

## Detect and Analyze the Performance of Lumbar Spinal Stenosis Detection from MRI Images by Using Semantic Segmentation Technique

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### Abstract

Lower back pain is mainly caused by some complications present in the lumbar spine. In general, human beings face a lot of problems with lower back pain and very few people figure out the exact cause, and most of them unable to find the exact cause behind the pain. As we know that the diagnosis of a medical record is very complex and plays a crucial role to the medical persons in order to treat the patients who suffer with low back pain. In general, the medical practitioner tries to study the abnormality present in the medical records like MRI or Scan images in a manual manner under direct eye contact, which is a very complicated task to figure out the minute abnormalities which is present inside the report. This motivated me to design this proposed application using machine learning (ML) models in the medical field for disease prediction and to guide the medical experts about the patient's current situation. In this present work, we try to identify the most important physical parameters which are required to figure out the spinal abnormalities which are collected physically from spine patients. Here we propose a novel method to predict and trace the lumbar spinal stenosis through semantic segmentation and delineation of magnetic resonance imaging (MRI) scans of the lumbar spine. By conducting various experiments on the spine dataset which contain nearly 575 MRI studies of patients who are having symptomatic back pain. Our theoretical and experimental results clearly state that proposed method produces a very good performance as compared with primitive region-based metrics.

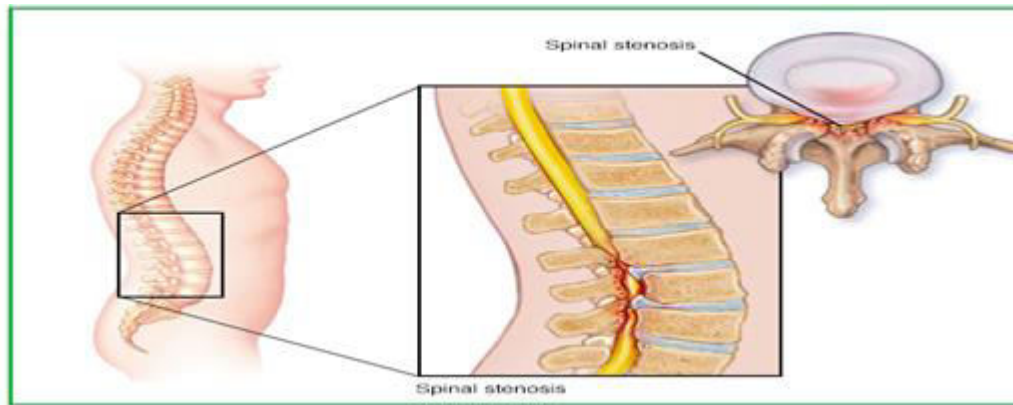
### Keywords:

Magnetic Resonance Imaging (MRI), Machine Learning, Lumbar Spinal Stenosis Detection, Semantic Segmentation, Clinicians.

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## 1. Introduction

Lumbar Spinal Stenosis (LSS) is one of the primary causes for patients who suffer from chronic lower back pain. This is mainly caused due to the narrowing of the lumbar spinal canal occurred by bone inflammation, which will in turn create more pressure on spinal cord roots or soft tissues that connect spinal nerves. The symptoms may include general radicular pain to a typical leg pain which may sometimes require some surgical treatment [1]. Almost this lower back pain is seen among lakhs of people around the continent. The LSS is the main cause which not only affects the health, social life but also suffers the person with employment due to severe back pain.



**Figure 1. Represent the Patient Suffering With Spinal Stenosis**

In most of the people, who is having spinal stenosis may not have symptoms; they don't feel any external symptoms [2] but do feel the pressure on nerves which are connected from the spine to the legs. But most of the people who are suffering from Spinal Stenosis may experience pain, tingling, numbness, muscle weakness and sometimes may also worsen periodically [3].

### TYPES OF SPINAL STENOSIS

There are mainly 2 types of spinal stenosis which is classified mainly from the place where the problem arises on the spinal cord. The following are two main types of spinal stenosis:

#### CERVICAL STENOSIS:

This is one form of spinal stenosis which cause the problem on the spine in our neck part which is connecting to our spine, those who gets some pain over the neck and gradually increases from time to time comes under this category.

#### LUMBAR STENOSIS :

This is second form in which the narrowing occurs in the part of the spine in your lower back. This form of abnormality has occurred in most human beings and we can see a lot of people suffer from the same problem.

## DIAGNOSIS OF LSS

In order to diagnosis the abnormality present in the LSS, we try to examine the patient through proper inspection of MRI spine scan images. The MRI images are the only one form which can predict the abnormality present on the spine. This can be used to visualize spine, slice by slice form and can able to view in 3 Dimensional views namely:

1. Frontal View (or) Coronal View
2. Side View (or) Sagittal View
3. Axial View (or) Top-Down View

Almost all three views are performed on the patients to identify the problem in Lumbar Spine. For most of the MRI scan images; the inspection is performed only when the patients lay in the supine position. But most of the medical superiors argue with this approach because this approach may not reflect the exact condition of the spine by eliminating some main viewpoints due to the patient's body weight is bearing on the patient. Later the medical examiners try to scan the patient when he is in an upright position by placing a lumbar pillow below him. In current days there were types of radiology techniques that came into medical clinics to test the abnormalities present on the spine. These advanced radiographic myelography tools enable the clinical persons to detect the immense abnormality which is present in some patients who are suffered from LSS. After a thorough analysis, we found that in most of the case reports MRI is ubiquitous in hospitals compared with other methods because the MRI scan which is taken in standing or sitting position is mostly affected by the patient's continuous movements due to very discomfort of the patient's various positions. Hence in most hospitals, only a supine MRI scan is used for abnormality identification compared with another type of scan and in simple words, we call it an MRI spine.

## 2. LITERATURE SURVEY

Literature survey is that the most vital step in the software development process. Before developing the new application or model, it's necessary to work out the time factor, economy, and company strength. Once all these factors are confirmed and got approval then we can start building the application. The literature survey is one that mainly deals with all the previous work which is done by several users and what are the advantages and limitations of those previous models. This literature survey is mainly used for identifying the list of resources to construct this proposed application.

## MOTIVATION

- 1) In the article "Diagnosis and Treatment of Degenerative LSS". Published In NASS ,2011.  
**AUTHORS:** D.Scott and J.Summers

In this paper, the authors mainly concentrated on the diagnosis and treatment of LSS, which is proposed by the North American Spine Society (NASS) Clinical Guideline. In this paper, the authors try to address key clinical questions that are currently under the diagnosis and treatment of degenerative LSS. The main goals of the guideline recommendations are to assist the users with minimum delivering function and also to address the recovery rate from the spinal disorder [4].

2) In the article " Lumbar Stenosis: Survey", Published In online with DOI: [10.4184/asj.2015.9.5.818](https://doi.org/10.4184/asj.2015.9.5.818)

**AUTHORS: S. Y.Lee and K.Jae**

In this paper, the authors mainly discussed magnetic resonance imaging which is termed as a non-invasive and good method for evaluation of lumbar stenosis. Although there are a lot of studies that are concentrated on the lumbar spine, very few of them are clearly observed in the natural progression[5] of lumbar spinal stenosis. For patients who fail to respond to non-operative management, they may undergo surgical treatments for abnormality identification such as decompression or decompression with spinal fusion. These restoration functions clearly give good results compared with primitive methods and in this paper, the authors want to design some more new methods which can give highly accurate results instead of using decompression methods.

3) In the article "Diagnosis and management of LSS in primary care in France"

**AUTHORS: Serge Poiraudaue**

In this paper, the authors mainly discussed the management of LSS in primary care France and this was a survey of general practitioners [6]. The authors conducted a cross survey from the primary care unit in France and they randomly observed all the cases who are admitted with LSS problem. The authors designed some questionnaires designed by 3 physicians who are experts in LSS treatment and asked all the patients to undergo these questionnaires and give answers for those questions. After a thorough analysis, they came to conclusion about the LSS and its problems that arise in the human body and what are precautions to be taken for avoiding this LSS spine problem.

4) In the article " A Review on the Use of Artificial Intelligence in Spinal Diseases",published in [Asian Spine J.](#) 2020 Aug; 14(4): 543–571.

**AUTHORS: [Sohrab Sadeghi](#) and [Ali Montazeri](#)**

In this paper, the authors mainly discussed the importance of ANN which is used for several applications in the real world environment. This is mainly becoming very famous in the medical field for identifying several diseases and in this paper the authors are used for spine disease identification. In order to propose AI in spinal cord disease treatment they studied a lot of electronic databases and gathered information from nearlu 1993 to till data all the publications related to the AI and its importance in spinal diseases detection.The main objective of writing this paper is to emphasis on the applications related to spinal cord abnormality detection and diagnostics of problems present in the spinal cord.

## TABULAR REPRESENTATION OF LITERATURE ON SPINE DIAGNOSIS

Liszka-Hackzell et al. [9]	2002	Sweden	30	10	MLP	LBP	NR	To explore new techniques of patient assessment that may prospectively identify of patients experience extended chronic pain and disability at risk of developing poor outcomes.	There was a good correlation between the true and predicted values for general health ( $r=0.96$ , $p<0.01$ ) and mental health ( $r=0.80$ , $p<0.01$ ). ANNs can be applied effectively to categorizing patients with acute and chronic LBP.
Lin et al. [10]	2008	USA	25 Patterns	12 Patterns	MLP: a multilayer feedforward, back-propagation ANN	Spinal deformity	NR	To identify the classification of unspecified patterns of the scoliosis spine models	The accuracy was within 2.0 mm. The study showed that the data do not seem to be adequate enough due to participate study were small. Nevertheless, ANNs was useful with high accuracy to identify the classification patterns of the scoliosis spinal deformity.
Sari et al. [11]	2010	Turkey	169	169	MLP the designed ANN consisted of feed-forward back propagation, two hidden layers	LBP	NR	Comparison of ANNs and adaptive neuro-fuzzy inference system for the assessment of the LBP	The results showed that the ANNs and adaptive neuro-fuzzy inference system behave very similar to real data. The use of these systems can be used to successfully diagnose the back pain intensity.

Veronezi et al. [12]	2015	Brazil	68 Radiographies for the training stage	68 Images for tests and 70 for validation	Neural networks	Osteoarthritis of the lumbar spine	NR	For the diagnosis of osteoarthritis of the lumbar spine	The validation was carried out on the best results, achieved accuracy of 62.85%, sensitivity of 65.71%, and specificity of 60%. Although the neural network presented an average efficacy, because this was an innovative study, its results showed a potential for the use of computer-based artificial neural networks to assist and support practitioners.
Zhang et al. [13]	2017	China	235 Radiographs	105 Radiographs	DNN	Scoliosis assessment	Yes	To perform automatic measurements of Cobb angle for scoliosis assessment	The differences between the computer-aided measurement and the manual measurement by the surgeon were higher than 5°. The variability of Cobb angle measurements could be reduced if the DNN system was trained with enough vertebral patches.
Jamaludin et al. [14]	2017	UK	90% in a training set of 1,806 patients	10% in an independent sample of 203 patients	CNN	Lumbar IVDs and vertebral bodies	Yes	To automate the process of grading lumbar IVDs and vertebral bodies from MRIs.	The detection system achieved 95.6% accuracy in terms of disc detection and labeling. The model was able to produce predictions of multiple pathological grading that consistently matched those of the radiologist. The system could be beneficial in aiding clinical diagnoses in terms of objectivity of grading and the speed of analysis.
Wang et al. [15]	2017	China	A set of 26 cases	A set of 26 cases	Deep Siamese neural networks	Spinal metastasis	NR	A multi-resolution approach for spinal metastasis detection in MRI	The results showed that the proposed approach correctly detects all the spinal metastatic lesions. The results indicated that the proposed Siamese neural network method, combined with the aggregation strategy, provided a viable strategy for the automated detection of spinal metastasis in MRI images.

Kim et al. [16]	2018	USA	15,840	6,789	ANNs	Posterior lumbar spine fusion	Yes	Comparison of ANNs, LR, and ASA class to identify risk factors of developing complications following posterior lumbar spine fusion	ANN and LR both outperformed ASA class for predicting all four types of complications. ANN had greater sensitivity than LR for detecting wound complications and mortality. In summary, machine learning in the form of LR and ANNs were more accurate than benchmark. ASA scores for identifying risk factors of developing complications following posterior lumbar spine fusion, suggesting they are potentially great tools for risk factor analysis in spine surgery.
Kim et al. [17]	2018	South Korea	Total training epoch was 200	The experiments were done using 5-fold cross validation and each experiment had 5 test images and 20 training images.	CNN	IVDs	Yes	To segmentation of the IVDs from MR spine images	The proposed network achieved 3% higher DSC than conventional U-net for IVD segmentation (89.44% vs. 86.44%, respectively, $p < 0.001$ ). For IVD boundary segmentation, the proposed network achieved 10.46% higher DSC than conventional U-net (54.62% vs. 44.16%, respectively, $p < 0.001$ ).
Kim et al. [18]	2018	South Korea	Four-fold cross validation on a patient-level independent split	Four-fold cross validation on a patient-level independent split	DCNN	Tuberculous and pyogenic spondylitis	Yes	To differentiate between tuberculous and pyogenic spondylitis on MR imaging, compared to the performance of skilled radiologists	When comparing the AUC value of the DCNN classifier (0.802) with the pooled AUC value of the three readers (0.729), there was no significant difference ( $p=0.079$ ). In differentiating between tuberculous and pyogenic spondylitis using MR images, the performance of the DCNN classifier was comparable to that of three skilled radiologists.
Han et al. [19]	2018	Canada	The dataset comprises 253 lumbar scans from 253 patients	The dataset comprises 253 lumbar scans from 253 patients	Recurrent neural network	IVDs, vertebrae, and neural foraminal stenosis	NR	To perform automated segmentation and classification (i.e., normal and abnormal) of IVDs, vertebrae, and neural foramen in MRI	Extensive experiments on MRIs of 253 patients have demonstrated that Spine-GAN achieved high pixel accuracy of 96.2%, Dice coefficient of 87.1%, sensitivity of 89.1%, and specificity of 86.0%, which revealed its effectiveness and potential as a clinical tool.

### 3. EXISTING SYSTEM AND ITS LIMITATIONS

In the existing system, there was no proper method to identify the spine-related problems automatically and find out the abnormalities which are present in the spine. But no method is having the ability to test the abnormalities automatically and find out the physical parameters to observe the spinal abnormalities. The following are the main limitations of the existing system.

#### LIMITATIONS OF THE EXISTING SYSTEM

- 1) Time Complexity
- 2) There is no automatic approach for abnormality detection.
- 3) All the abnormalities are found in a manual way which is very complex for normal users.
- 4) There is no automatic approach for identifying the physical parameters.

### 4. PROPOSED SYSTEM AND ITS ADVANTAGES

The proposed application is designed using machine learning and deep learning models in the medical field for disease prediction and to guide the medical experts about the patient's current situation. In this present work, we try to identify the most important physical parameters which are required to figure out the spinal abnormalities which are collected physically from spine patients. Here we propose a novel method to predict and trace the lumbar spinal stenosis through semantic segmentation and delineation of magnetic resonance imaging (MRI) scans of the lumbar spine.

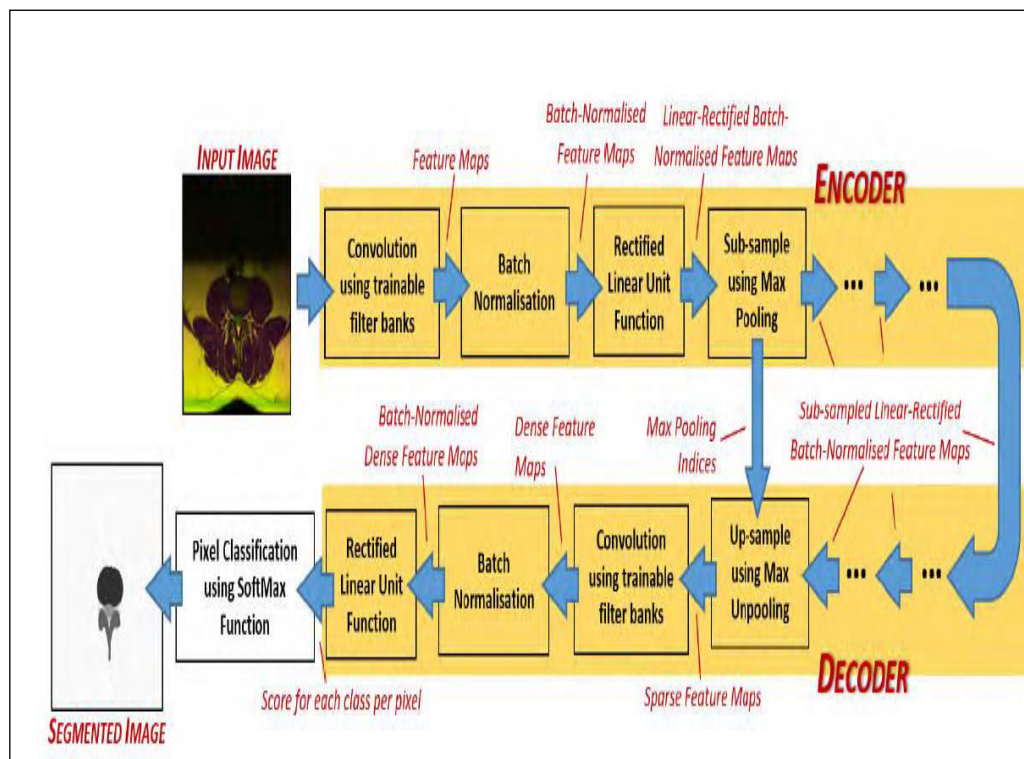
#### ADVANTAGES OF THE PROPOSED SYSTEM

- 1) By using the proposed deep learning model prediction of abnormalities in the spinal cord are very easy.
- 2) It generates a very accurate result

- 3) It is less time complexity
- 4) This reduces a lot of effort for the medical experts to find out the abnormalities.
- 5) This is very efficient in finding the lumbar spine using an MRI scan images.

#### 4. PROPOSED LUMBAR SPINAL STENOSIS DETECTION THROUGH SEMANTIC SEGMENTATION

From the below figure 2, we can clearly identify the abnormality of the spine lumbar which is present in MRI images and we try to segment that affected part from that original image. Initially, we try to take an MRI image as input, and from that image, we try to apply CNN using trainable filter banks so that the main features are extracted. Once the main features are extracted from that input image we try to separate that image as a Normalized image and this normalized image is now formed into Batch Normalized Feature Maps. Here we try to apply the VGG 16 Deep Learning pretrained model to visualize the MRI images.



**Figure. 2. Represents the Proposed Model**

The input data contains not a single image but a collection of several MRI images that are not labeled with trained values [20]. Initially, they are raw label images and which don't have any ground truth label images. Here we try to use the SegNet framework to detect lumbar spinal stenosis. Now the sub-sampled data is applied with a softmax classifier in order to figure out pixel by pixel for identifying the abnormality which is present on sample MRI images. Now the input image is converted into an encoded manner and now this encoded data is taken as input and now trained with some pre-defined values which are already loaded in the system in the reverse process. Once the data is decoded now we can get the result as a segmented image. For getting the image segmentation we try to apply the PixelLib library which is very easy in a python programming language to train the image for abnormality detection under pixel-level verification.

## 5. EXPERIMENTAL RESULTS

Implementation is a stage where the theoretical design is converted into a programmatic manner. In this proposed application we try to use PYTHON as a programming language in which Google Collaborator is used as a working platform to text the current application.

### 1) IMPORTING ALL NECESSARY LIBRARIES

Dataset needed (see Related Links for download links)

- MRI\_Data
- Manual\_Label\_Data
- Ground\_Truth\_Data (optional)

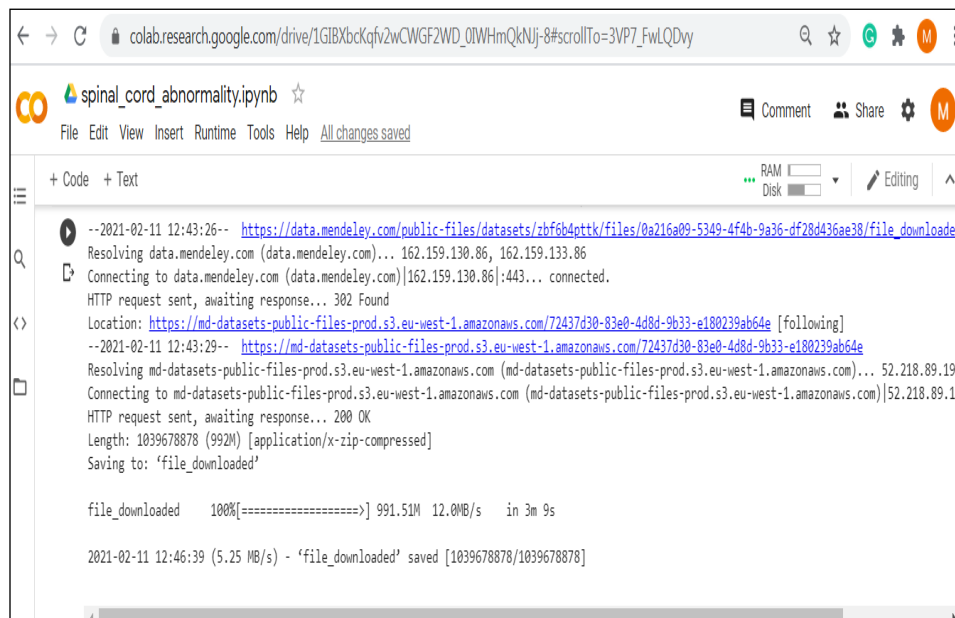
Additional programs and MATLAB library needed:

- VGG16 (<https://uk.mathworks.com/matlabcentral/fileexchange/61733-deep-learning-toolbox-model-for-vgg-16-network>)

```
# !wget https://md-datasets-cache-zipfiles-prod.s3.eu-west-1.amazonaws.com/zbfb6b4pttk-2.zip
!wget https://data.mendeley.com/public-files/datasets/zbfb6b4pttk/files/0a216a09-5349-4f4b-9a36-df28d436ae38/file_downloaded
```

From the above pseudo code we can see all the requirements for implementing this current application. Here as an input, we require MRI\_Data which contains all the MRI images related to spine and also we require another folder name Manual\_Label\_Data which is used for loading all the manual labeled MRI images data. Also, we require Ground\_Truth\_Data which is required to extract the processed or segment data into that folder location.

### 2) USER TRY TO EXTRACT THE INPUT DATA WHICH IS IN ZIP FORMAT



```
colab.research.google.com/drive/1GIBXbcKqfv2wCWGF2WD_QjWHmQkNj-8#scrollTo=3VP7_FwLQDvy
spinal_cord_abnormality.ipynb
File Edit View Insert Runtime Tools Help All changes saved
+ Code + Text RAM Disk Editing
--2021-02-11 12:43:26-- https://data.mendeley.com/public-files/datasets/zbfb6b4pttk/files/0a216a09-5349-4f4b-9a36-df28d436ae38/file_downloaded
Resolving data.mendeley.com (data.mendeley.com)... 162.159.130.86, 162.159.133.86
Connecting to data.mendeley.com (data.mendeley.com)|162.159.130.86|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com/72437d30-83e0-4d8d-9b33-e180239ab64e [following]
--2021-02-11 12:43:29-- https://md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com/72437d30-83e0-4d8d-9b33-e180239ab64e
Resolving md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com (md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com)... 52.218.89.192
Connecting to md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com (md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com)|52.218.89.192
HTTP request sent, awaiting response... 200 OK
Length: 1039678878 (992M) [application/x-zip-compressed]
Saving to: 'file_downloaded'

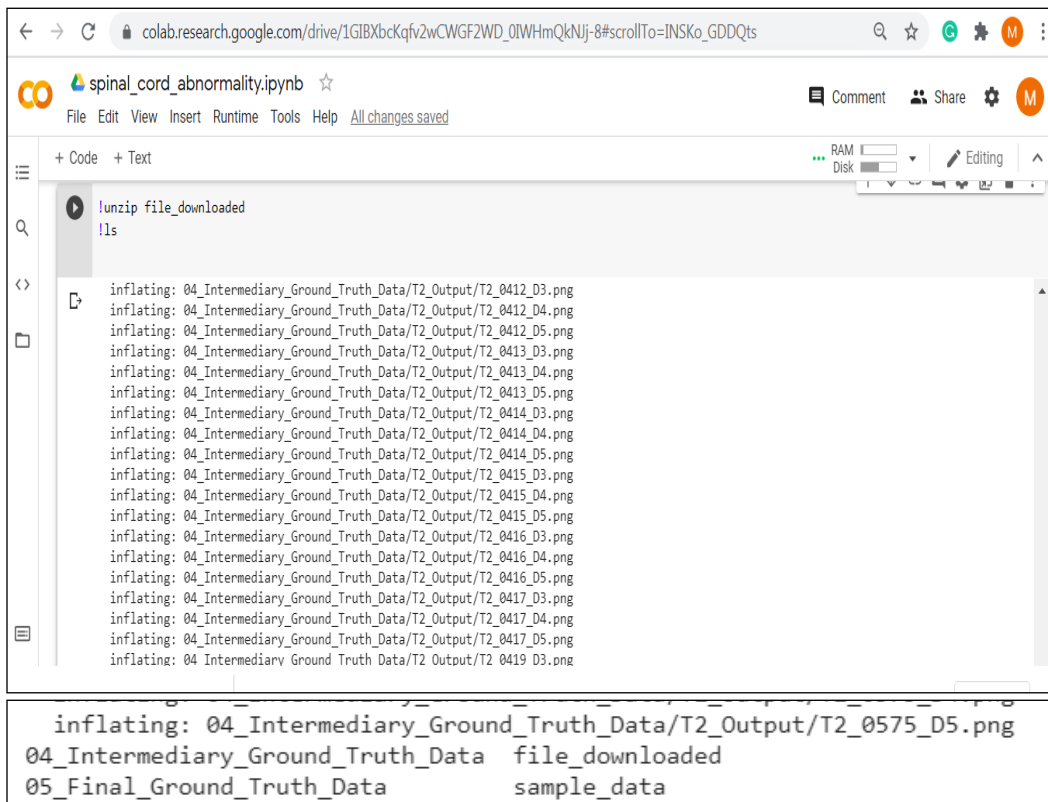
file_downloaded 100%[=====] 991.51M 12.0MB/s in 3m 9s

2021-02-11 12:46:39 (5.25 MB/s) - 'file_downloaded' saved [1039678878/1039678878]
```

Figure . Represents the User try to Extract the Input Data



From the above figure, we can clearly see that the user try to browse MRI data from Mendeley.com, and now the data is loaded into GPU in zip format. So we try to unzip that file before we apply the mechanism to find out the abnormalities which are present on spine images.



```
colab.research.google.com/drive/1GIBXbcKqfv2wCWGF2WD_0IWHmQkNj-8#scrollTo=INsko_GDDQts
spinal_cord_abnormality.ipynb
File Edit View Insert Runtime Tools Help All changes saved
+ Code + Text
!unzip file_downloaded
ls
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0412_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0412_D4.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0412_D5.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0413_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0413_D4.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0413_D5.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0414_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0414_D4.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0414_D5.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0415_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0415_D4.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0415_D5.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0416_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0416_D4.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0416_D5.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0417_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0417_D4.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0417_D5.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0419_D3.png
inflatina: 04_Intermediary_Ground_Truth_Data/T2_Output/T2_0575_D5.png
04_Intermediary_Ground_Truth_Data file_downloaded
05_Final_Ground_Truth_Data sample_data
```

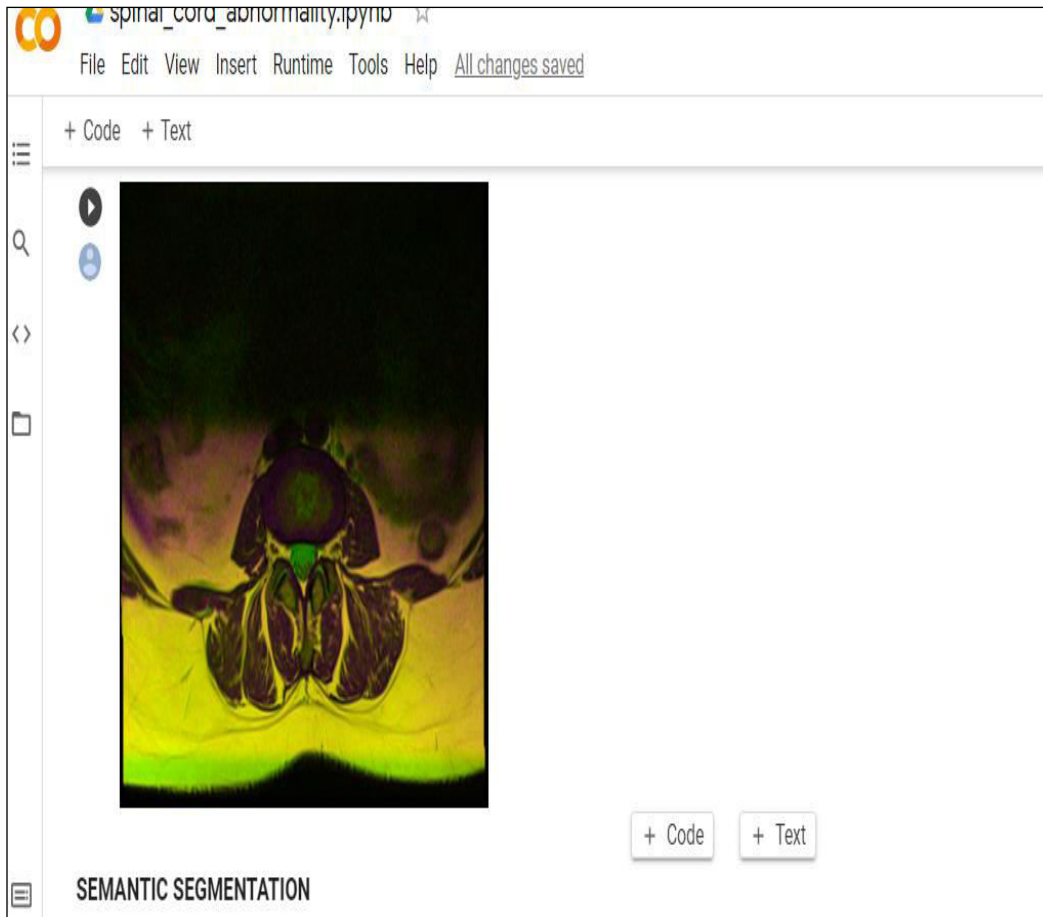
Now we can see the file is loaded successfully and all the images are unzipped and stored into the Google Collaboratory location. Here we can clearly see totally 575 raw MRI images are extracted from that MRI folder [21].

### 3) USER TRY TO LOAD ONE IMAGE AS SAMPLE



```
data='Composite_Images/C1_0010_D3.png' # composite images are input image and label images are output image
img2=cv2.imread(data)
cv2.imshow(img2)
```

Here we try to apply load one image as a sample image from the set of all images and we can see the overview of that Spine Image. From that image, we cannot directly check the abnormality without having complete knowledge of that spine data.



BERT summarizer method and find out the MCQs for that given phrase

#### 4) IMPORT PRE-TRAINED LIBRARIES TO PREDICT ABNORMALITY

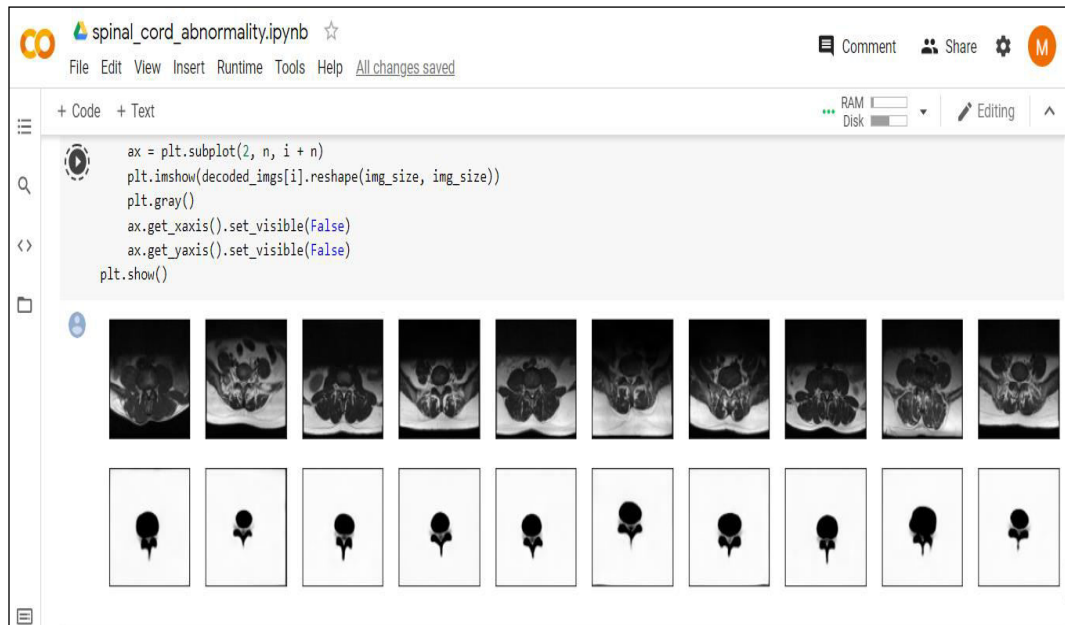
```
[8] # !pip install pixellib
    # !pip install tensorflow
    # !pip install scikit-image
```

```
[9] !ls
```

04_Intermediary_Ground_Truth_Data	Composite_Images	Label_Images
05_Final_Ground_Truth_Data	file_downloaded	sample_data

From the above figure we can clearly see that input data is divided into two categories one is: Composite Images with Label\_images as one category and the second one is Sample\_Data which need to be examined and trained for abnormality detection.

## 5) IMAGE SEGMENTED



From the above figure we can see segmented part which contains the spine abnormality from the sample set of images and we finally came to an clear idea about the LSS suffered patients by using semantic segmentation method.

## 6. CONCLUSION

In this current work we for the first time designed and implemented an application using machine learning (ML) models in the medical field for disease prediction and to guide the medical experts about the patient's current situation. In this present work, we try to identify the most important physical parameters which are required to figure out the spinal abnormalities which are collected physically from spine patients. Here we propose a novel method to predict and trace the lumbar spinal stenosis through semantic segmentation and delineation of magnetic resonance imaging (MRI) scans of the lumbar spine. By conducting various experiments on the dataset which contain nearly MRI studies of 515 patients with symptomatic back pains. Our evaluation results clearly state that the proposed segmentation and the delineation results show that our proposed methodology produces a very good performance as measured by several contour-based and region-based metrics.

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