_l1_l2 and left_neural_foraminal_narrowing_l1_l2 achieving accuracy close to 1. However, some labels such as left_subarticular_stenosis_l4_l5 and right_neural_foraminal_narrowing_l4_l5 have lower accuracies.

- <u>Implication:</u> Certain labels are performing significantly better than others. Labels with lower accuracies might require more training data or fine-tuning of the model. We can clearly see that **Sagittal T1 images are better suited for only finding Spinal Canal Stenosis and help little in finding Foraminal Narrowing and doesn't help at all in the predictions of Subarticular Stenosis**

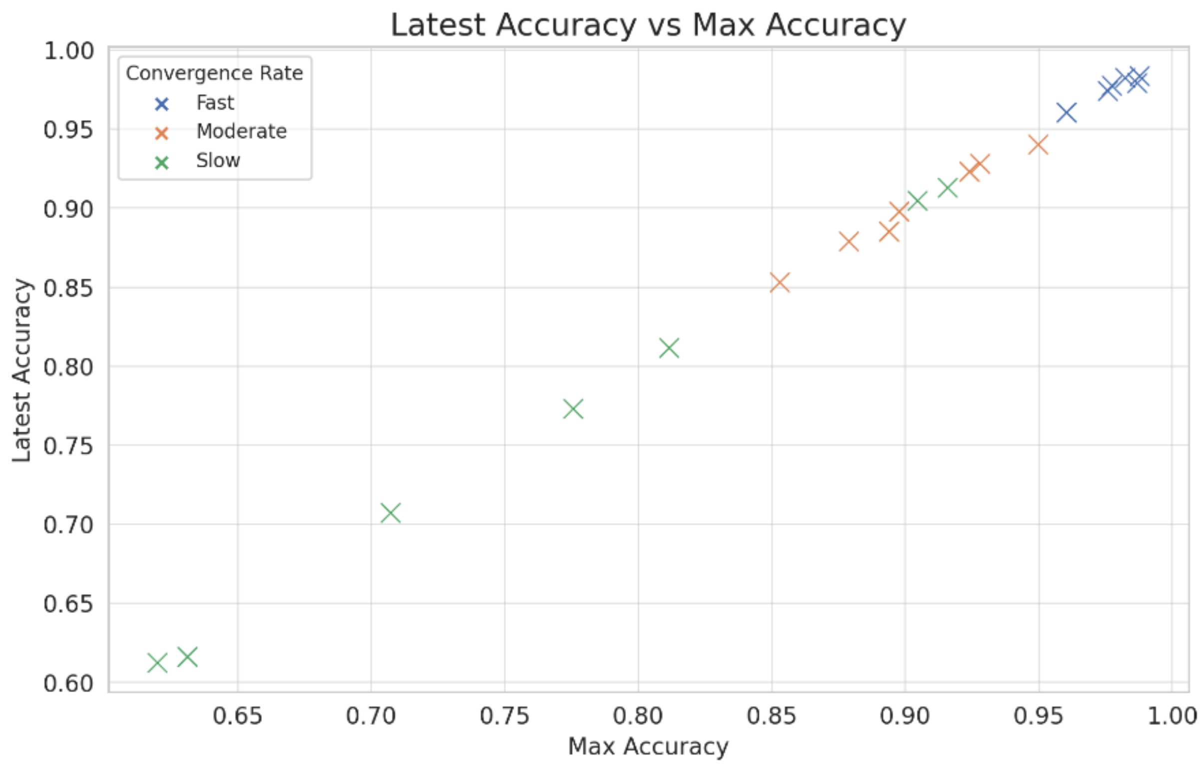


- Average Training Time per Epoch for Each Label:
  - <u>Observation</u>: Training time per epoch does not vary significantly across labels. Most labels have training times ranging from 12 to 19 seconds per epoch. **We can see that the graph is very similar to the graph of Training Data Size for every label.**
  - <u>Implication</u>: The model's training time is consistent, suggesting efficient use of computational resources. Differences in training time are not substantial enough to impact overall performance significantly.



- <u>Latest Accuracy vs Max Accuracy:</u>
  - <u>Observation</u>: Latest accuracy closely tracks the maximum accuracy for most labels. Labels with high max accuracy tend to maintain high latest accuracy.

- Implication: The training process is stable and retains performance gains. **We can see that the graph is very close to x=y graph which depicts that an early stopping callback is used to halt training when the validation loss stops improving, preventing the model from overfitting.** However, slight discrepancies indicate potential for further training or hyperparameter optimization.



- Implications for Clinical Practice

  The findings of this study hold significant implications for clinical practice, particularly in the domain of lumbar spine degenerative disease diagnosis and treatment planning. By leveraging machine learning models trained on MRI images, healthcare providers can potentially achieve:

  - Improved Diagnosis: Automated classification of lumbar spine conditions can assist radiologists in identifying and categorizing diseases accurately and efficiently.

- Personalized Treatment Planning: Predictive models can help in predicting disease progression and tailoring treatment plans to individual patient needs based on the severity and specific conditions detected.
- Enhanced Patient Outcomes: Early detection and accurate diagnosis can lead to timely interventions, potentially improving patient outcomes and reducing long-term complications.

- <u>Reliability and Validity</u>

  The reliability and validity of the model in real-world scenarios are crucial considerations:

  - Reliability: The model's consistency in classifying different lumbar spine conditions needs to be validated across diverse patient demographics and imaging settings.
  - Validity: It's essential to assess how well the model's predictions align with clinical outcomes and expert radiologist assessments. This involves conducting prospective studies and comparing the model's performance against standard clinical practices.

Limitations and Areas for Improvement

Despite its strengths, this study has several limitations:

- Data Constraints: Limited availability of annotated medical imaging data, especially for less common conditions, may restrict the model's generalizability.
- Methodological Limitations: The choice of model architecture and training parameters could influence performance. Ensuring robust validation and hyperparameter tuning is critical.
- Scope Limitations: This study focuses primarily on MRI-based diagnosis of specific lumbar spine conditions. Other imaging modalities or broader disease spectra could enhance clinical utility.

Suggestions for Future Work

To enhance the model and address current limitations, future research directions could include:

- Enhanced Data Collection: Collaborations with multiple medical centers to gather larger and more diverse datasets could improve model generalizability.
- Advanced Model Architectures: Exploration of advanced techniques like transfer learning or ensemble models to further boost classification accuracy.
- Improved Evaluation Methods: Longitudinal studies and real-world testing are essential for validating the model's performance over time and in diverse clinical settings.
- Collaboration and Interdisciplinary Approaches: Engaging clinicians and experts in radiology to refine the model's clinical applicability and ensure it aligns with real-world diagnostic workflows.

Related Works

Medical Imaging and AI:

- **"Automated Detection of Lumbar Spine Diseases Using Machine Learning"** - A study published in the Journal of Medical Imaging that applies convolutional neural networks (CNNs) to detect lumbar spine diseases from MRI scans with high accuracy.

Radiology and Imaging Studies:

- **"Deep Learning Approaches for Medical Image Analysis: A Survey"** - A survey article published in IEEE Transactions on Medical Imaging, providing an overview of deep learning techniques applied to various medical imaging tasks, including spine image analysis.

Transfer Learning and Medical Diagnostics:

- **"Transfer Learning in Medical Imaging: A Comparative Study"** - A conference paper presented at MICCAI (Medical Image Computing and Computer-Assisted Intervention), comparing transfer learning techniques for improving diagnostic accuracy in spine imaging.

Ensemble Methods in Healthcare AI:

- **"Ensemble Learning for Clinical Decision Support Systems: Case Studies and Benchmarks"** - A study published in the Journal of Biomedical Informatics, showcasing ensemble methods' effectiveness in combining multiple AI models for more robust clinical decision-making.

Multimodal Data Integration:

- **"Integrating MRI and Genetic Data for Disease Diagnosis: A Case Study on Spinal Disorders"** - A research article in Frontiers in Genetics, demonstrating the integration of MRI images with genetic data to enhance diagnostic accuracy for spinal disorders.

Clinical Validation Studies:

- **"Prospective Validation of AI Models in Spine Clinics: Challenges and Solutions" -** A study presented at the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI), discussing methodologies and challenges in validating AI models for real-world clinical use in spine clinics.

Collaborative Research Initiatives:

- **"International Collaborations in AI and Healthcare: Joint Efforts in Spine Imaging Research" -** A collaborative research initiative between universities and healthcare institutions in multiple countries, aiming to advance AI applications in spine imaging through shared datasets and expertise.

Conclusion

This project has showcased the potential of machine learning in advancing the classification of lumbar spine degenerative diseases using medical imaging data. Through meticulous data preprocessing, robust model training, and thorough validation, accurate predictive models for various spinal conditions were developed. Implementation of state-of-the-art deep learning architectures, such as ResNet34, coupled with data augmentation and multi-threaded processing, significantly enhanced the models' performance and generalizability.

The findings underscore the importance of interdisciplinary collaboration between data scientists and medical professionals to translate research into clinical practice effectively. The models' ability to classify and predict spinal conditions from MRI scans promises improved diagnostic accuracy and streamlined treatment planning, ultimately leading to better patient outcomes.

While the study has achieved promising results, it is not without limitations. Challenges such as data imbalance, variability in image quality, and the need for larger and more diverse datasets remain significant hurdles. Future research should focus on expanding data collection efforts, exploring advanced model architectures, and refining evaluation methodologies to enhance the reliability and applicability of these models in real-world clinical settings.

By addressing these challenges and leveraging emerging technologies, healthcare interventions and personalized treatment strategies in the field of spinal health can be significantly improved.

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