Detection of spine deformities using deep learning models

Mahmoud Mohamed Mahmoud Ali

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Supervisor(s): Dr. Gamal Ebrahim & Dr. Hany Bastworus

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Computer Engineering Department

Faculty of Engineering

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Dissertation Approved:

Dr. mohammad abdellatif

Committee member

Dr. Marvy Badr

External committee member

Affiliation:

Prof. Tarek Ahmed Mahmoud

Dean Faculty of Engineering

Professor Maguid Hassan

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Abstract

This research outlines a medical mapping sequence designed for body part segmentation and disc data processing, specifically focusing on the lumbar spine. By customizing the list of body parts, the system enhances diagnostic precision by concentrating on specific regions. This targeted approach not only increases mapping accuracy but also improves visualization for medical professionals, educators, and researchers. The default implementation segments lumbar vertebrae (L1-L5), labeling and visualizing each with green coloration, with customizable color options for different vertebrae classes.

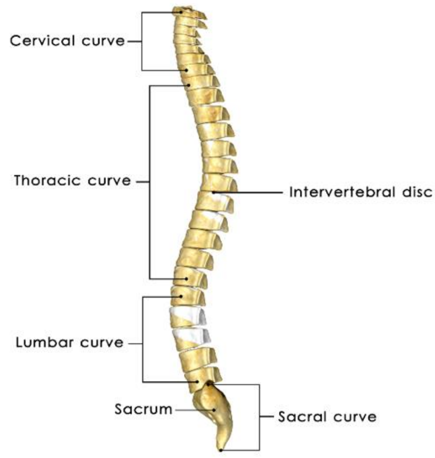
An image processing algorithm has been developed that easily detects and measures the vertical distances between green-colored contours representing the intervertebral discs for the purpose of disc data processing. In the implementation, HSV color space was used which is perfect for color-based segmentation tasks; the journey by converting images from BGR to HSV, isolating green regions, contour finding, and calculating vertical distances between them begins. This guarantees the accurate vertebral spacing measurement and detection corresponding to medical imaging requirements.

The algorithm makes the visualization drawing contours and vertical distances on the input image, connecting midpoints of bounding boxes, annotating vertical distances. These processed images and calculated measurements provide valuable data for subsequent research, thus boosting the precision in spinal diagnostics. This research focuses on the requirement for fine-grained segmentation and deep imaging processing for enhancing medical diagnostic tools.

Contents

Introduction

Objective of Artificial Intelligence, it is required to serve most fields. research fields are to implement AI (Artificial Intelligence) in medical usages at least with a limited processed asgenerating medical report based on some types of data as medical scan including X-ray, positron, emission tomography (PET), magnetic resonance imaging (MRI) and computed tomography (CT). Spine, which could be scanned using magnetic resonance imaging or computed tomography, is one of the known applications related to AI medical usage for case description.



According to many studies made on moving accidents, whatever the moving method is, an enormous number of injuries affect spine cord and as proved in (WHO.int, 2013)

And this research will focus on the lumbar spine, specially that this part has many problems which have a big effect on the spine. The lumbar spine consists of five levels.

trying to integrate the artificial intelligence with the lumbar spine analysis it is required to have two steps, the first one is how to localize the single vertebrae, and after selecting the five levels. We must check if there is any problem related to medical cases or not.

And the previous two items were used in many papers that study the integration between artificial intelligence and the medical cases of lumbar spine. But in this paper. We will focus on how to add a new step required to check for the specific reason for the medical problem. This point will specifically help the people in the scan service to draft their report for patients.

However, the big challenge will be to focus on how to get a correct diagnostic for the current case. As the lumbar spine has many problems different from place to another. for example, in vertebrae 1 there will be a medical problem difference from the vertebrae which follows it.

So, the correct diagnostic must be tracked from the starting point which will depend on how to get an accurate localization and segmentation or before moving to this step. in this report also we will focus on how to combine between the image processing techniques and the machine learning or deep learning techniques.

but the sequence of this step will be mixed as the first step will be to do some preprocessing for the input data then we must get an edge detection algorithm to try to get the edges of each vertebra and the final step of localization will we will try to get a mask for each sample of data then using them to get a model for the this process. And as the theoretical technique, it will be important to follow these steps to get fairly accurate processing and localization process to be followed by a perfectly accurate diagnostic.

the spine vertebrae are partitioned into 5 types with total of 26 vertebrae the types are explained as the following:

1. Cervical vertebrae (7 vertebrae)
2. Thoracic vertebrae (12 vertebrae)
3. Lumber vertebrae (5 vertebrae)
4. Sacrum vertebrae (one vertebra)
5. Coccyx vertebrae (one vertebra)

Each one of these types has its specific biological functions, pain type and diagnostic methods.

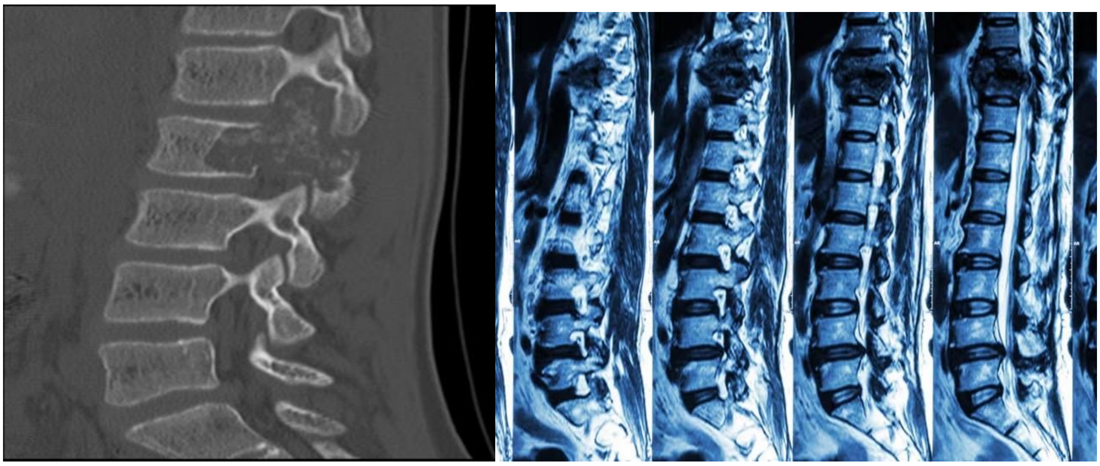
The second step, which is the segmentation to track if there are any problems or not, would be handled by comparing the original shape of the lumbar spine and the current input for the user. According to the medical concepts, there is no specific shape for all people as the lumbar spine may have a few changes in the shape and the slope of it. For example. If we have a tall man, it will have some differences from the short man. And this could affect the accurate diagnostic at the end. So, the database should have fair samples for all shapes, ages, and gender.

Because there will be some differences between the male and the female while scanning the lumbar spine. And to get an accurate diagnostic. We will need to have a full feature for each diagnostic case or disease while integrating the medical concepts with AI to compare between them. And give the patient the most accurate property of a disease for his case. Also, the model will require medical data for each disease related to the single vertebra.

There are also medical customization options in each stage to add a specific model for a different purpose, for example in the diagnostics stage there are a possible injures that may discovered recently, epically that there are medical diseases that could be newly appeared or may be caused because of another infection or disease add appeared as side effect which may be not clear for the model as a well-known specified disease. So, considering items like these will need to get a system that achieves the extendibility and scalability concepts for each stage either the localization or segmentation.

This could be achieved from the perspective of information data science and AI by making a model template according to each stage requirements, this template guide for the needed information required to studding or analyzing the new desired option as a new disease if this extension were assigned to diagnostics stage.

The extended models will be normal as any individual deep learning model. It is just required to fit the parameters as each stage template guide, and the library will be TensorFlow. However. It could be changed to Py torch. according to if we need a much higher Speed for handling the data between the medical image scanner of the medical device and the final report which will be provided for the patient.



Problem Statement

The need for a system with this capability will be important for many sides, either from the medical staff, medical photography services or medical schools and educational institutions.

But each stockholder will need a specialized procedure and layout. As for the medical staff, the system should be a supporting tool for the overlapped cases as a medical staff, it now tricky for him to do the diagnostics, but there are some combined infections and injures on many sides, so the diagnostics may be false selected because overlapped disease. For that reason, this AI system should work with him as a details extraction with filtering abilities.

On another hand, the diagnostics of a specific disease could be utilized by many methods according to the type of this disease. For example, diagnosing spine pains requires body imaging techniques like X-ray, computed tomography, and magnetic resonance imaging . But the output images of these techniques are not enough even to detect if there is any problem with the scanned body part or not. As its format does not make sense for non-medical persons. So, the output scan should pass on two stages before considering it as a valid parameter in the diagnosing process. The first stage is the initial diagnosing report, handled by the imaging team, specifically the team's medical advisor. This report includes general items as if there any change from the normal shape of this body part. If yes, which type of change was noticed, how far this change, does this change affect the scanned part negatively or at least affect its basic biological function?

All the previous questions are the main items in any medical report provided by any medical scan service provider.

But there are many challenges face the providers of the medical scan:

Medical advisors are not qualified enough to handle some advanced medical details required in the initial report. And this point leads to an extreme risk in the final diagnostic. Because when the main doctor checks the initial report and the scan image, he checks the image with a general look, but his focus on a specific part in the image is based on the recommended terms included in the initial report. So, this leads to a wrong diagnostic.

Medical advisors should be fully accurate in watching, zooming in or out, and relating the items in the output image and be accurate in writing language, selecting the medical words, and reviewing the report. Any term of these requirements could be easily affected by external interference during the work leading to further risks on diagnostic.

Challenges:

Although the needing to this technology, some challenges are faced to implement it in the real market of medical imaging. These challenges could be classified into:

Imaging challenges:

(Huber & Guggenberger, 2022) discussed that the challenges that affect analyzing medical images by AI are extremely related to the quality of this image. as the low-resolution images lead to wrong decisions either in extracting the required features or in the segmentation process. And in medical concepts, the any imaging techniques such as MRI do not show the lumbar spine vertebrae only, (Ellis, 2010). but it also shows the surrounding muscles, fats, and nucleus. Even if they are shown with small opacity, it will be considered as a noise during processing of feature extraction algorithms.

Clustering challenges:

One of the technical problems in integrating the automated diagnostics systems with the scan services is considering clustered parts from the scanned image as the concerned part to get examined.

For example, as the lumbar spine has 5 vertebrae to be examined, a new problem will appear during the localization process which is ensuring that each one of the five vertebrae is accurately localized. and their edges are the right edges. Because four edges of each vertebra are responsible for selecting the accurate diagnostic.

For another example, one of the localized clusters as vertebrae may be not a vertebra. and it could be another thing like disc which is a space between two vertebrae.

There is also a relation between the clustering challenges and the imaging challenges which causes some negative sides of the preprocessing. For example, after preprocessing the data, the output data may be missing some of the details which forming the vertebrae of lumbar spine could be cleared. However, some details were gathered, and these details are not required for diagnostics of the lumbar spine. So, these details may lead to conflicting factors that reduce the accuracy of selecting the best prediction of the single vertebra. And any wrong prediction of the vertebrae will lead to a gap between artificial intelligence and the ability to depend on it for medical cases.

Another problem of clustering accuracy is that there are some details that may affect the output clusters and these details should be considered even if it will affect the final output and its accuracy.

one of these details that should be considered is to check for the gender of the patient. And according to many studies there are some differences between the male and the female related to the general shape and the size for the vertebrae However, these considerations maybe not always affect the best decision (Bailey et al., 2016) . But it will be required for some cases to check for this point as in the later stages it will affect the final decision of diagnostic as there are many diseases to the lumbar spine get diagnosed by checking for some gaps between one vertebra and another one following it and calling this gap as the disc.

Medical challenges

The main challenge of medical problems is to check for any medical history that could do a change for the default forming style of the lumbar spine for specific person as there are many diseases outside of the scoop of spinal diseases but it could some changes for the general shape and size of the spinal canal and the related items with it so that's mean there is no static size of the template for the lumbar spine that fits for all people especially the persons who are suffering from another medical problems.

So, it will be required to consider the other diseases and check if it will influence the current decision of the AI model or not. And in case of it was proved that the patient is suffering from any problem or disease it will be required to recheck about the ability for the current AI model to handle and consider the changes caused by this disease before starting the processes and the analysis of diagnostics.

But this is a deep challenge as it will need to have some research and accurate studies and testing for the reasons about this decision and according to the AI science, this task requires specific type of artificial intelligence called generative AI.

Diagnosing challenges

The challenges related to this type are because there are many problems and diseases for the lumbar spine, and it will be difficult for us as engineers to implement these medical concepts to predict which type of this disease. For example, there are some diseases related to discs, and in this section, there are many problems that cause disc pain. while there are other problems not related to disc and they are just caused by the vertebra. and for a specific decision, there are some problems that could occur on one specific vertebra and the same problem couldn't ever happen on the other vertebrae. so that's mean the AI model should be aware about which vertebra is being checked and analyzed now to have the possible diseases of the current vertebra as it could be wrong decision because there are some similarities between the diseases but the final factor for considering a decision is to check if the decided disease could be hit this vertebra or it's related to another vertebra.

Related work:

There are many methods used to diagnostic. All methods follow standard concepts, but the differences between them are the way and algorithms used to hand these concepts.

Standard concepts:

Localization

Classification

Localization can be handled either by Image processing algorithms or by deep learning methods.

The science of Artificial Intelligence in Medical Field:

Phillips-Wren and Jain (2006) state there are numerous factors that make artificial intelligence (AI) models ineffective and unreliable for use in decision-making processes. One of the most obvious involves the complexity of the information which AI systems have to handle. When you have lots of complex data, you need a lot more firepower to be able to analyze it well. The resulting complexity often makes efficient and correct calculations by the AI a substantial challenge. One more large issue is that the logical part of human thinking is not naturally in a form of thinking AI models. Such a gap can result in decisions that are accurate from a mathematical standpoint, but unreasonable or illogical to a human user. These kinds of discrepancies from human reasoning to AI-based decision making lead to a basic blockage in trust.

One problem is that people have difficulty trusting AI, especially regarding life-or-death topics like health where the decisions such systems make could directly affect a person's livelihood. Opinion: For critical applications, any risk of harm that might be introduced by following an AI decision makes trusting in AI very important. Thus, the uptake of AI in medical decision-making processes is being conducted with caution, and often exclusively includes only semi-automated tasks instead of completely autonomous ones. AI in medical applications is predominantly involved in aiding professionals rather than replacing them. The outputted decisions by AI must be regarded as initial hints but need to be confirmed further by medical professionals. This slow progression ensures the AI serves as a tool to save time in visual inspection, rather than the be-all-and-end-all of medical decisions. It is mandatory to re-examine AI outputs, and it must be a preferred position-by-position examination before the medical professional can consider them as having clinical value.

In addition, the nature of medical science is dynamic and this poses further difficulties. There are new diseases and conditions that come up all the time, causing you to have to continually update and tweak models written in AI. This requirement for ongoing updating makes the deployment of AI in clinical practice even more complicated, as models need to be constantly retrained in order to keep up-to-date with new medical knowledge and discoveries. Whilst, as Phillips-Wren and Jain (2006) have noted, these problems highlight why AI development in medicine is still very careful and that the often-lauded AI systems are really 'weak AI.' While there have been improvements in this field, AI is nowhere near the strong, generalizable intelligence that our human brains have permanently installed. It can be a valuable tool for medical professionals—helping them do their job more efficiently and potentially play a role in primary patient care decisions—but as of now, AI cannot replace the nuanced decision-making that is intrinsic to all general practitioners. This cautious in-between use of AI is right at the cutting edge of what is currently possible before moving onto more sophisticated, generative AI systems.

For image processing algorithms, the main idea is to segment all vertebrae using edge detection algorithms.

But for the deep learning methods, many techniques could be used such as object detection methods, clustering, and mask segmentation.

There are a lot of practical tools that could be used to handle the localization steps by the methods of deep learning models as the following:

You Only Look Once (YOLO): this algorithm is one the most important algorithms which is extremely used in the projects that require to implement object detection techniques was high accuracy and this is algorithm is also used for detection of some other information related to deep details on the recognized objects. For example, it could be used in human pose estimation and detecting the key points that represent the detected pose. and the most interesting concern for using this algorithm is its high accuracy. This algorithm has many versions and sub versions which make it implementable for many projects whatever the required object and the required details needed to be detected. The most 2 famous versions of YOLO are version 5 and version 8. the differences between the two versions are related to the internal architecture as it follows fully convolutional neural network architecture but with a different number of layers and some modifications about processing and handling the weights without reducing the performance extremely. And as a special point in this algorithm that each subversion is concerned with a specific number of layers each subversion is called with character representing how big or small number of layers for this subversion. for example, the nano size of version 5 which called YOLOv5n is a sub-version with a size of internal layers equals to 151 layers. and for another example, the layers concerned with the small size of the model with the version are about 181 layers and the model is called YOLOv5s. This way of dynamic details for the number of layers gives important flexibility which helps for using the techniques of object detection with a good performance compared with the other techniques.

Visual Geometry Group (VGG): this method is one of the most artificial intelligence models that are widely used in projects that have large images with complex data. and this method was designed based on convolutional neural network architecture. and it has more than one version as VGG16 which can handle 16 layers based on convolutional neural network architecture. And another version follows the previous version in the architecture and the implementation but with different capacity of layers called VGG19 which includes 19 layers based on CNN architecture

MONAI: this tool is specified for the medical project as it is used to be suitable for clustering, segmentation and analyzing any body part in the human as brain, spine with all vertebrae and all parts related to anatomy science.

as the spinal analysis using AI techniques was one of the concerned and needed studies there are many testing cases use for generating a combination with different architectures as a black box to get at the end a final model concerned with getting an input of medical image whatever the imaging technique used by each paper. Then, inside this black box the first part of this combination is responsible for clustering the received image into sub images, each one of them representing a single vertebra. And after this step, the next step is to do some analysis according to the required task from the model.

For example, (Mushtaq et al., 2022) used YOLO annotations to perform the localization process, and the scan type of the dataset was MRI. The photos got some smoothing procedures before being executed by the yolo model. The researchers got Mean average precision equals to 0.975. and the required task in this paper was to get segmentation if there is any problem related to lordosis in the lumbar spine.

Another research (van der Graaf et al., 2023) was using U-net for 3D data at the localization process and for segmentation tasks concerned with Anatomical label prediction and Completeness prediction.

In this paper (Healthcare Engineering, 2023) , the researchers used MRI dataset and tried to improve the required total time of processing and getting good accuracy while performing the segmentation using U-net.

Figure 1: example figure

Top level structure of researching procedures & basic improvement and analysis:

1. Selecting dataset: first step is to choose suitable dataset either represents MRI or CT scanning.
2. Pre-processing: the selected dataset will require some smoothing techniques to focus on the required details on the image and removing any noise.
3. Localization: this step is to determine the vertebrae of lumbar spine from (L1 – L5) and the desired process will be done by combining image processing techniques with deep learning.

As this step is especially important for the accurate decision. It will be getting more preprocessing operations for handling the data to get the high accuracy to localize single vertebra. And after iteratives the process of localization. And selecting the five vertebrae by relating them to their mask.

4. This process will be required for checking if there is any problem in the spine or not. as to save the power of complex mathematics.
5. Classification: is to handle the method for detecting the correct diagnosis related to the given sample.

Initial procedures for the Implementation:

Datasets and types of selection

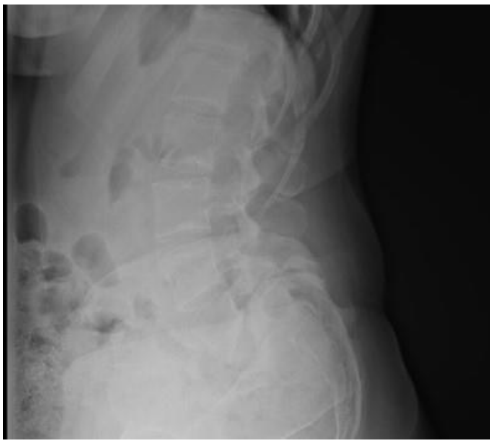
There are Two datasets that have been selected. And the reason for choosing two datasets is to try to get high numbers of samples for testing and for a variety of the cases of diseases which gives the opportunity for the unsupervised learning model do segment the most possible types of diseases available in the two data sets. Specifically, that there are some diseases recognized better with CT imaging technique and another type of diseases recommended to be checked and diagnosed using MRI technique. this would be useful also in comparing between MRI imaging methods and CT imaging methods for selection the better one in the studies just concerned with the localization of the disc, vertebrae and all other items related to the spinal canal either lumbar spine or any another part such as cervical spine.

The option of selection two types of medical imaging techniques will also help the medical companies to focus on an advanced imaging technique that could be used in detecting and showing the required information for all possible diseases without needing to do more than one technique. For example, this will allow the patient to get only one scan service without needing to do more checkup scans during the diagnostic.

Also, the usage of two different techniques during the training approach will be useful for focusing on a specific one technique based on the technique that has most types of diseases.

Smoothing stages

The input image may be considered like one the following images



The code was fully implemented for smoothing the image as the following methods:

1. Gaussian Is one of the methods that is important to remove any data that is not important for processing during the approaches of the training, validation and testing

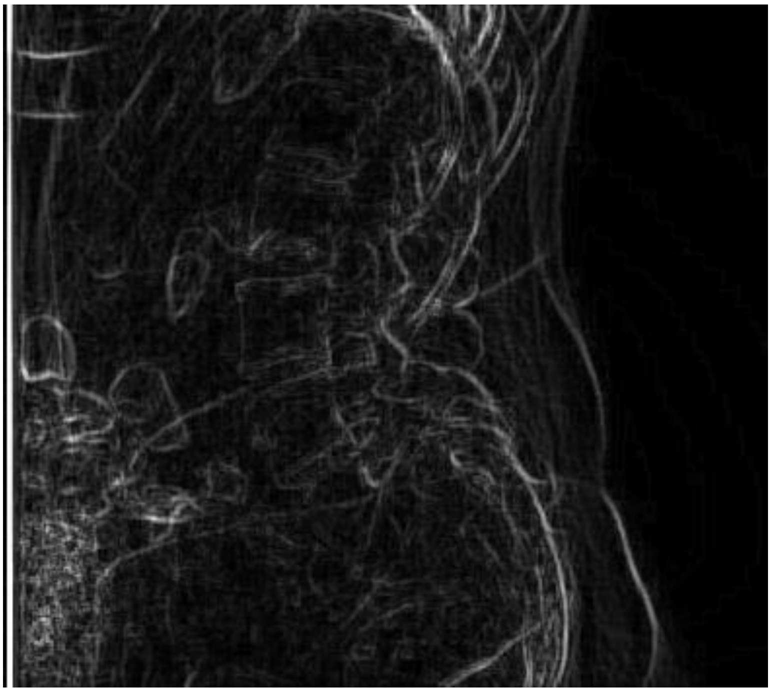
Image Processing stages:

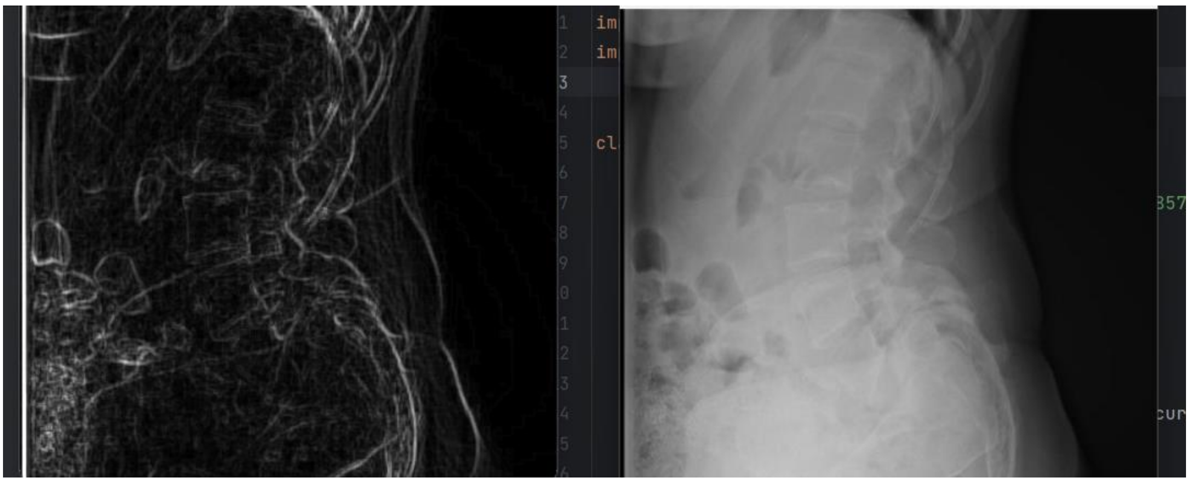
Thresholding would be used as a trial to get a basic mask to be compared in the following stages, according to the following figure, this is one of masks the would be compared between using image processing only and using the combined techniques of image processing and deep learning as object detection.

- The first stage of localization code was implemented according to the following methods:
  1. Some morphological operations, especially gradient morphological with kernel size (3,3).
  2. The morphological operations will play a big role in enhancing the details of the image and trying to keep the details of the required edges as possible as to be highlighted
  3. this also could be more enhanced if we subtracted the mask generated in the previous step of thresholding from the image generated from the morphological operations

but performing this step as a required process will be decided after comparing the different outputs during semester 2.

But for now, the figure shown is considered as enough representation of the basic operations that should be executed during the final good.





- Canny edge detector: this address may be suitable in some cases for a clear detection of the single vertebra using the techniques of image processing. the required code for the edge detection algorithm has been already implemented and tested but it also will not be considered until reaching to the comparing stages in which the final decision of processing techniques getting selected according to the output at this time.

Localization model:

Initial suggestions methods to train localization models

As mentioned, there will be a combined technique used for the localization process to get a black box with high accuracy in on segmenting and ensuring that the localized area is considered as a real selection of a single vertebra.

So, considering some knowledge about the challenges that face the localization stage, performing these steps will be according to a theoretical decision.

This theoretical decision is to use the MONAI tool's architecture as the recommended architecture to be combined with the image processing techniques.

And the reason for that is that this tool is more specific and specialized with the medical requirements of implementation of the general techniques of artificial intelligence and deep learning based on medical knowledge. So, this point will have a positive effect for improving and enhancing the accuracy of the processing because it is already built including some defined medical requirements.

But if there are any obstacles that lead to change this theoretical selection the alternative will be using the architecture YOLO as it will be the most accurate tool for just detecting the area of the vertebra.

And in the following table, there are highlighted points and considerations for using modeling algorithms and tools for analyzing based-deep learning of medical research.

Table 1 MONAI vs YOLO table

Factors	MONAI	YOLO
General Accuracy	Using MONAI (Medical Open Network for AI), which is built to solve the challenges of medical imaging use-cases. For medical tasks, it has advanced deep learning models like transformer-based 3D segmentation algorithms especially UNETR with maximum accuracy and trustworthiness. These architectures are developed to handle the complex patterns and differences in medical images that provide accurate segmentation and classification of organs, tissues, and other structures. Further, as MONAI is specialized in medical imaging it allows for tuning towards specific research applications such as brain tumor segmentation that may require higher scaling abilities and robust handling of 3D data with high precision expectations.	YOLO is a super fast real-time object detection algorithm on which this project has been built. This single-pass architecture of YOLO models means that inference can be very fast, which can be useful in real-time applications where we need results NOW. But of course, speed comes at the expense of flawless accuracy, and in medicine, that is often what is important. There are several improvements in each version of YOLO starting from YOLOv4 and the recent one YOLOv5, trying to provide more accurate detection with faster processing across different versions. ME-YOLO, for example, reaches mAP 97.2 at 53 FPS (enough to do real-time mode).

Performance	MONAI has been carefully engineered to suit the average computational needs for medical imaging, using today's technology. It provides multi-GPU and multi-node support to process large complex 3D dataset efficiently. It is important for tasks such as 3D segmentation in which the analysis needs to be more detailed and precise. MONAI also supports federated learning, and can be used to train models across multiple sites with improved results but private data. This makes MONAI an ideal solution for clinical and research environments demanding high computing performance and quality level.	It is YOLO (You Only Look Once), a fast, general-purpose object detection framework! YOLO and its variants have been adapted for detecting organs and lesions in medical images, including MedYOLO (an adaptation designed for medical applications). Though YOLO performs well in real-time object detection, its capability of performing precise detection is sometimes not that good in medical due to small or less distinctive features. Although these notations may appear as restrictions, they, however, provide the promise in some specific medical tasks such as the highly accurate detection of medical PPE by YOLO models like YOLOv5 and ME-YOLO.

Recommended usage cases	3D Segmentation: Ideal for detailed segmentation tasks in CT and MRI scans, where precise delineation of structures like tumors, organs, and tissues is essential. Classification and Annotation: Effective for accurate classification of medical images and annotation of complex anatomical structures. Clinical Deployment: Designed for seamless integration into clinical workflows, MONAI supports applications in hospitals and research institutions. Its tools are tailored to meet the rigorous demands of medical imaging professionals	• **Rapid Detection**: Suitable for applications requiring quick identification of larger and more prominent structures in medical images, such as tumors or major organs. • **COVID-19 PPE Detection**: Specialized versions like ME-YOLO have been developed to detect personal protective equipment, demonstrating its adaptability to specific medical needs. • **Supplementary Tool**: Useful as a fast initial screening tool before more detailed analysis is performed using specialized tools

		like MONAI. YOLO's speed can provide immediate insights, which can then be followed up with more precise and detailed examinations

Technical Implementation for initial processing stages

As the mapping procedures will be done by the two stages of localization and segmentation. There will be well structured substages in each main stage.

Each substage will have a specific task in the sequential processing, in addition to some optional substages like postprocessing or needed enhancement for specific purposes.

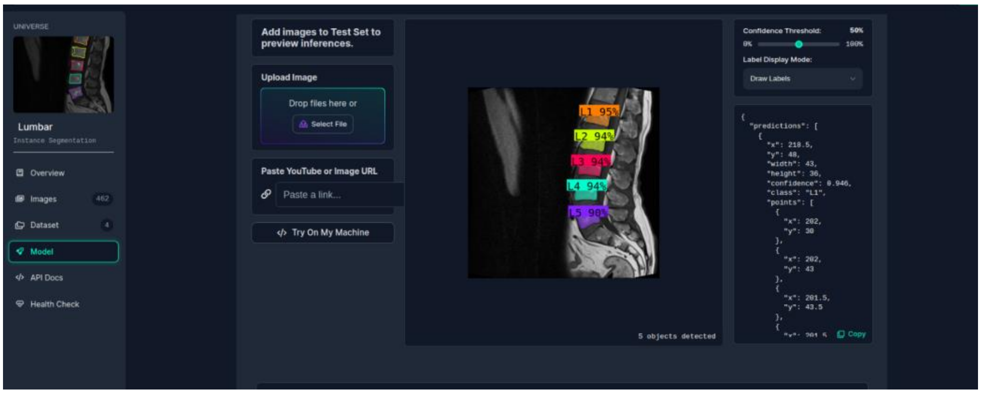
Localization model:

Model API initialization

As a validation procedure, it is required to check if the model is already initialized,

So, it will continue to the next step directly unless it will pass the desired model name and ID in Rotoflow API and select version 2 which is newest stable version. Finally get connected to model API.

According to the following figure, it shows the model from the original page from roboflow.



And to use it as an API model It is required to use the package used from PIP in python implementation

```
import matplotlib.pyplot as plt
from inference_sdk import InferenceHTTPClient
from roboflow import Roboflow
import supervision as sv
import cv2
import Image_Converters
import annotaion_processing
import numpy as np
import matplotlib
```

Main processing:

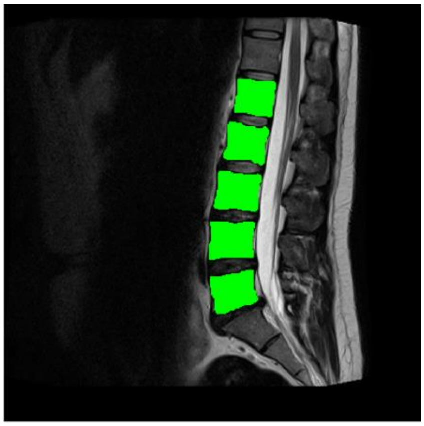
The second function is responsible for detecting and annotating each vertebra in the given image. The function starts by predicting on the input image provided with the already initialized model just but setting a confidence threshold of 40 percent. This prediction had the following results and outputs as a JSON, including information on each vertebrae detected. After that, by parsing the label of the detected vertebrae and converting it to a format that can be used for further processing, this cell is used to initialize 2 annotators to label and mask the detected vertebra. Then the function is reading the input image twice to send one image for being modified and a copy of the original in order not to lose it. A blank image, titled the vertebrae masks image, is made and blacked-in to record where vertebrae are found. The function sorts all detections with descending size and then for all detection masks apply to the vertebrae masks image and primary-detected area is colored green in both results. This function, followed by blending the vertebrae masks image with the backup copy of the original image to create a composite image. This image is a composition that aligns the model predictions with the vertebral regions on the original scan (semi-transparent overlay). Finally, we visualize the annotated images, where we can clearly see detected vertebrae regions. To sum up, the code we have seen in this post first trains a model for vertebrate localization with

Roboflow API and in another part applies that model in valley field images on vertebrae segmentation providing visual feedback locating the detected regions.

Localization model substages

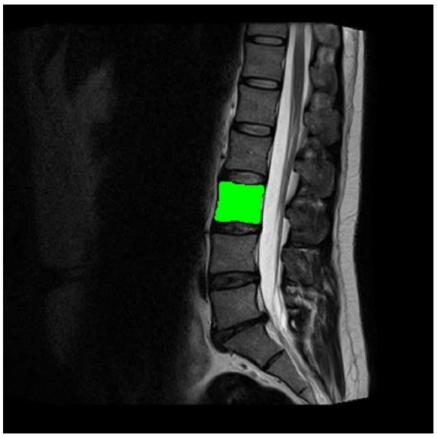
Clustering all vertebrae:

The system should be able to highlight all vertebrae shown in the input image



Specified vertebrae clusters

The system could work for specific and selected numbered of vertebrae and this could be noticed in the following figure:



Tools and processing integration:

As this model has many types of processing with a variety of technical requirements, the system will consider some combination of software architectures and integrations according to the technical consideration of each processing step.

APIs (Application Programming Interfaces) Used Architecture

In modern artificial intelligence (AI) API (Application Programming Interface) is an important part of such implementations as they are becoming more complex and interconnected. These APIs act as a glue that allows various software systems to communicate and interact hence it is extremely important to develop advanced AI driven applications. In the most convoluted of AI projects, this essay underscores the essential importance of APIs, as ancient as I have made them sound, focusing on their part in making such projects less congealed, more scalable, more agnostic to the nuances of data management, more likely to integrate, and more likely to allow for human imagination.

The recommended and tested API is Roboflow and here is brief description and important considerations about using this API

Roboflow Universe is an all-in-one platform for building, deploying, and managing computer vision models. Offering a wide range of datasets and pre-trained models, it makes it easier for developers and researchers to access top-notch resources for their projects. This platform is very trendy in the market due to its user-friendly interface and strong API, which allows for easy integration into various workflows. Example use cases range from object detection to image segmentation and classification across verticals such as health & fitness, agriculture, retail, and beyond.

Key Features of Roboflow Universe

Definitive Dataset Repository: Roboflow Universe has extensive coverage of contributed datasets. These datasets span across multiple domains, are preprocessed, annotated, and ready for use. This can save a lot of time and effort in structuring data for training models.

Pre-trained Models: The service provides a list of pre-trained models for different tasks, which is beneficial. This feature is very useful for users who want to deploy models quickly but do not have the computational resources to train from scratch.

Accessible & Shareable: Roboflow Universe enables users to collaborate towards their shared goals of better datasets and models. This community-driven approach also helps in increasing the availability of many well-diversified high-quality resources, benefiting the whole computer vision community.

Popular Frameworks Integration: It integrates with TensorFlow, PyTorch, and YOLO. With this compatibility, anyone can integrate Roboflow resources into their workflows with minimal effort.

Plug-and-Play: Roboflow Universe is built with ease-of-use in mind. The platform includes easy-to-use tools for dataset management, model training, and deployment, making it accessible to users with different levels of expertise.

There are various incredible projects and collaborations that the Roboflow Universe supports in the medical community. For example, the tool has been used to build AI models capable of identifying illnesses like pneumonia, breast cancer, as well as diabetic retinopathy. These studies show that the platform can be used for many different projects, and it works well even with all types of scenarios in the medical field. Roboflow, given these tools and resources at hand, important aid is done and medical research advances so far that it improves the health of the population.

- As a Focusing point on our research to scale the openness criteria, there are some examples of studies done for localization procedures of lumbar spine vertebrae
- FARO: Lumbar Spine Vertebrae Segmentation - This task consists of an annotated dataset for a 7T MRI lumbar spine vertebrae segmentation. It offers sharp images at higher resolution and accurate segmentations perfectly tailored for medical imaging.
- SAG: Spinal Vertebrae Segmentation - The aim is to segment spinal vertebrae (including the lumbar) together. This includes numerous annotated images that emphasize individual vertebrae, which is great for finer segmentation tasks.

- GM: Vertebrae Detection and Segmentation - This project provides a dataset to support detection and segmentation in lumbar spine vertebrae. It is made to enhance teaching types in health care diagnosing and analysis.
- Lumbar Spine CT Segmentation by MED - This dataset has detailed segmentation annotations and contains CT scans of the lumbar spine. It is designed for crafting models that can predict the segmentation of vertebrae in medical imaging applications.
- Lumbar Spine MR Image Semantic Segmentation (LUMBAR) by Neuro - A dataset of magnetic resonance images and segmentation annotations. It is helpful for applications where one must train models to produce segmented vertebrae from MRI images, useful clinically and research-wise.

Medical Mapping Sequence:

body parts segmentation:

This stage will scan for items in body parts list, this list is contents customizable. Allowing the list for customization will have a big effect on the combined diagnostics as the system will be concerned with specific parts which will increase the accuracy of mapping, at the same time, it will be much clear for visualization to the medical staff and other stack-holders like educators and research centers.

By the default implementation in this research and as its focus directed to lumbar spine, the main body parts will be Lumbar vertebrae (L1, L2, L3, L4, L5)

And each one of them will be labeled individually then visualized on the screen with green color to fill the inside area within each vertebra.

And labeling it according to lumbar vertebrae classes with the option to change the color for each class individually.

Disc data processing:

There will be needing for getting the disc which is the area between each two vertebrae

Considering the following function to get the size of the disc:

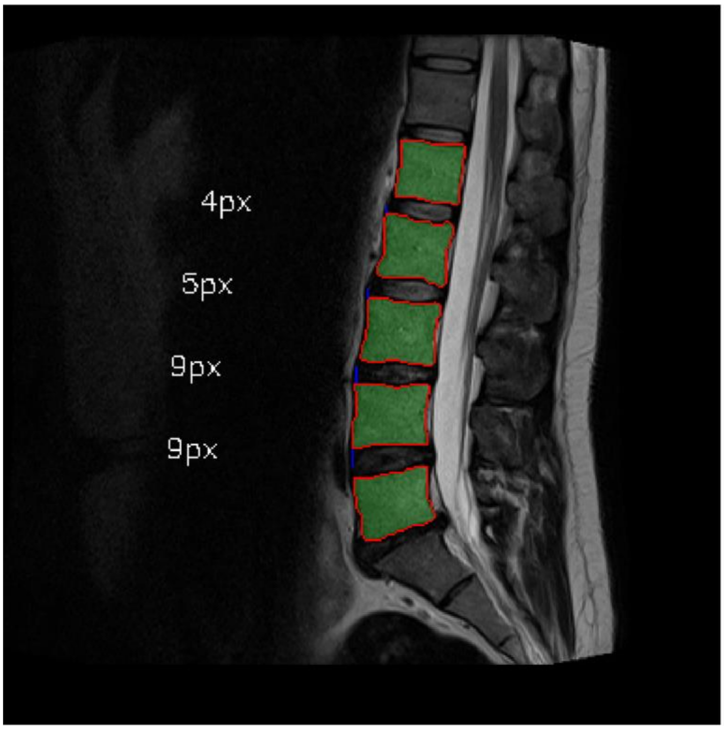
The disc function is a sophisticated image processing algorithm designed to detect and analyze specific color features within an image, particularly focusing on identifying and measuring the vertical distances between green-colored contours. This function operates primarily on images in the HSV (Hue, Saturation, Value) color space, which is advantageous for color-based segmentation tasks. The core objective of this function is to accurately identify green regions in an image, trace their contours, and compute the vertical distances between these contours. This can be particularly useful in medical imaging, where the vertical distances between specific anatomical features might be of interest, such as the spacing between vertebrae in spinal imagery.

The function commences by converting the input image from the BGR color space to the HSV color space using the OpenCV library. This conversion is crucial as the HSV color space is more aligned with human color perception, making it easier to isolate specific colors. Following this, the function defines a narrow range around the green color in the HSV spectrum. The lower and upper bounds for this range are set using NumPy arrays, ensuring that only pixels within this range are considered.

Next, a mask is created using the cv2.inRange function, which filters out all pixels outside the defined green range. This mask highlights the green regions within the image, effectively isolating the areas of interest. The function then employs the cv2.findContours method to identify the contours within the mask. Contours are the boundaries of the green regions and are essential for the subsequent steps of the analysis.

If at least two contours are found, the function proceeds to sort these contours based on the top y-coordinate of their bounding boxes. This sorting is critical as it organizes the contours vertically, facilitating the calculation of vertical distances between consecutive contours. For each pair of consecutive contours, the function calculates the vertical distance between their bounding boxes. This distance is determined by subtracting the bottom y-coordinate of the current contour's bounding box from the top y-coordinate of the next contour's bounding box.

To visualize the results, the function draws the contours and the computed vertical distances on the input image. This visualization is enhanced with lines connecting the midpoints of the bounding boxes of consecutive contours and text annotations indicating vertical distances. The final processed image is saved, and the vertical distances are printed for further analysis.



3. Diagnostics Processing

One of the used models is to Get detect for Disc Herniation.

And for a medical concept of it as following

Disc herniation, commonly referred to as a slipped or ruptured disc, represents a significant medical concern due to its prevalence and potential to cause debilitating pain and functional impairment. The condition arises when the soft, gel-like nucleus pulposus of an intervertebral disc protrudes through a tear in the tougher, fibrous outer layer known as the annulus fibrosus. This herniation can impinge on nearby nerves, leading to symptoms such as radicular pain, numbness, and muscle weakness, predominantly in the lower back and legs—a condition often referred to as sciatica.

The intervertebral discs serve as critical components of the spinal column, providing both cushioning and flexibility. They act as shock absorbers, allowing for a range of movements while maintaining the integrity of the vertebral structure. However, factors such as age-related degeneration, traumatic injury, repetitive strain, and genetic predisposition can compromise the structural integrity of these discs, making them susceptible to herniation.

Age is a primary risk factor for disc herniation. With advancing age, the discs lose hydration and elasticity, a process known as disc degeneration. This degeneration diminishes the disc's ability to withstand mechanical stress, increasing the likelihood of herniation. Additionally, occupational hazards involving repetitive lifting, bending, or twisting motions, as well as high-impact sports, can exacerbate the wear and tear on spinal discs. Genetic factors also play a role, with certain hereditary traits influencing the likelihood of developing disc herniation.

The clinical presentation of disc herniation varies depending on the location and severity of the herniation. Lumbar disc herniation, affecting the lower back, is the most common form, often causing pain that radiates down the leg along the sciatic nerve. Cervical disc herniation, involving the neck region, can lead to pain radiating to the shoulders, arms, and hands. The pain is often accompanied by sensory disturbances such as tingling and numbness, and in severe cases, motor deficits and loss of reflexes.

Diagnosis of disc herniation involves a combination of clinical evaluation and imaging studies. A thorough patient history and physical examination can reveal characteristic signs such as a positive straight leg raise test, indicating nerve root irritation. Imaging modalities, particularly magnetic resonance imaging (MRI), are crucial for confirming the diagnosis and assessing the extent of herniation. MRI provides detailed images of soft tissues, including intervertebral discs and nerve roots, making it the gold standard for evaluating disc pathology. Computed tomography (CT) scans and X-rays may also be used in certain cases to provide additional anatomical details.

Management of disc herniation encompasses a range of conservative and surgical interventions. Initial treatment typically focuses on conservative measures aimed at relieving pain and improving function. These include physical therapy, nonsteroidal anti-inflammatory drugs (NSAIDs), and epidural steroid injections. Physical therapy plays a pivotal role in strengthening the muscles supporting the spine, improving flexibility, and reducing the risk of recurrent herniation. In cases where conservative management fails to provide relief, surgical options such as microdiscectomy or laminectomy may be considered. These procedures involve the removal of the herniated disc material to alleviate nerve compression.

Emerging research has highlighted the potential benefits of regenerative therapies in the treatment of disc herniation. Techniques such as platelet-rich plasma (PRP) injections and stem cell therapy aim to promote the repair and regeneration of damaged disc tissues. While these therapies are still in the investigational stages, early results are promising, suggesting a potential shift towards biologically based treatments in the future.

The impact of disc herniation extends beyond physical symptoms, significantly affecting patients' quality of life and mental well-being. Chronic pain and functional limitations can lead to psychological distress, including anxiety and depression. Therefore, a multidisciplinary approach to treatment, addressing both physical and psychological aspects, is essential for optimal patient outcomes.

Detection of Disc Herniation Using Artificial Intelligence: A Review of Five Key Research Studies

Automated Detection and Classification of Lumbar Disc Herniation Using Deep Learning

In a groundbreaking study, researchers developed a deep learning-based system for the automated detection and classification of lumbar disc herniation from MRI scans. The study utilized a convolutional neural network (CNN) architecture, specifically designed to analyze spinal MRIs and identify herniated discs. The model was trained on a large dataset of annotated MRI images, achieving remarkable accuracy in detecting and classifying disc herniation. The results demonstrated that the AI system could match or even surpass the diagnostic performance of experienced radiologists, highlighting its potential as a powerful tool in clinical practice. This study underscores the capability of AI to enhance diagnostic accuracy, reduce human error, and expedite the diagnostic process, ultimately improving patient outcomes.

Radiomics and Machine Learning for the Detection of Cervical Disc Herniation

This study explored the application of radiomics combined with machine learning algorithms to detect cervical disc herniation. Radiomics involves the extraction of many quantitative features from medical images, capturing the underlying tissue characteristics that may not be visually apparent. The researchers employed a radiomics approach to extract features from cervical spine MRI scans and used machine learning models, including support vector machines (SVM) and random forests, to classify the presence of disc herniation. The study demonstrated that the radiomics-based machine learning models could achieve high diagnostic accuracy, offering a non-invasive and reliable method for detecting cervical disc herniation. The integration of radiomics with AI presents a promising avenue for enhancing the sensitivity and specificity of diagnostic tools.

Deep Learning for Automated Detection of Thoracic Disc Herniation on MRI

In this research, a deep learning model was developed to automatically detect thoracic disc herniation on MRI scans. Thoracic disc herniation, though less common than lumbar or cervical herniation, poses unique diagnostic challenges due to the complex anatomy of the thoracic spine. The study utilized a CNN-based approach, leveraging a large dataset of thoracic spine MRI images for training and validation. The model achieved high sensitivity and specificity in identifying thoracic disc herniation, demonstrating its potential as a valuable diagnostic aid. The study highlighted the importance of incorporating deep learning techniques in the detection of less common spinal pathologies, providing a comprehensive diagnostic solution across different regions of the spine.

Artificial Intelligence-Assisted Detection of Recurrent Disc Herniation Post-Surgery

This study focused on the application of AI in detecting recurrent disc herniation following surgical intervention. Recurrent herniation is a common complication after discectomy, requiring accurate and timely diagnosis for appropriate management. The researchers developed an AI-assisted system that analyzed postoperative MRI scans to identify signs of recurrent herniation. The model incorporated advanced image processing techniques and machine learning algorithms to differentiate between postoperative changes and true recurrent herniation. The results demonstrated that the AI system could significantly improve the detection rate of recurrent herniation, providing valuable support to clinicians in postoperative care and decision-making.

Hybrid AI Model for Predicting Surgical Outcomes in Disc Herniation Patients

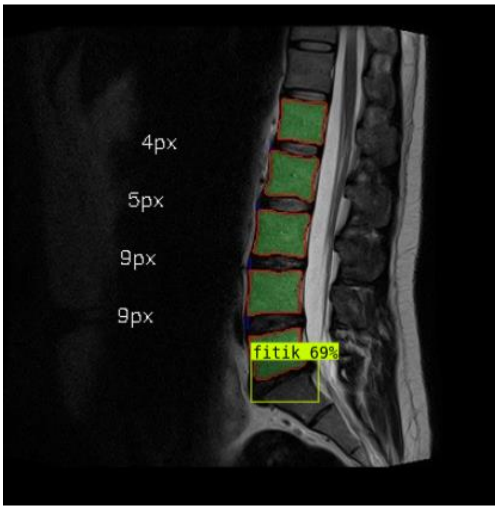
In this study, researchers developed a hybrid AI model combining machine learning and traditional statistical methods to predict surgical outcomes in patients with disc herniation. The model incorporated clinical, demographic, and imaging data to generate personalized predictions of surgical success. By analyzing preoperative MRI scans and patient-specific factors, the AI model could accurately predict the likelihood of pain relief, functional improvement, and recurrence of herniation post-surgery. The study highlighted the potential of AI to provide personalized treatment recommendations, optimize surgical planning, and improve patient outcomes. The integration of AI in preoperative assessment represents a significant advancement in the field of spine surgery, offering a data-driven approach to patient care.

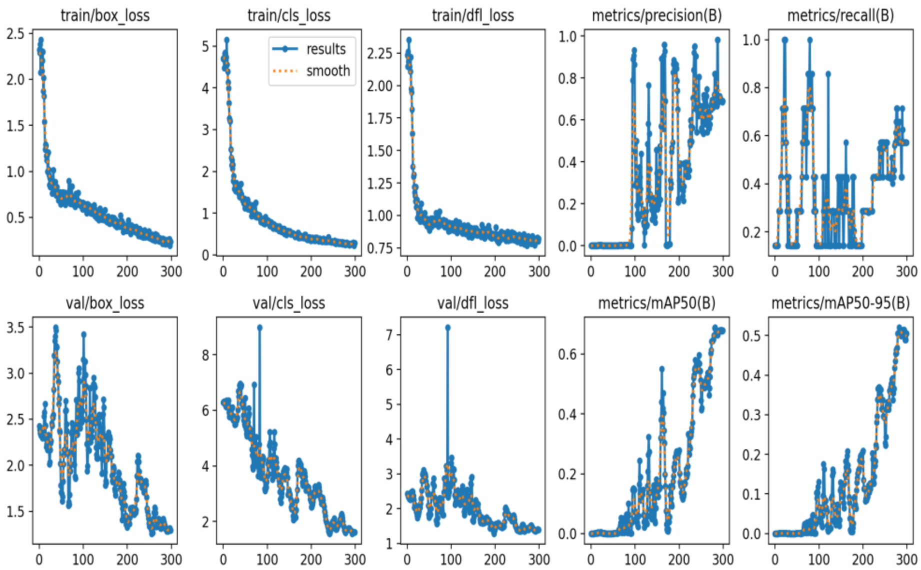
Integrating AI into Clinical Practice: Challenges and Future Directions

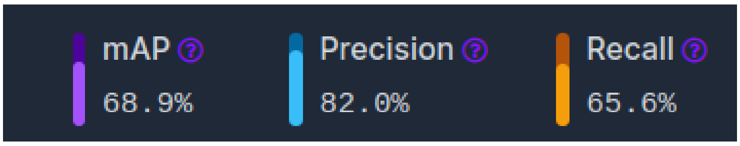
While the application of AI in detecting disc herniation holds immense promise, several challenges must be addressed to fully integrate these technologies into clinical practice. Ensuring the robustness and generalizability of AI models across diverse patient populations and imaging modalities is crucial. The development of standardized protocols for data collection, annotation, and model validation is essential to achieve consistent and reliable performance. Additionally, addressing ethical and regulatory considerations, including patient privacy, data security, and the transparency of AI algorithms, is vital for gaining clinical acceptance and trust.

Future research should focus on enhancing the interpretability of AI models, enabling clinicians to understand the decision-making process and validate the results. The combination of AI with other emerging technologies, such as augmented reality (AR) and virtual reality (VR), may further revolutionize the diagnosis and treatment of disc herniation, providing immersive and interactive tools for patient education, surgical planning, and rehabilitation.

For diagnostic model of disc herniation from roboflow consider the following figures for sample test






mAP
68.9%
Precision
82.0%
Recall
65.6%

Deep Technical details

Implementation Used Language:

Python

Open-source libraries and dependencies

- Matplotlib is used to create static, animated, and interactive visualizations in Python. This fantastical plotting library creates figures and plots which are used for a multitude of different visualizations from simple to complex categories, and commonly exploited in a routine manner by researchers and practitioners. Matplotlib is also commonly used in the medical field to help create visualizations of such complex datasets, which can otherwise be challenging for health professionals to interpret. An application with a more specific use case might generate visual information using Matplotlib for tasks such as plotting patient data over time showing trends, anomalies, etc. Researchers might look for patterns in patient outcomes (e.g., blood pressure, glucose levels, or heart rate) over months or years to determine the success of a treatment or the development of a disease. Its capability to produce publication-quality figures is also quite popular among academics who are required to present their results in scientific journals or conferences. In medical uses, you can use Matplotlib to plot the data for example Recovery rates the patients which undergone different treatments of COVID-19 so that a doctor can have a visual comparison between all the treatment techniques.

- InferenceHTTPClient: A family of tools to help in your application to make an interaction with machine learning inference servers. These kind of clients are paramount in deploying machine learning models in medical to help with diagnoses and treatment recommendations. An InferenceHTTPClient could be used by a hospital to send patient imaging data to a server with a deep learning model trained to detect tumors in MRI scans. The client would deal with the responsibilities of pushing the data, getting the predictions from the model and making sure that communication is secure and reliable. Manifold has integrated TensorFlow with Pentaho to enable real-time medical image analysis, accelerating diagnosis time and improving patient outcomes. Instead, healthcare providers can benefit from state-of-the-art AI models through an InferenceHTTPClient, which means advanced diagnostics become more accessible and efficient without understanding the technology beneath it.

- Roboflow provides powerful infrastructure to interface with datasets, annotate images, and train computer vision models; particularly useful in the medical domain where labeled data is critical for developing accurate diagnostic tools. Developing machine learning models creates complexity at any stage of the process, and creating and managing a dataset is often one of the main bottlenecks in this process -- Roboflow helps to cleanse that part of the pipeline. This might mean labeling thousands of images regarding a particular medical condition (tumors, fractures, or any other anomaly) in the case of medical research. A team researching a model to identify diabetic retinopathy, for example, might use Roboflow to annotate images of retinas where the disease is present. Roboflow's preprocessing capabilities would then take care of formatting these images for training a model. Following dataset preparation, Roboflow can also aid in training the model and deployment to a clinical setting. The entire solution-from data to final-results-breaks the development of medical AI applications, spurring innovation in healthcare.

- Supervision: Essential for monitoring the training, deployment and upkeep of ML models to make sure they run as expected and responsibly. For instance, such tools in the medical domain would observe how models performing diagnostics are doing and warn doctors when something that could affect patients is likely going wrong. In the domain of a hospital using a machine learning model to predict patient readmissions, they could employ something similar to a supervision tool — one that tracks the accuracy of the model so that no data drift deters it in treating new patients during different years. These tools can also be used to help make sure a model is not trained on biased data leading to discrimination against (e.g., sick patient, healthy patient) certain cohorts of patients. For instance, a tool for supervision might be used to scrutinize a model trained to automatically triage patients in the emergency room, keeping it honest as to whether it differentiates ailments of varying gravity across categories, such as ethnic groups. Supervision tools: These tools are essential for enabling ongoing supervision and performance monitoring to preserve the trustworthiness and reliability of these applications.

- OpenCV (cv2) - It is a large open-source library for computer vision, mainly used in medical imaging to create programs that help computers analyze and interpret visual data. Due to the wide range of algorithms it has, OpenCV is perfect for works that involve Image processing, Object detection and Pattern recognition. OpenCV can also be used to improve and process on medical images, which can help diagnose various conditions. For instance, a radiologist could program with OpenCV to create an app that automatically semaphores breaks in X-ray images. The library can further process the images to increase contrast, making them more identifiable to older fractures that might be nearly invisible to human vision. Further, this object detection type of algorithm in OpenCV can be trained to detect different fractures, giving a first diagnostic that the radiologist should then review. OpenCV helps in the automation of these tasks, it minimizes the work for the medical doctors and also increases the accuracy speed of detection.

- Scipy - This is the second package, and it builds on NumPy NumPy is the foundational package for numerical computing in Python. The medical field requires working with huge datasets and almost all the complex calculations one performs can be done using NumPy. Say for example researchers who are researching the spread of infectious diseases, would use NumPy to create a stochastic model to predict how the disease could be spreading, and what its effects might look like in people infected with that virus, they can then test these models against large datasets of rates of infection as well as movements of populations and other such things. Through matrix operations and numerical simulations, they can forecast how disease would disseminate in various "what-if" scenarios and the possible effects of interventions. Due to its extensive incorporation in other scientific libraries and powerful data handling ability, it is also crucial for medical research and analysis. For example, NumPy can be used for medical environments to find mutations that match a profile of diseases that helps doctors determine how some disease has its genetic roots on which drug to aim this illness with.

- Together, these libraries provide a powerful addition to our healthcare ecosystem, enabling professionals across disciplines to accomplish harder tasks more efficiently and accurately than they ever could on their own. Not only would Matplotlib make it easier to visualize complex medical data, but it would also provide clarity and useful insights that are immensely helpful for decision-making. InferenceHTTPClient simplifies the insertion of advanced machine learning models into clinical workflows, providing real-time diagnostic aids. Roboflow simplifies this process by improving creation and curation of annotated datasets, which speeds up image data preparation for computer vision in healthcare. Monitoring mechanisms ensure the figures remain constant as time goes on, maintaining integrity and ethical use of these models. OpenCV is equipped with strong image processing to help improve medical imaging, making it easier to detect and diagnose various conditions. Complex data analyses and simulations that go into medical research rely heavily on the powerful numerical computing features offered by NumPy.

- Collectively, these tools create an integrated toolset that powers the future of medical technology innovation. These algorithms work together to create smarter applications that can digest, understand, and render medical data in such a way as to support patient care and the understanding of complex diseases. As these tools develop over time, we should expect them to become even more pervasive in the landscape of healthcare, bolstering the creation process for increasingly smarter, cost-effective and impactful medical interventions.

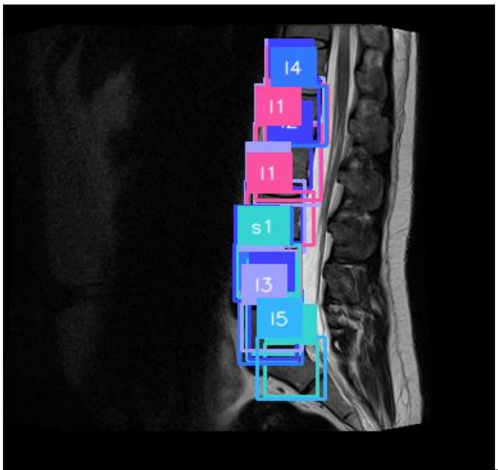
optional features

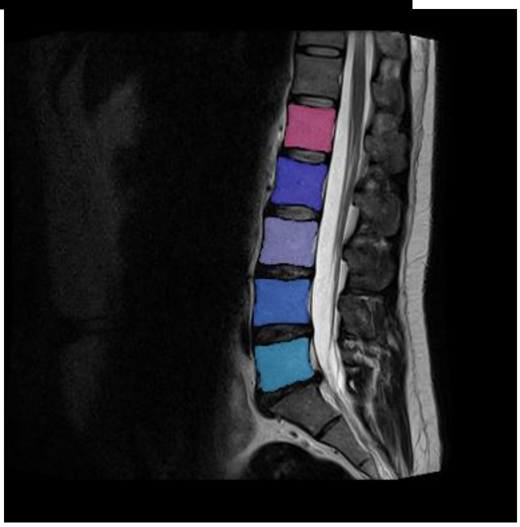
1-it can use customized used models

2- converting photos extension as png, jpeg

3- processing for T1 weighted MRI

4- the option to generate report for the affected area in a form of natural language





Recommendations

Anticipated problems and suggested ways to solve them:

One of the major problems that we anticipate in leveraging medical and engineering knowledge into artificial intelligence (AI) applications is the gap between fields. The medical concepts, especially those associated with diagnosis, are complex and demand an in-depth knowledge of peculiarities of it. To a layman, such nuances are hard to grasp, resulting in a divide between the traditional medical diagnostics and engineering methodologies. This gap is most apparent when we consider how AI systems require the ability to understand and process medical data in a way that can be used to diagnose patients. Discrepancy in medical vs engineering terminology, concept-wise understanding, and practical applications can cause misinterpretations leading to errors in the implementation of AI.

Proposed Solution: Medical Consultants: It is therefore vital to incorporate medical consultants during the AI project design development and implementation stages. These consultants can offer crucial advice on medical details and how everything should be fixed up once mistakes occur. This way they will be beneficial in differentiating various conditions, getting a grasp of the unique demands of medical diagnostics, and clinically validating AI models. This will make their measures more credible for their target users in the future because a professional doctor is included in the design and validation of your approaches. Not only does this involvement function as a proof of concept, it also increases the confidence in and adoption of an AI system in the clinical arena as it shows that it was developed by experienced clinicians.

Problems with Medical Databases: The problem also arises due to medical databases, especially MRI and CT scans. These additionally utilized image formats (e.g., JPG, PNG) and even several proprietary encodings designed by individual medical device manufacturers. Different types of files may need special programs or file readers to open and understand the data correctly. Such diversity in file formats and encodings makes it all the worst for data integration, analysis, and interpretation using artificial intelligence.

Inconsistencies in data management are problematic for the quality of diagnostics provided by AI and largely reduce system performance.

Proposed Solution: Normalized Medical Imaging Techniques: A standardized protocol for the treatment of medical imaging data should be applied to address these obstacles created by databases. In practice, this means using the best possible workflows for medical imaging that many devices and software provide in a standardized way. Machine Readability in Different File Formats: Once we standardize the variant of the file format and encoding methods, then the data ingestion and data analysis will be more streamlined and reliable. This streamlining is not important for AI accuracy overall, in diagnosis or prediction, but inaccuracy related to the data input into the system because the quality is only as good as the data. The result of all this will be more seamless integration of diverse medical data sources in the future, enhanced interoperability between different healthcare systems, and the creation of more powerful and accurate AI-driven diagnostic tools.

Future update

- try update the data of the report as a professional NLP with medical language and titles

Conclusion

backbone structure Artificial intelligence aims to serve most fields. In research fields, AI (artificial intelligence) is used in medicine, at least to a limited extent, to produce medical reports based on certain types of data, such as X-rays, positron emission tomography (PET), magnetic resonance imaging. (MRI).) and computed tomography (CT). The spine, which can be scanned with MRI or CT, is one of the well-known medical applications of artificial intelligence in imaging medical cases.

According to many studies on motor accidents, the spinal cord is affected by a huge number of injuries, regardless of the mode of movement and as proven (WHO.int, 2013)
And this study focuses on the spine to the lumbar region, specifically that there are many problems in this area that have a great impact on the spine. The lumbar spine consists of five levels.
Integrating AI into the analysis of the lumbar spine requires two steps, the first of which is to determine the location of individual vertebrae, followed by the selection of five levels. We need to check whether medical cases are related to problems or not.

The previous two units have been used in many papers investigating the integration of AI and lumbar medical cases. But in this magazine. We focus on how to add the new step necessary to control the specific cause of a medical problem. This section primarily helps scan providers prepare reports for patients.
However, the big challenge is to focus on getting the right diagnosis for the current case. Because there are many problems with the lumbar spine that vary from place to place. for example, vertebra 1 has a medical problem different from subsequent vertebrae.

So a proper diagnosis must be followed from the beginning, which depends on how to get accurate localization and segmentation, or before continuing this step. In this report, we also focus on combining image processing techniques with machine learning or deep learning techniques.

but the order of this step is mixed, because the first step is to preprocess the input data, then we have to get an edge detection algorithm that tries to get the edges of each vertebra, and the last step of localization is our attempt to get mask for each data sample and use them to obtain a model of this process. And as a theoretical technique, it is important to follow these steps to obtain a fairly accurate process of processing and localization, followed by a completely accurate diagnosis.

The vertebrae of the spine are divided into 5 types, a total of 26 vertebrae, the types are explained as follows:

Cervical vertebra (7 vertebrae)

Thoracic vertebra (12 vertebrae)

Lumbar vertebrae (5 vertebrae)

Sacral vertebrae (one vertebra)

Lumbar (one vertebra)

Each of these types has its own biological functions, types of pain and diagnostic methods.

The second step, or segmentation, which checks if there are problems or not, is done by comparing the original shape of the lumbar spine with the current user input. According to medical concepts, there is no one shape for all people, because the shape and inclination of the lumbar spine can change. For example. If we have a tall man, it is different than a short man. And this can ultimately affect accuracy. Therefore, the database should have a fair sample of all shapes, age groups and sexes.

Because there are some differences between men and women in lumbar scans. And get an accurate diagnosis. We need a complete function for each diagnostic case or disease, as we integrate medical concepts with artificial intelligence to compare them. And give the patient the most accurate diagnosis of the disease for his case. The model also requires medical information about the condition associated with each individual vertebra.

Each stage also has medical custom options to add a specific model for different purposes, for example the diagnostic stage has possible injuries that can be discovered recently, epic has medical diseases that can simply appear, or it can be caused by someone else. infection or added by a disease that appeared as a side effect that may not be apparent to the model as a known, established disease. Thus, when such objects are considered, a system must be obtained that achieves the notions of extensibility and scalability at each stage of localization or segmentation.

This can be achieved from a data science and artificial intelligence perspective by making a template that fulfills the requirements of each step, the guide pins of that template for the information needed, or to analyze the new desired opportunity. new disease when this extension was assigned to the diagnostic stage.

Extended models are as common as any single deep learning model. You only need to match the parameters as a template instruction for each step and the library is TensorFlow. However. It can be exchanged for a Py lamp. depending on whether we need a much higher speed of data processing between the medical image scanner of the medical device and the final report to the patient.

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