Swiss Data Science Center

First National Call for Projects – 2024

# **Full Proposal Submission**

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| --- | --- |
| **Project Title** | Self-supervised learning of human spinal cord anatomy towards therapeutic optimization after neurological deficit. |
| **Acronym** | SpineGPT |
| **Main applicant** | Assistant Professor, Henri Lorach |
| **Project abstract** | Personalized spinal cord models based on medical imaging are crucial for enhancing the efficacy of epidural electrical stimulation (EES) therapies, which aim to restore movement in individuals with spinal cord injury (SCI) and Parkinson’s Disease (PD). These models assist in accurately positioning multielectrode EES implants by identifying optimal placements which maximize the nerve responses to the stimulation in-silico. Building these models depends on acquiring and processing custom medical imaging of patients’ spinal cords through MRI and CT scans. Extracting the necessary information from these scans, such as segmenting several spinal tissues or identifying lesions, requires expert annotations. This process is labor-intensive and time-consuming, which limits the scalability of the usage of personalized spinal cord models in EES based therapies. Consequently, there is an imbalance between the quantity of labeled and unlabeled medical imaging data for the spinal cord.  Artificial neural networks (ANNs) offer the potential to reduce the need for expert intervention. However, they are challenged by the limited availability of annotated medical images. As a result, ANNs trained on specific conditions, like particular MRI sequences or anatomical regions, often fail to generalize to novel conditions not encountered during training. Self-supervised learning (SSL) techniques, on the other hand, can leverage large amounts of unlabeled medical imaging data to develop generalist spinal cord models. This project aims to develop SpineGPT, a self-supervised framework to learn informative representations of spinal cord MRI scans. SpineGPT will be further trained to perform clinically relevant tasks like spinal tissue segmentation, artifact affected region reconstruction, and MRI resolution enhancement, with minimal expert intervention. An added natural language interface will allow clinicians to interact directly with the model, supporting efficient data analysis and enhancing EES therapy planning. |
| **Free Keywords** | Spinal cord; Personalized models; MR imaging; Self-supervised learning; Foundation models |

This is a submission to the following track:

⬜ General (G)

⬜ Environment, Climate and Energy (ECE)

☑️ **Health and Biomedical Sciences (HBMS)**

⬜ Data Science for Large Scale Infrastructure (LSI)

The applicant hereby confirms that all the information provided in this proposal, as well as in the attached data form, resource form, and other additional attachments (if any), is true and correct. They were prepared with the consent of the persons involved.

Place, date Signature

**List of Partnering Teams**

|  |  |
| --- | --- |
| **Partnering team (PT) 1 (Project lead)** | **.NeuroRestore** |
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# **Proposal** (15 pages, excluding references)

# **Summary** (max 500 words)

Personalized spinal cord models play a crucial role in enhancing the effectiveness of epidural electrical stimulation (EES) therapies aimed at restoring movement in individuals with spinal cord injury (SCI)1–4 and Parkinson’s Disease (PD)5. These models guide neurosurgeons in the precise placement of EES implants, ultimately improving surgical outcomes. However, creating these models involves the segmentation of spinal tissues from medical imaging data, a time-intensive and labor-intensive task that requires expert annotations. This demanding process limits scalability.

While traditional artificial intelligence (AI) methods, like artificial neural networks (ANNs) trained in a supervised fashion, offer potential to reduce the manual workload, they face challenges due to limited access to high-quality, labeled medical data. This makes it difficult for them to generalize across diverse scan types or adapt to novel cases, often resulting in suboptimal performance when applied to real-world situations that differ from the specific conditions on which they were trained.

To overcome these challenges, we are leveraging self-supervised learning (SSL), a powerful technique that learns from large amounts of unlabelled data. SSL is the approach behind successful models like ChatGPT6, which learn language patterns by predicting missing words based on context. By learning from unstructured data, SSL has revolutionized fields like natural language processing, and our goal is to harness its potential for medical imaging.

This project aims at implementing SSL strategies for learning a generalist model of spinal cord MRI scans useful to perform clinically relevant tasks with minimal expert intervention. More precisely we will build upon a generative model we developed for this purpose, called SpineGPT. SpineGPT is pre-trained through SSL to reconstruct missing sections of spinal cord MRI scans, capturing essential structural information of the spinal cord. SpineGPT will be then fine-tuned for downstream tasks useful for building personalized spinal cord models, such as enhancing MRI volume quality, segmenting different spinal tissues and reconstructing artifact-affected regions. So far, in a preliminary stage, SpineGPT has demonstrated promising results in tissue segmentation and artifact removal. This project aims to further develop this approach and build a tool that allows clinicians to efficiently perform relevant analysis through a natural language interface. By facilitating a more accessible and efficient creation of personalized spinal cord models, SpineGPT has the potential to improve treatment outcomes for patients with SCI and PD.

# **Overview**

## Motivation, context, and objectives (max 350 words)

Personalized spinal cord models are essential for enhancing the effectiveness of epidural electrical stimulation (EES) therapies aimed at restoring neurological functions in individuals with spinal cord injury (SCI)1–4,7,8, Parkinson’s Disease (PD)5 and Multiple Systems Atrophy (MSA)9. Built on detailed, patient-specific medical imaging data, both MRI and CT scans, these models play a critical role in both the pre-operative planning and post-operative fine-tuning of multielectrode EES implant placements (Figure 1).

EES implants pre-operative planning is conducted in two stages, both utilizing pre-operatively acquired MRI and CT scans. First, manual anatomical measurements of the spinal canal in the implantation area on MRI and CT images are used to identify any anatomical abnormalities and constraints. Second, spinal tissues are manually segmented and brought together into a personalized bioelectrical model of the spinal cord around the lesion region. The model is subsequently used to carry out electromagnetic and neuronal simulations. The anatomical measurements and simulated EES response together inform the choice and position of optimal implants. This approach has been successfully applied in previous1–5,7–9 and ongoing clinical studies (NCT05111093, NCT04994886, NCT02936453).

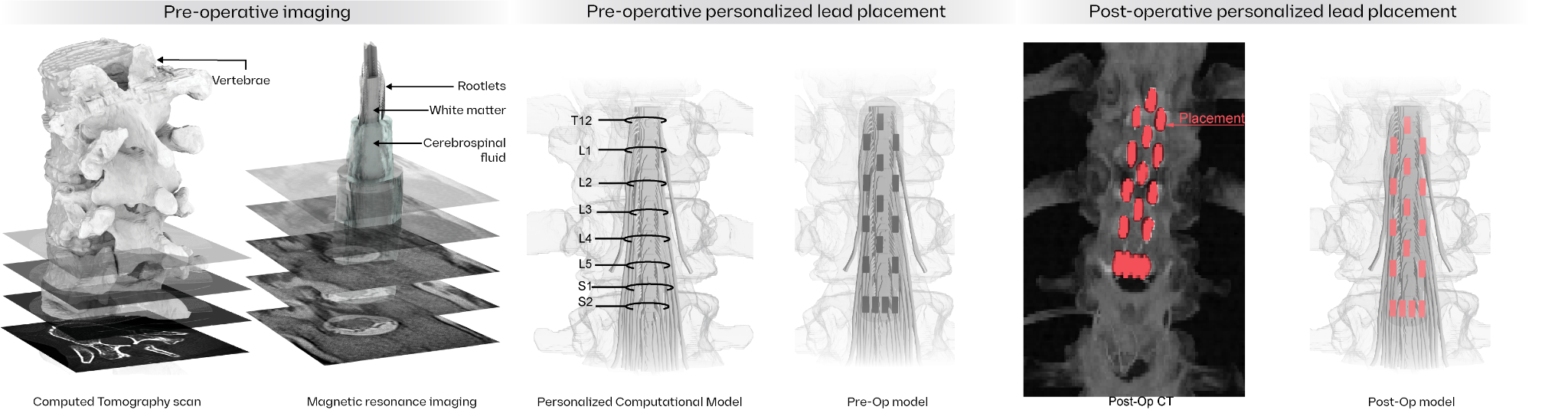
The meticulous processing and annotation of the medical imaging required to create the spinal cord personalized model is labor-intensive and time-consuming3. Anatomical tissue segmentation is a bottleneck for the scalability and widespread clinical adoption of personalized spinal cord models.

Artificial neural networks (ANNs) hold promise for automating tissue segmentation from medical imaging, thereby reducing reliance on manual intervention10. Nevertheless, they face significant challenges due to limited labeled medical data, variability between patients, imaging protocols, anatomical regions, and scanner types and vendors11,12.

Self-supervised learning (SSL) has emerged as a powerful method for deriving meaningful data representations without human supervision. SSL has fueled the success of natural language processing (NLP) models like ChatGPT6, which learn language structure and semantics by predicting masked words within a sentence based on surrounding context. This approach allows NLP models to perform tasks like translation efficiently and accurately.

Taking inspiration from NLP, we use SSL to leverage the unlabelled MRI volumes to develop spinal cord models that can be adapted to tasks with minimal expert intervention. We will expand our existing framework, SpineGPT, a generative autoencoder model applied to spinal cord MRI volumes. Similar to NLP models, SpineGPT learns by reconstructing masked parts from their visible counterparts, extracting representations that capture the spinal cord’s underlying structure and variability. We will use these representations to fine-tune SpineGPT to solve clinically relevant problems such as tissue segmentation, artifact-affected regions reconstruction, and MRI quality enhancement.

Inspired by recent interfaces that use natural language6,13, SpineGPT’s interface will enable users to interact with the model, and its downstream tasks fine-tuned versions, through natural language queries. In the future, this framework could be integrated into medical tools, enabling doctors to deliver personalized treatments more quickly, accessibly, and effectively across various medical fields.



**Figure 1: Personalized model reconstruction for pre- and post-operative EES lead placement.** The pre-operative phase (left) includes computed tomography (CT) and magnetic resonance imaging (MRI) scans to visualize vertebrae, white matter, cerebrospinal fluid, and spinal roots. These tissues are segmented from the medical imaging. These segmentations are the basis of the creation of personalized computational models of the spine. This detailed model is leveraged to guide the placement of the EES lead. In the post-operative phase (right), CT imaging confirms the EES lead placement, which is then incorporated into a post-operative model for ongoing treatment optimization. This process enables precise targeting of spinal structures, enhancing the effectiveness of EES therapies for SCI and PD patients.

## Scientific and Societal Impact (max 250 words)

SpineGPT will have a profound impact on both scientific research and clinical practice. Scientifically, it will push the boundaries of medical imaging and machine learning by demonstrating the potential of SSL in healthcare applications, reducing the need for large volumes of annotated data. By developing generalized models adaptable to various clinical tasks, SpineGPT will pave the way for more efficient, scalable solutions in imaging-based diagnostics and therapeutic planning, especially for SCI and PD.

In addition, SpineGPT will accelerate research and innovation in medical imaging by illustrating how SSL can be applied effectively in healthcare. Its success will inspire further exploration of AI-driven approaches in diagnostics and therapeutic planning, potentially accelerating advancements in precision medicine.

From a societal perspective, the project aims to ultimately improve the treatment outcomes for individuals with SCI and PD. By contributing to the fast and precise creation of personalized spinal cord models, SpineGPT will enhance EES therapies, leading to improved patient mobility and long-term quality of life.

The project’s commitment to open science will further democratize access to advanced medical imaging technologies. By making the models and data publicly available, it will foster collaboration and innovation within the scientific community. SpineGPT can be envisioned as a versatile tool and foundational model for MRI and medical image processing, extending its benefits to domains where expert annotation is both challenging and costly, and supporting the transition toward automated diagnosis and precision medicine in healthcare.

## Alignment between project and call (max 250 words)

The SDSC offers access to a team of data scientists with expertise in novel methods in AI and self-supervised learning (SSL). This expertise is crucial for the successful development and optimization of SpineGPT, ensuring that state-of-the-art data science techniques are effectively applied to medical imaging challenges.

The computational resources provided by the SDSC, including CPU/GPU access and data storage, will be essential for training, validating, and scaling up the models we will develop on high-dimensional MRI data. This will largely accelerate the project's progress and success.

# **Project description**

## Detailed research plan (max 2500 words)

We envision the development of SpineGPT in three stages. The first stage will involve using SSL methods to enable the framework to learn intrinsic and meaningful features of the spine. In the second stage, the framework will be fine-tuned for specific clinically relevant tasks. Finally, the third stage will refine the framework for broader, general-purpose usage.

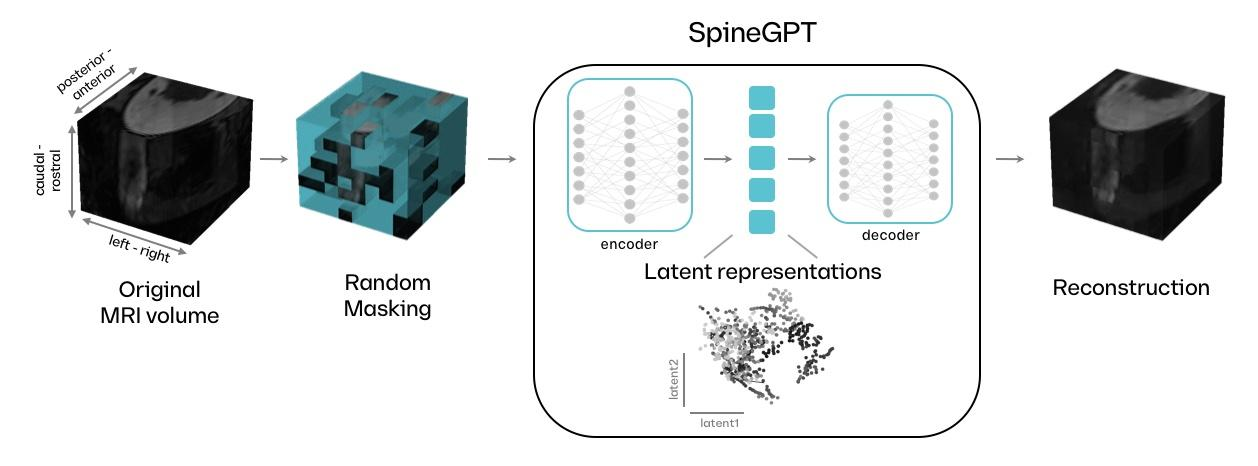
**SpineGPT Model Development and Optimization**

Our current implementation of SpineGPT builds on masked-autoencoding techniques from computer vision, learning self-supervised representations of MRI scans through a self-reconstruction objective. In this process, a 3D chunk of the scan is partially masked at random and used as input to an autoencoder neural network, which is trained to reconstruct the missing portions from the visible parts (Figure 2). Through this approach, the model’s encoder learns to map the original volume to a latent representation that captures informative and essential structural details.

In this project, we will further develop this self-supervised framework, exploring and optimizing the architecture and learning paradigm to enhance the representations it learns. SpineGPT’s current encoder and decoder consist of standard Vision Transformer layers adapted for 3D volumes. We will adjust this architecture to suit MRI volumes by integrating more efficient tokenization methods and improved attention mechanisms, allowing for a detailed capture of both local and global information. Additionally, we’ll optimize the masking strategy by introducing structured masks along specific axes and incorporating positional encodings to provide anatomical context, such as spinal regions or MRI sequence types. This will guide the model in learning meaningful concepts along defined logical axes, improving its efficiency and semantic understanding.

In this stage, we will leverage all available unlabeled data (Datasets 1-7 in the annexed Data Form), totaling over 1,300 diverse MRI volumes of the spine. The .NeuroRestore spine dataset (Dataset 1) offers a unique dataset of several MRI sequences per individual, including unique ultra-high-resolution MRI volumes with labels of various anatomical tissues.

We will evaluate the quality of the representations learned by the model through both supervised and unsupervised methods. Since labeling is often costly and specific tasks may not be predefined, unsupervised evaluations are crucial. To this end, we propose using metrics like the effective rank of the latent representations, which will help maximize information content and prevent dimensional collapse.



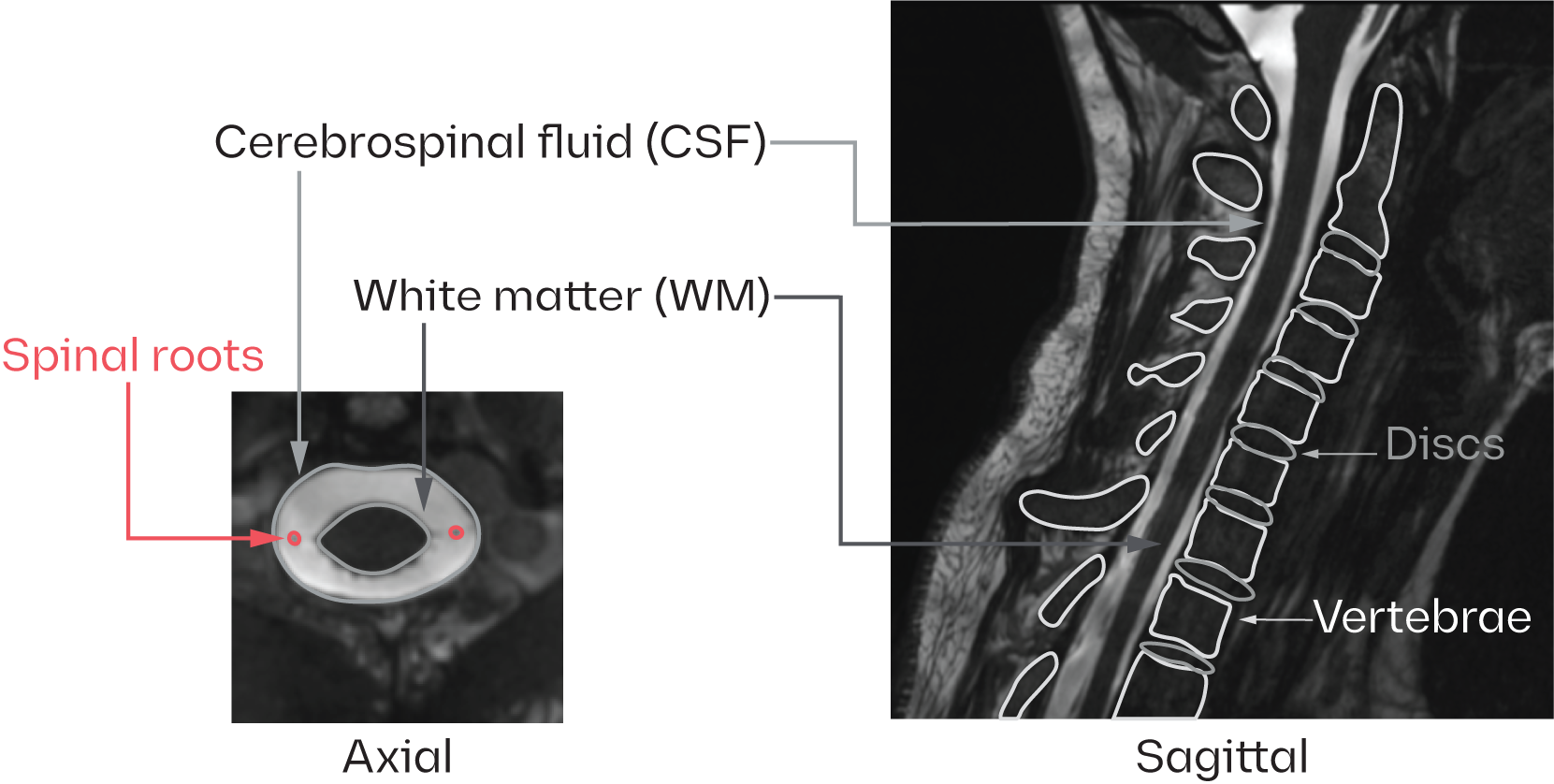
**Figure 2: SpineGPT self-supervised learning framework.** The original MRI volume undergoes random masking. The masked volume is then input to the encoder, which generates latent representations capturing structural features of the spinal cord. The decoder reconstructs the original volume by filling in the missing parts based on the learned latent representations. This self-reconstruction objective enables SpineGPT to develop a comprehensive understanding of spinal anatomy from unlabeled data.

**Application on Clinically Relevant Downstream Tasks**

We will apply SpineGPT to address clinically relevant tasks by using it as a generalist feature extractor and fine-tuning it with minimal expert supervision.

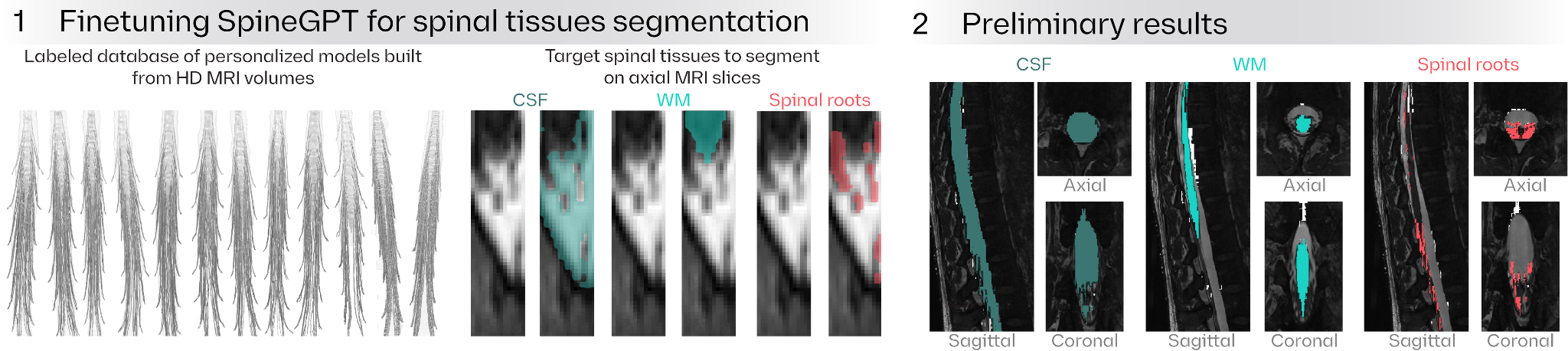
1. **Spinal Tissue Segmentation (Datasets 1, 3 and 6)**

Segmenting various spinal tissues is vital for developing personalized spinal cord models used in EES therapies. These tissues (Figure 3) include spinal roots, white matter (WM), cerebrospinal fluid (CSF), vertebrae, and intervertebral discs (IVD).



**Figure 3: Spinal tissues of interest on a T2 MRI volume (axial and sagittal views).** Key tissues are the vertebrae, intervertebral discs, cerebrospinal fluid (CSF), white matter (WM), and spinal roots. These structures are essential for developing accurate personalized spinal cord models for EES therapies.

Our goal is to segment these tissues with minimal labeled data. We have proposed a strategy of freezing the encoder of SpineGPT and finetune the decoder to infer the previously described spinal tissues, leveraging SpineGPT’s latent representations (Figure 4).



**Figure 4: SpineGPT pipeline for spinal tissue segmentation. (1)** Finetuning SpineGPT for spinal tissue segmentation: A labeled database of personalized models, built from high-definition MRI volumes, is used to target specific spinal tissues: the cerebrospinal fluid (CSF), white matter (WM), and spinal roots. **(2)** Preliminary results of segmentations of CSF, WM, and spinal roots across axial, sagittal, and coronal views, showing SpineGPT’s promising ability to accurately delineate spinal structures in MRI scans.

In our preliminary approach, we selected a subsample of labeled MRI volumes from the .NeuroRestore dataset (Dataset 1) to segment the CSF, WM and spinal roots tissues to finetune Spine GPT. We achieved promising preliminary results, with Dice scores of 0.849, 0.781 and 0.821 for segmentations of CSF, WM and spinal roots respectively (Figure 4).

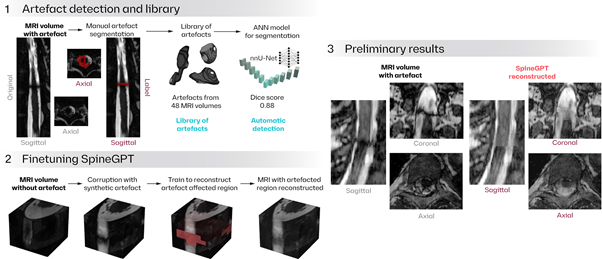
Based on this preliminary success, we are confident that fine-tuning SpineGPT using all the available datasets (Dataset 1 and the publicly available Datasets 3 and 6) will achieve the state-of-the-art comprehensive and accurate spinal tissue segmentations to date.

1. **Artifact-Affected Region Reconstruction (Dataset 1)**

Magnetic field inhomogeneities often impact MRI volumes in different forms14. Ultra-high-resolution MRI volumes inhomogeneities are manifested as bending artifacts, dark thin structures caused by the airaround the neck or present in the lungs of the indiviudal. These artifacts can significantly compromise image quality, posing a challenge to obtaining clean and clinically useful images (Figure 5). We propose to fine-tuned SpineGPT to effectively identify and remove these artifacts, addressing a critical need in high-quality spinal imaging.

One major challenge in this task is the absence of a ground truth dataset for artifact removal, as no MRI volumes are available with both clean and artifact-affected versions for direct comparison. To address this, we manually created a dataset of artifacts in a subset of our .NeuroRestore dataset (Dataset 1) creating a library of real artifacts (Figure 5). We then trained an ANN to detect and segment artifact-affected regions in our MRI dataset based on the nnU-Net framework10 (Figure 5). From this library, we generated synthetic artifacts to apply to clean MRI regions, resulting in a labeled dataset that distinguishes between clean and corrupted areas (Figure 5). We propose to fine-tuned SpineGPT to reconstruct these corrupted areas.

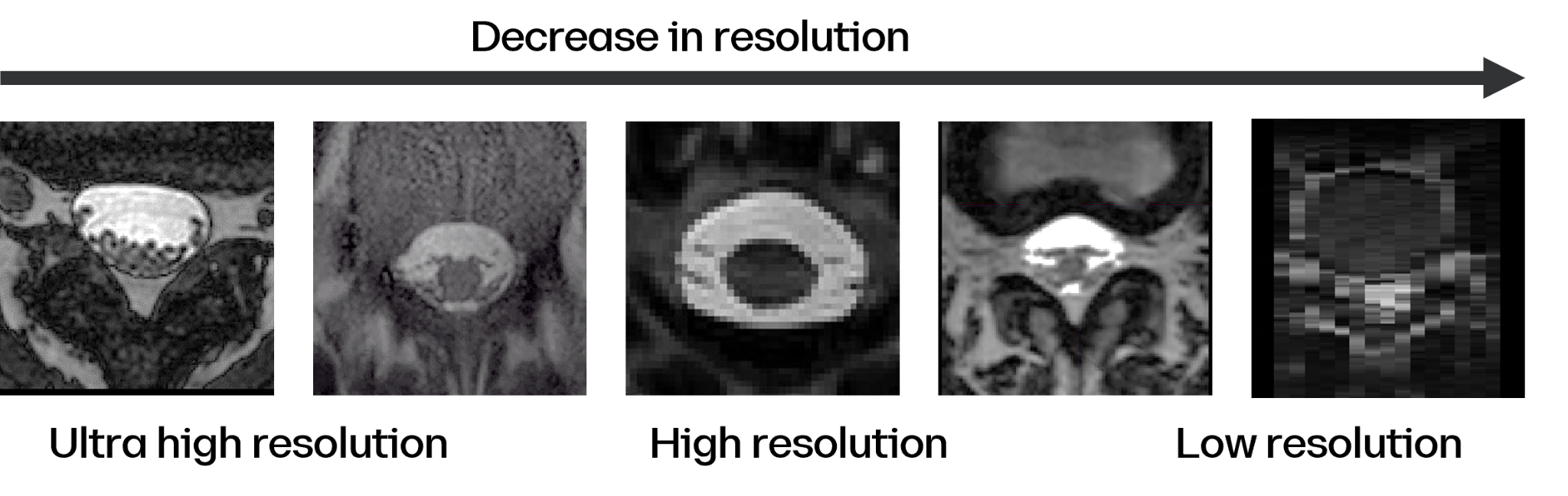
Our preliminary pipeline achieved a Mean Absolute Error (MAE) score of 2.251, showing promising reconstruction of artifact affected regions (Figure 5). We are confident that further training and optimization of SpineGPT will consequently improve SpineGPT’s ability to reconstruct artifact affected regions, ensuring cleaner and more accurate MRI scans.



**Figure 5: artifact detection and reconstruction using SpineGPT.** **(1)** artifact detection and library creation: MRI volumes with artifacts are manually segmented to build a library of artifacts, which is used to train an artificial neural network (nnU-Net10) for automated artifact segmentation with a Dice score of 0.88. **(2)** Finetuning SpineGPT: Synthetic artifacts are generated in clean MRI volumes to train SpineGPT to reconstruct artifact-affected regions. **(3)** Preliminary results: artifact affected regions of MRI volumes (left) are reconstructed by SpineGPT (right) in coronal, sagittal, and axial views.

1. **Resolution Enhancement (Datasets 1, 2, 3 and 6)**

Higher-resolution MRI scans provide critical information on specific tissues, such as spinal root trajectories, which are difficult to visualize at lower resolutions (Figure 6). However, these sequences are time-consuming to acquire and challenging to set up, even for expert MRI technicians. We, and others, have collected multiple sequences of the same spinal cord at various resolutions. Additionally we can artificially reduce the resolution of MRI volumes.



**Figure 6: T2 MRI images of the spinal cord at various resolutions, ranging from ultra-high to low resolution.** As resolution decreases, anatomical details become less distinct, impacting the visibility of structures such as the spinal cord and surrounding tissues. SpineGPT aims to enhance lower-resolution scans to higher resolutions, enabling clearer visualization of fine anatomical features even in time-constrained or resource-limited clinical settings.

We propose further fine-tuning SpineGPT for resolution enhancement, enabling the progressive upscaling of low-resolution MRI scans to high-resolution volumes. We hypothesize that the latent representations learned by SpineGPT will support this enhancement, preserving essential anatomical details as the resolution increases. This approach could simplify and accelerate the acquisition of ultra-high-resolution spinal cord images, making advanced imaging more accessible.

**Development of a Generalist Tool for Medical Imaging Processing to Assist Researchers and Clinicians**

Our goal is to integrate all the processing components developed in this project to create a generalist toolbox that supports researchers and clinicians in analyzing MRI volumes for constructing personalized spinal cord models. This toolbox will include:

* **User-Friendly Graphical Interface**:

A simple interface that allows clinicians and researchers to use SpineGPT for various tasks, such as tissue segmentation and artifact-affected region reconstruction, without requiring advanced technical knowledge.

* **Interface for Fine-Tuning**:

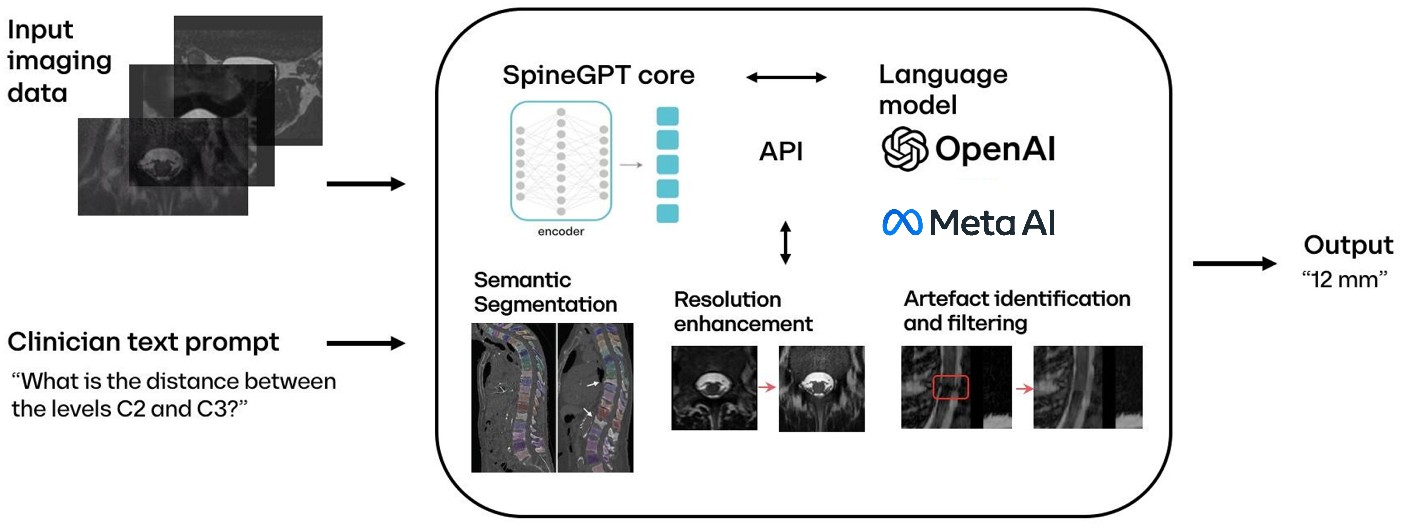
A flexible interface enabling users to fine-tune SpineGPT’s foundational model for additional tasks, adapting it to different clinical and research needs with minimal supervision.

* **Natural Language Interface**:

This interface will bridge the gap between clinician input and SpineGPT’s capabilities, allowing users to interact with the model through natural language queries (Figure 6)13. Clinicians could specify goals like "segment the lumbar spinal cord around the lesion for patient X" and a language model (e.g., Llama 2) would translate them into computer-executable code through a custom API we will develop. This would allow for interactive analysis making the processing and extraction of useful information from MR volumes more efficient and accessible for life scientists. The API would consist of building blocks and methods for MRI processing, spatial and semantic reasoning, as well as visualization, using SpineGPT’s (pre)computed outputs. For example, the interface could use the segmentation model to provide a semantic and spatial decomposition of the spinal cord and then provide useful metrics and visualizations to the clinician.

Examples of useful clinician text prompts:

* “Plot a sagittal view of the region around the lesion in patient X”
* “Filter the artifacts and enhance the quality of this MRI volume”
* “Generate a 3D reconstruction of the thoracic spine for this patient and export the file in STL format”
* “What is the intervertebral distance between regions C1 and C2”
* “Compute spinal cord diameter variabilities across patients for the lumbar regions, and export the result as a csv file”
* “Compute the rostrocaudal between the lesion of the spinal cord and the conus medullaris.”



**Figure 7: Integration of SpineGPT with a language model for enhanced clinical interaction and analysis.** Input imaging data, such as MRI scans, are processed by the SpineGPT core, which performs tasks like semantic segmentation, resolution enhancement, and artifact identification and filtering. Clinicians can interact with the model using natural language prompts, such as “What is the distance between the levels C2 and C3?” The language model (e.g., OpenAI's GPT-4 or Llama) interprets these prompts and communicates with SpineGPT via an API, generating precise outputs. This integration facilitates intuitive, text-based access to advanced imaging analyses, supporting clinical decision-making.

## Data (max 1500 words)

The **companion Data Form** provides detailed information about the various datasets used in this project. MRI volumes are anonymized and stored in compressed Nifti format (.nii.gz). When labeled data is available, it is also saved as a compressed Nifti volume, with file names including a suffix to identify specific tissues (e.g., “WM” for white matter) after the original volume name. For consistency, all data will be organized in the BIDS format throughout the project. **Dataset 1** consists of a custom-acquired MRI dataset from .NeuroRestore, with a sample of ultra-high-resolution MRI volumes accessible via this link:<https://drive.switch.ch/index.php/s/KyoKQ7mYnTOBRai> (password: *NeuroRestore2024*).

Since .NeuroRestore is part of EPFL, and the clinical trials are EPFL-sponsored, the data transfer and user agreement processes are streamlined as long as the data remains anonymized—a standard practice at .NeuroRestore. Publicly available datasets (**Datasets 2 to 7**11,12,15–20) are formatted and ready for use, with any differences in orientation easily resolved using preprocessing scripts provided by .NeuroRestore. We provide a description of each publicly available data set in the companion form.

## Collaboration and contribution (max 250 words)

This project leverages the complementary expertise of .NeuroRestore in spinal cord research and advanced imaging, together with the data science capabilities of the SDSC. .NeuroRestore provides a deep understanding of spinal cord anatomy and clinical challenges, while the SDSC brings cutting-edge knowledge in self-supervised learning (SSL) and machine learning techniques.

Data scientists from the SDSC will play a pivotal role in developing and optimizing the models, ensuring they are suitable for clinical applications. Their expertise will enhance SpineGPT’s performance, from initial training to fine-tuning for specific medical tasks. Close collaboration between the SDSC team and .NeuroRestore’s clinical and imaging experts will ensure that the models are not only scientifically robust but also aligned with practical clinical needs.

By bridging the gap between advanced AI methods and clinical practice, this partnership will enhance the clinical relevance of SpineGPT, making it a valuable tool for developing personalized treatment plans. Ultimately, this collaboration will lead to better patient outcomes and more effective EES therapies for individuals with spinal cord injuries and Parkinson’s Disease.

## Work Packages, Milestones and Deliverables

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| *WP* | *Partner*  *(short name)* | | *Year and Quarter* | | | | | | | |
| *.NR* | *SDSC* | *2025* | | | | *2026* | | | |
| *1* | *2* | *3* | *4* | *1* | *2* | *3* | *4* |
| *WP1: Data* | *L* | *P* | *M1.1* | *M1.2* | *M1.3* |  |  |  |  |  |
| *WP2: Fondation* | *P* | *L* |  |  | *M2.1* | *M2.2* |  |  |  |  |
| *WP3: Downstream Tasks* | *L* | *P* |  |  |  | *M3.2* | *M3.1* | *M3.3* |  |  |
| *WP4: NLP Interface* | *P* | *L* |  |  |  | *M4.1* |  | *M4.2* | *M4.3* | *M4.4* |

*Table 1: Overview of work packages with associated partners and timing for the milestones. Work package leader is marked with the letter “L”, Participants are marked with the letter “P”. Milestones are indicated in the corresponding year and quarter.*

**WP1: Data Preparation (Lead: .NeuroRestore, Contribution: SDSC)**

* **Objectives**:
  + To collect, anonymize, and pre-process MRI volumes of the spinal cord.
  + To standardize the anonymized dataset into a unified format for self-supervised learning (SSL) models.
  + To prepare specific datasets for the different downstream tasks
* **Tasks**:
  + **T1.1:** Collect MRI data from the NeuroRestore spine anonymized dataset and public sources, ensuring comprehensive coverage of spinal regions.
  + **T1.2:** Utilize NeuroRestore's preprocessing pipelines to label, and prepare MRI data.
  + **T1.3:** Prepare and process the dataset for the different downstream tasks.
  + **T1.4:** Organize the datasets in standardized format (e.g. BIDS format), processing and facilitating model training.
* **Milestones**:
  + **M1.1:** Completion of dataset collection and organization (Q1, 2025).
  + **M1.2:** Full data preprocessing and quality validation (Q2, 2025).
  + **M1.3:** Different preprocessed datasets for the different downstream tasks (Q3,2025)
* **Deliverables**:
  + **D1.1:** Standardized and anonymized MRI datasets, fully prepared for SSL model input.
  + **D1.2:** Preprocessed datasets, for the different downstream tasks.

**WP2: SpineGPT Foundation Model Development and Training (Lead: SDSC, Contributions: .NeuroRestore)**

* **Objectives:**
  + To develop and train the SpineGPT foundation model using SSL for effective feature extraction from MRI data.
* **Tasks:**
  + **T2.1:** Design and optimize SpineGPT’s masked autoencoder backbone architecture and learning strategy.
  + **T2.2:** Implement SSL strategies to facilitate informative MRI-based feature learning and generalization across tasks.
  + **T2.3:** Train the model on unlabeled MRI data across modalities (e.g. different patients, MRI resolutions, …)
  + **T2.4**: Evaluate and tune the model using unsupervised and supervised metrics (e.g., effective rank, segmentation accuracy).
* **Milestones:**
  + **M2.1:** Finalized model architecture (Q3, 2025).
  + **M2.2:** Completion of model training and initial performance evaluation (Q4, 2025).
* **Deliverables:**
  + **D2.1:** Trained SpineGPT foundation model.

**WP3: Downstream Task Fine-tuning (Lead: .NeuroRestore, Contributions: SDSC)**

* **Objectives:**
  + To fine-tune SpineGPT for downstream tasks, based on the foundation SSL model. Downstream tasks include spinal tissue segmentation, artifact detection, artifacted region reconstruction and resolution enhancement.
* **Tasks:**
  + **T3.1:** Fine-tune SpineGPT on labeled datasets for precise spinal tissue (CSF, WM, spinal roots) segmentation.
  + **T3.2:** Develop a pipeline for automatically detecting artifact-affected MRI regions and generating augmented labeled dataset.
  + **T3.3**: Fine-tune SpineGPT for reconstructing artifact-affected MRI regions.
  + **T3.4**: Fine-tune SpineGPT for resolution enhancement
* **Milestones:**
  + **M3.1:** Optimized segmentation pipeline (Q4, 2025).
  + **M3.2:** Optimized artifact detection & artifact reconstruction pipeline (Q1, 2026).
  + **M3.3:** Optimized resolution enhancement pipeline (Q2, 2026)
* **Deliverables:**
  + **D3.1:** Clinically validated SpineGPT models for deployment in spinal cord MRI analysis

**WP4: Natural Language Interface Integration for Spinal Cord Analysis (Lead: SDSC, Contributions: .NeuroRestore)**

* **Objectives:**
  + To incorporate a natural language interface into SpineGPT, allowing clinicians and researchers to interact with MRI data and perform spinal analysis through intuitive language-based commands.
* **Tasks:**
  + **T4.1:** Develop a simple natural language interface, utilizing an LLM (e.g., GPT-4) to interpret user prompts and convert them to specific MRI analysis.
  + **T4.2:** Development of an API incorporating building blocks and functions for interfacing, semantic understanding, and basic processing.
  + **T4.3:** Design error handling, rephrasing, and self-correction mechanisms to improve the system’s robustness and accuracy when handling ambiguous or out-of-scope commands.
  + **T4.4:** Conduct testing with end-users to refine the interface and ensure that commands align with common clinical and research needs for spinal cord imaging analysis.
* **Milestones:**
  + **M4.1:** Completion of the initial NLP interface design and preparation for the integration with SpineGPT (Q4, 2025).
  + **M4.2**: Integrate the interface with SpineGPT and its downstream tasks (Q2, 2026)
  + **M4.3:** Initial user testing and iterative refinement of the language interface (Q3, 2026).
  + **M4.4:** Final release of full package (Q4, 2026).
* **Deliverables:**
  + **D4.1:** A fully functional natural language interface for SpineGPT, enabling clinicians and researchers to perform MRI analysis tasks through language commands.
  + **D4.2:** Documentation and training materials for end-users on how to interact with the NLP interface effectively.

## Risk assessment and mitigation (max 500 words)

One of the main risks associated with this project is the potential lack of sufficient labeled data for downstream tasks, such as spinal tissue segmentation. To mitigate this risk, we have developed an in-lab semi-automatic segmentation framework for spinal cord tissues, including spinal roots, white matter (WM), cerebrospinal fluid (CSF), intervertebral discs (IVD), and vertebrae5,8. This tool, specifically designed for T2 ultra-high-resolution images, enables fast segmentation. It requires expert supervision and correction for accuracy. If labeled data proves insufficient, this tool and accompanying expert knowledge will be employed to annotate additional data, ensuring steady project progress. We provide such expertise at .NeuroRestore.

Another potential risk is a shortage of unlabeled data, which is essential for self-supervised learning (SSL) techniques like those used by SpineGPT. To address this, we have the capability to acquire additional MRI data through one of our ongoing human research protocols, providing a reliable supply of unlabeled data for training and enabling the model to generalize effectively.

The natural language interface also presents a risk of generating incoherent or inaccurate outputs (hallucinations). To minimize this, we propose the development of an API of basic building blocks that perform controlled, accurate processing with rule-based checks, maximizing the reliability of the language interface.

Finally, the project’s reliance on advanced computational resources introduces potential risks related to system performance or resource availability. To mitigate this, we will work closely with the SDSC to ensure that the necessary infrastructure is available and optimized for handling large-scale data processing and model training tasks.

In summary, while there are risks related to data availability and computational resources, we have established several strategies to mitigate these challenges. Through the use of semi-automatic annotation tools, the ability to acquire additional data, iterative model development, and careful management of computational resources, we are confident in our ability to overcome potential obstacles and ensure the successful completion of the project.

# **Resources**

## SDSC Staff (max 150 words)

We will leverage the expertise of SDSC data scientists in advanced AI techniques, particularly autoencoding and SSL, to develop SpineGPT. Their knowledge will be instrumental in creating a robust and scalable model.

We estimate that one Full-Time Equivalent (FTE) over two years will be sufficient to build and optimize SpineGPT. This effort includes making the model open-source and collaborating on a conference paper, as well as a high-impact journal submission, to share the project’s results with the scientific community.

## Compute and storage resources (max 250 words)

For this project, we estimate the following computational and storage resources:

* **CPU Cores**: We anticipate needing 16-32 CPU cores to handle data pre-processing, model training, and evaluation tasks efficiently.
* **RAM**: To manage the high memory demands of processing large, high-resolution MRI volumes, we require 128-256 GB of RAM.
* **Data Storage:** Approximately 500 GB of storage will be needed to accommodate both raw and processed MRI datasets, as well as intermediate outputs, model checkpoints, and logs during the training and evaluation stages.
* **GPU Boards**: For fast and efficient model training and inference, we estimate the need for 2-3 high-performance GPU boards (such as NVIDIA A100 or V100).

## Contributed resources (max 250 words)

**Personnel**

Professor Henri Lorach (10%)

Sergio Daniel Hernandez Charpak - PhD student (50%)

Icare Sakr - PhD student (50%)

Léon Muller - EPFL Master student (100%)

Labeling expert (10%)

Clinical expert (10%)

**Resources**

Laboratory shared computing workstation

EPFL storage servers

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