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DEGENERATIVE SPINE DETECTION

Arti Rathore
Department of Computer Science and Engineering,
New Government Engineering College, Raipur, Chhattisgarh, India
Email id: aartirathore112@gmail.com

Riya Tiwari
Department of Computer Science and Engineering,
New Government Engineering College, Raipur, Chhattisgarh, India
Email id: riyascitech.1717@gmail.com

Krati Sachan
Department of Computer Science and Engineering,
New Government Engineering College, Raipur, Chhattisgarh, India
Email id: krati.sachan19@gmail.com

ABSTRACT

Spinal Misalignment is a chronic disease that is widespread across the world. It causes different diseases such as Stenosis, Scoliosis, Osteoporotic Fractures, Thoracolumbar fractures, Disc degeneration, etc. The diagnosis of such disease is generally done by analyzing the Magnetic Resonance Imaging (MRI) scan of the lumbar spine region. MRI analysis is done by well experienced medical professionals (radiologists and orthopedists). The flip side to this inspection is that it is time consuming and may be subjected to a lack of accuracy. The manual segmentation of MRI scans from a large number of scan images is a tedious and time - consuming process. Thus, there is a need for automatic segmentation and analysis of spine MRI scans to improve clinical outputs and the accuracy of spinal measurements. In recent years, the rise of deep learning technologies is making a revolution in medical systems. It is capable to examine a big amount of data thus yielding a better accuracy. So, deep learning approaches can be efficiently used for the automatic segmentation of MRI scans. For Disc degeneration detection we trained two models namely normal CNN Model and Densenet121 model. Out of these two models the Densenet121 model performed the best against our standards. It achieved training Accuracy of 99.75% , validation accuracy of 93.74% , testing Accuracy of 92.74% and hence was chosen as the final model for Disc degeneration detection.

Keywords: Convolutional Neural Network, Deep Learning, Transfer Learning, Densenet121

INTRODUCTION

Vertebral Misalignment is a disease caused by defects present in the spinal region which comprises the vertebral column containing the cervical , the thoracic and the lumbar spine. The vertebral column plays a vital role in safeguarding the spinal cord which comprises the central nervous system of our body and it also gives support to the body. If there is any damage in this region of the body ,the whole body stops functioning properly, any damage in this area also causes immense pain due to the large concentration of nerves . It is divided into five parts , Lumbar vertebrae, is one of the segments of the vertebral column whose function is to bear the weight of the body .The lower vertebra endures most weight as compared to the other portions. The five lumbar vertebrae (L1-L5) is the largest vertebrae in the vertebral column , making it strong enough to support the weight of the upper portion of the human body. This structure keeps all the bones, joints, nerves, ligaments, and the muscles intact, each of them contributing to supporting, strengthening and maintaining the

body's flexibility. Back pain comes under the most prevalent common health problems in the world. Such problems in the lower back may be caused by innumerable circumstances which can be problems such as irritation or the spine structures malalignment. These abnormalities in the lower back such as an uncomplicated muscle strain and osteoporotic fractures might cause serious problems that may require emergency medical treatment, whereas some problems such as disc degeneration and scoliosis will cause pain and may be treated by physical therapy.

METHODS AND TECHNIQUES

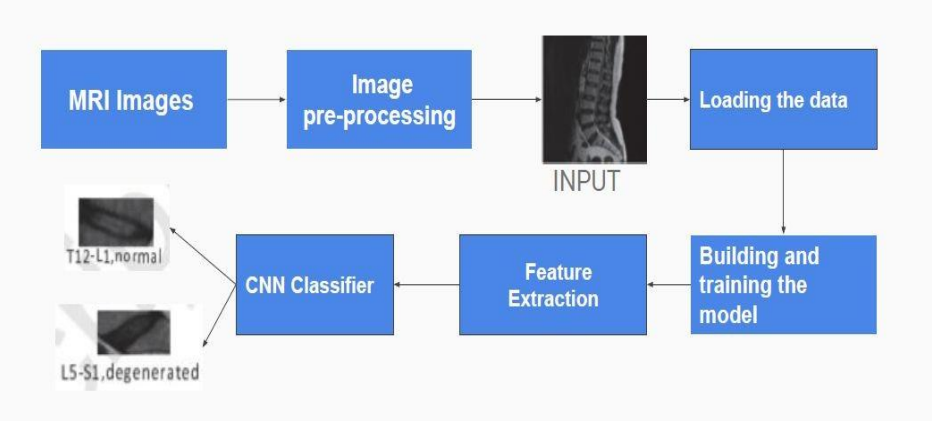

Fig 1: Work Plan

Dataset analysis

The dataset for Disc degeneration detection contains 4041 MRI images. These images were obtained from 278 different patients. The images were then split into three sets namely training set which contains 2828 images, validation set that contains 607 images and testing set that contains 606 images. Our dataset consists of 2 categories- Normal and Degenerative spine images. There are 104 normal spine patients and 174 degenerative spine patients.

Image preprocessing

For this we have used the openCV method. This includes cropping the image and converting to grayscale image. This is basically beneficial for removing the noise and finding out the clear region of interest by performing a series of erosions and dilations. Then we find the contours in threshold image and extreme points and crop the new image out of the original images.

Extraction of Region of interest(ROI)

Since the variation of image ratios was very high so we cropped the images to extract the region of interest in the first place. The algorithm works in the following way:

1. Get the original images one by one from the datasets.
2. Find the biggest possible contour on the image. This was accomplished using the 'crop_spine_contour' method where we implemented openCV. This method returned all the possible contours in the image. Now using the 'threshold', 'erode', 'dilation' function in the openCV library we took the contour with the contour where we threshold the image, then perform a series of erosions dilations to remove any small regions of noise.
3. Now using the 'max' function in the openCV library we took the contour with the maximum area in it. This gave us the biggest contour in the image.

4. Now find the extreme points on this contour. Extreme points are the coordinate of the points which are on the extreme positions of the x and y coordinate system.
5.Crop the image by drawing the rectangles through extreme points.

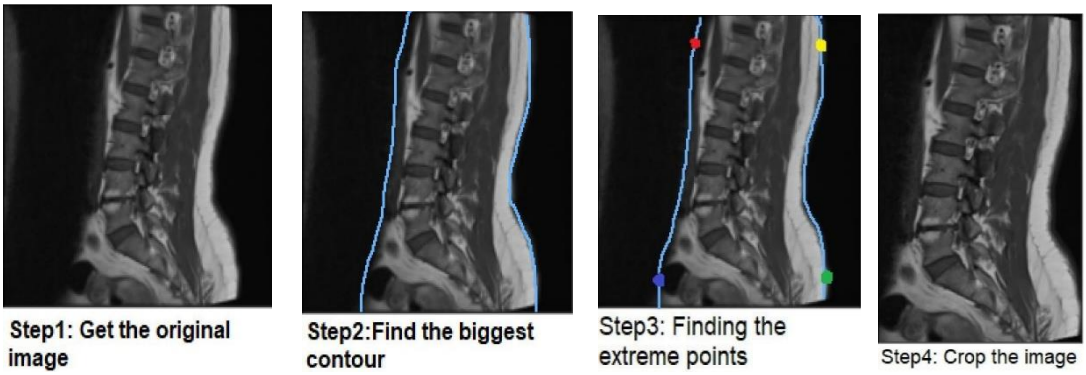

Fig 2: Steps to crop the ROI

Resizing

After the images were cropped they were resized to the dimension (224,224,3).For resizing the images we used a method called intercubic interpolation of openCV. After that model specific preprocessing function was applied to the images in the datasets to shift the range of the pixels and normalize each image.

CNN

The proposed methodology uses CNN (convolution neural network) algorithm for extracting relevant features from images by convolving it with neurons set

1 CNN model simply takes an image as input, performs image processing and then classifies it under certain categories.

2 CNN is usually preferred for region of interest (ROI) recognition and image classifications through objects detection, recognition, extraction etc.

3 Input images pass through a series of convolution layers having pooling layers, filters (kernels), fully connected layers (FC) and softmax function for classification of objects with probabilistic values between 0 and 1.

The main advantage of CNN compared to its predecessors is that it automatically detects the important characterstics without any human administration.

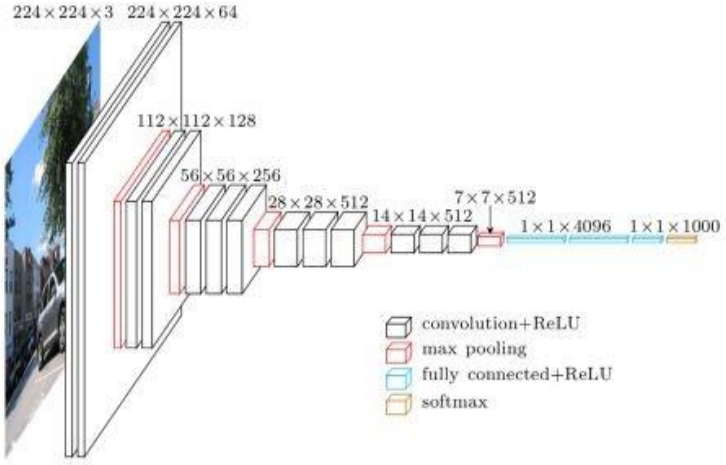

Fig 3: CNN Architecture

Transfer learning approach(Densenet121)

Transfer learning process train a model for some specific problem transfer this knowledge to other related problems.

1. One or more layers from the trained model are then used in a new model trained on the problem of interest.
2. The weights in re-used layers may be used as the starting point for the training process and adapted in response to the new problem.
3. Transfer learning has the benefit of reducing the training time for a neural network model and can result in lower abstraction error.

RESULTS

We developed a model for Disc degeneration detection. The results for Disc degeneration detection models are compiled below.

Normal CNN model

This result shows the training loss, training accuracy, validation loss, validation accuracy on each epochs and we obtained:

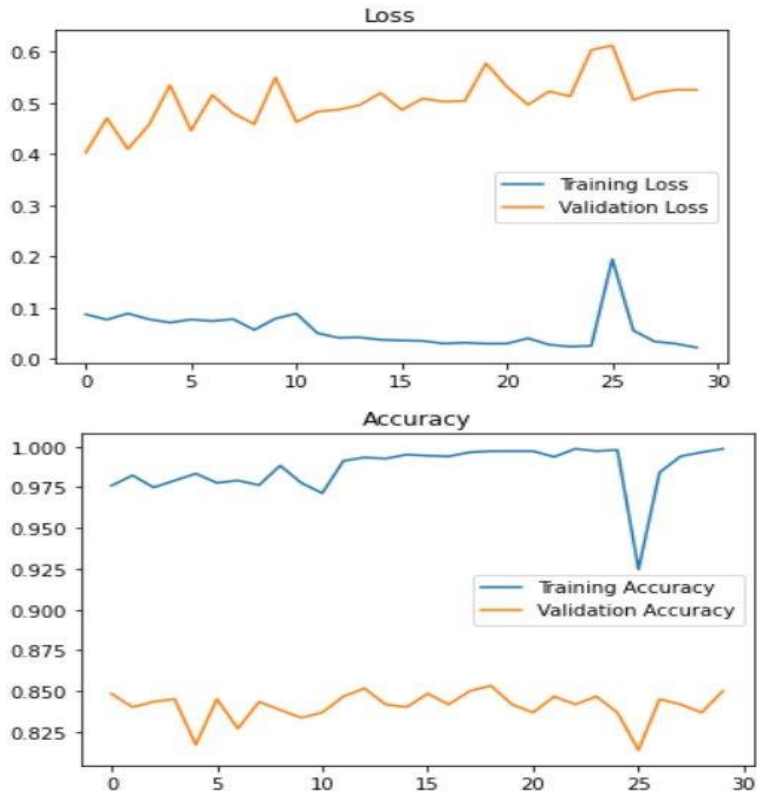

Fig 4: Result of Normal CNN mode

Densenet121 model

It achieved training Accuracy of 99.75% validation accuracy of 93.74%,testing Accuracy of 92.74% and hence was chosen as the final model for Disc degeneration detection . The following shows the confusion matrix for densenet121:

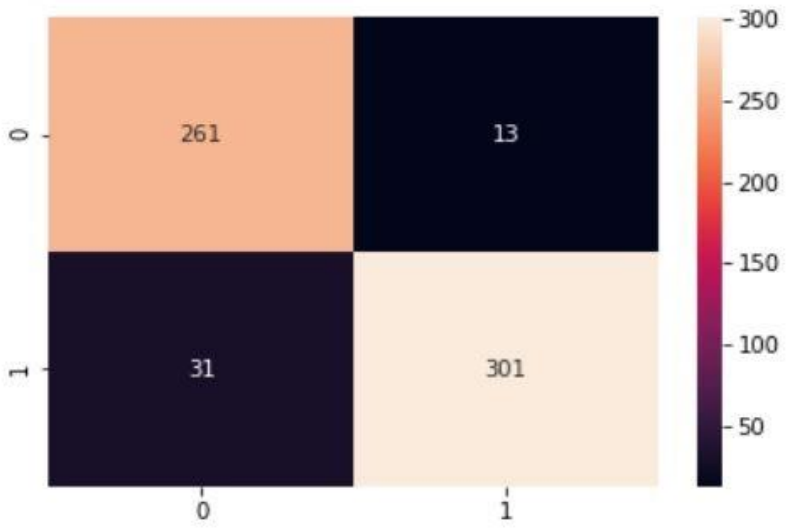

Fig 5: Confusion matrix

Y axis refers to True Labels , X axis refers to Predict labels
0(true)-0(predicted) - false negative-261 images
1(True)-1(predicted) - true positive-301 images
0(true)-1(predicted) - false positives-13 images
1(true)-0(predicted) - true negatives-31 images
The above confusion matrix has been obtained from our testing set consisting of606 images. It has been further divided into as number of images which were actually degenerative or normal and what the algorithm has predicted.

Degenerative disc detection result

Table1: comparison between models proposed

Model	Training Accuracy(%)	Validation Accuracy(%)	Testing Accuracy(%)
Normal CNN Model	99.86	85.01	84.56
Densenet121 Model	99.75	93.74	92.74

For Disc degeneration detection we trained two models namely normal CNN Model and Densenet 121 model. Out of these two models the Densenet121 model performed the best against our standards. It achieved training Accuracy of 99.75% validation accuracy of 93.74% ,testing Accuracy of 92.74% and hence was chosen as the final model for Disc degeneration detection.

CONCLUSION

Spinal misalignment causes serious health issues if not diagnosed at earlier stages. MRI scans play a major role in the detection and diagnosis of spinal malalignment. The MRI scan images are segmented to identify disorders. The manual prediction of spinal disorders in the MRI scans is laborious and might produce inaccurate results. This emphasizes the need for the implementation of automatic segmentation techniques of the spinal MRI. This paper comprises various deep learning methodologies such as **Normal CNN,** and **Densenet 121**among others. The **Densenet121** architecture is better designed as compared to other algorithms since it works with fewer training images and it produces more accurate segmentation. However, automatic segmentation has its limitations such as analyzing a large amount of data to train the network model .

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