Int. J. Nonlinear Anal. Appl.
Volume 12, Special Issue, Winter and Spring 2021, 1595-1604
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2021.5832

Cervical spondylosis detection using deep dense auxiliary inception network

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(Communicated by Madjid Eshaghi Gordji)

Abstract

Cervical Spondylosis is a recurring spinal syndrome in which the spine progressively tightens and that can eventually become fully rigid. Early diagnosis is really an efficient way of improving the recovery rate and reducing costs. Due to the difficult and comprehensive procedure for recognizing cervical spondylosis in initial stages, this area is untreated. Strong correlations of the vertebrae makes the automatic detection procedure challenging. These minor variations in the X-ray image makes visual interpretation a challenging task involving skilled explorers. Even after this, the problem still remains untreated and also the feasibility of even an automatic detection framework has still not been addressed for this application. Thus, the Deep learning based method used to predict the some potential relevance of Cervical Spondylosis has. The proposed system can be used to detect the onset of cervical spondylosis in early stages using deep learning techniques.

Keywords: Cervical spine, Cervical spondylosis, Deep learning, X-Ray imaging, inception

1. Introduction

Cervical Spondylosis is a recurring spinal syndrome in which the spine progressively tightens and that can eventually become fully rigid. According to a latest analysis by the Office for National Statistics, individuals with lower back pain and neck pain are rising every day, which is a major symptom of CS. Which impacts their work performance. According to this survey, 31 per cent of males and 20 per cent of females are facing the problem.

Cervical spondylosis causes intermittent pain in the neck of middle and elderly patients. These are induced often due to degenerative disk disease. Because of change regular work, immobilization in

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Received: August 2021 *Accepted:* November 2021

neck, asynchronous movements, and therapies. CS pain is noticed. The most severe and active state of this cervical spondylosis is the cervical spondylotic myelopathy. Cervical spondylosis occurs due to disk degeneration, that disintegrates, loses water content and collapses during natural aging [1, 2]. Intervertebral disk degeneration enhanced mechanical stress mostly on end plates at cartilagin body lip. Disks in between third and seventh cervical vertebrae will be most frequently affect [7].Cervical spondylosis may leads to symptomatic contraction of the spinal cord [3]. The development of the an incurably small spinal canal, 10 to 13 mm in diameter, would be a crucial potential biomarker in individuals with spondylotic myelopathy.

Early detection of cervical spondylosis can help to reduce the risk of disease. Early diagnosis is really an efficient way of improving the recovery rate and reducing costs. Due to the difficult and comprehensive procedure for recognizing cervical spondylosis in initial stages, this area is untreated. Also Strong correlations of the vertebrae makes the automatic detection procedure challenging.

Cervical spondylosis is a common and non-specific concept which includes a wide range of symptoms but can still be comprised of 3 clinical syndromes for clarification purposes [26]: Type 1 Syndrome (Cervical Radiculopathy); Type 2 Syndrome (Cervical Myelopathy); and Type 3 Syndrome (Axial Joint Pain).

The paper is organized as follows. Section 2 presents the literature survey of the CS and deep learning. Section 3 and 4 presents the background and proposed detection methodology. Experimental results and Dataset information is explained in Section 5. Finally, Section 6 conclude the Proposed methodology and its performance.

2. Literature survey

M. Sreeraj et.al [23] Built and developed to identify and predict the severity of cervical spondylosis in initial stages utilizing incorrect posture videos. This machine learning approach offers a low cost and reliable method for initial stage spondylosis detection. This framework could also be improved by parallel processing. L. Zhang et.al [30] uses three layered structure for segmentation of vertebrae, in which firstly adaptive threshold filter and PointNet++ are used for segmentation of the tissue in between cervical vertebras and individual vertebra form CT scan images. Lastly converge segmentation is performed to extract the boundary region of vertebrae. N. Wang et.al [27] implement electromyography based CS detection using deep learning. They proposed a multi-channel EasiCS-Deep algorithm using the convolutional neural network. Paul A et.al [18] automatically identify and interpret cervical spondylosis in X-ray images using morphological segmentation, edge detection and classification-based method. B. Chanda et.al [4] proposed identification of cervical X-ray spondylosis with supervised segmentation. They extract the features using the Kirsch template and the classification is performed using the Fuzzy C-means Classifier. H. Bae et.al [11] proposed 2D convolutional neural network for the recognition of superior and inferior vertebrae in CT and further segmentation and differentiation of cervical vertebrae is done using U-Net model. Kara B.et.al [12] used diffusion tensor imaging (DTI) techniques to detect cervical spondylotic myelopathy at an early stage. They generated apparent diffusion coefficient and fractional anisotropy maps for detection.

S. Singh et.al. [21] correlate the factors such as age, gender, race, profession, vertebral body dimension, canal thickness, canal body proportion of cervical spine to cervical spondylosis patients for general population. They claim that differences within canal dimension, the canal body proportion, the vertebral body dimension of the cervical vertebrae and the race, height and weight of individual would not risk variable for cervical spondylosis. Age, gender and profession have been the only possible causes for cervical spondylosis. X. Yu et.al [28] suggest classification of cervical spondylosis in X-ray radiograph using Fuzzy decision.

Y. Li et.al [17] proposed a CNN architecture for recognition of lumbar vertebrae in X-ray scan. Contour and texture are extracted using Sobel and Gabor features and a feature level fusion DNN is implemented. R. Sa et al. [19] propses Faster-RCNN deep network for segmentation of lateral lumbar vertebrae from X-ray imagery.C. Kuok et.al. [14] suggest a effective CNN framework vertebrae detection on large 3D data. Further A sequence of simple image processing steps are applied for the intervertebral plane detection. R. Janssens et.al. [10] proposed cascaded 3D FCNN which is combinantion of a Segmentation-Net and a Localization-Net to a detect the individual vertebrae.

3. Background

Mild symptoms and Strong correlations of the vertebrae increase the complexity of diagnosing, particularly in patients initial stage. Due to the difficult and comprehensive procedure for recognizing cervical spondylosis, this area is untreated. Also makes the automatic detection procedure challenging. In initial stages, clinical manifestations and spinal abnormalities are fairly benign and this makes the diagnostic complexity more. Thus, a convenient, low-cost intelligent CS detection method at early stage is needed. At present, medical diagnosis relies primarily on the doctor's opinion on the clinical manifestations and spinal anomalies of the CT scan. Advancement of changes in spondylosis may contribute to stenosis of a spine even spinal canal may be become narrow. The spine and its nerve could impaired, causes of acute of myelopathy or radiculopathy [16].

4. Methodology

In most hospitals, X-ray is often used as a standard screening method for clinical findings, if any. The Cervical Spondylosis has various forms which have slight modifications to the X-ray images, so it is important for identification to treat them with various treatments. These minor variations in the X-ray image makes visual interpretation a challenging task involving skilled explorers. Even after this, the problem still remains untreated and also the feasibility of even an automatic detection framework has still not been addressed for this application. Thus, the Deep learning based method used to predict the some potential relevance of Cervical Spondylosis has. DCNN, as one type of Deep learning, are known to be an important framework as it have better memorizing i.e .learning capability [5, 24, 25].

Here, we elaborate our proposed framework. The proposed system can be used to detect the onset of cervical spondylosis in early stages using deep learning techniques. Cervical spine impairment has been the main pathogenic cause concerning cervical spondylosis, that can cause major nerve compression of a cervical spinal cord, loss of feeling, weakening, and sometimes even paralysis of the legs. Automatic detection is challenging due to Strong correlations between the vertebrae , so segmentation of the vertebrae is of significant importance. In this research , Deep Dense Neural Network is proposed to achieve automatic and accurate C1-C7 detection from X-ray images.

Conventionally, trained classification models employing blockwise or region based techniques most widely used to detect the object . Blockwise Processing always provide deeper inside into an image, but sometimes it quite slow to highspeed applications because of low reliability.

A. Deep dense neural network

For datasets that constitute a huge collection of images to reduce address the possibility of overfitting, the number of hidden layers needs to be extended [15] including the size of the layer [20, 29] as well as the optimal use of the dropout [9]. Although the maxpooling layer results in the loss of the contextual piece of information are used in classification type of problem [13, 8].

Motivated by the neurological concept of the Primate Visual Cortex, proposed method used a sequence of fixed Gabor wavelet of variable size to accommodate different scales. All filter in the googlenet Neural network are substituted by the Wavelet transform. Also, 1x1 convolutionary layers are commonly used in the proposed network, raising its depth.

We used this framework extensively in architecture. From this adjustment, we limit size of the image, therefore eliminating the issue of the conceptual bottleneck. This form of problems would reduce the size and complexity of the network. This framework is built to be more effective than the existing system. The framework has 22 layers with variables and 27 layers if the max pooling is considered. If each layer is interpreted separately, it's around 100. This layer has a deeper insight with gradient backpropogation throughout the entire layer effectively. This approach improves discriminatory functionality to each and every equivalent network. The primary goal of the Inception Layer is to determine exact sparse nature in handwritten textures via an established dense layer. The auxiliary layer facilitates discrimination of data by raising the gradient of back-propagation which makes the models normal. During most of the training process, the losses are summed up until the estimation phase, after that the auxiliary layer has been ejected.

The proposed framework of the auxiliary layer would be as follows: The average pooling layer is $5x5$ filter size and phase 3, that offers $4x4x512$ outcome and $4x4x528$. $1x1$ convolution layer has 128 filter that are essential to minimise dimension and rectified linear activation. A fully connected layer is of 1024 components and rectified linear activation in the system. The drop-out layer has been used to slip outcome at a rate of 70 percent. The linear layer together with the softmax loss function as a classification model that can estimate a certain 1000 categories as the primary classification model. This layer is often used for the terminal phase of learning. This could be excluded at inference time. Three Inception frameworks used under various conditions are presented: usually, $1x1$ convolution can be used in Inception to evaluate reductions prior to $3x3$ and $5x5$ convolutions

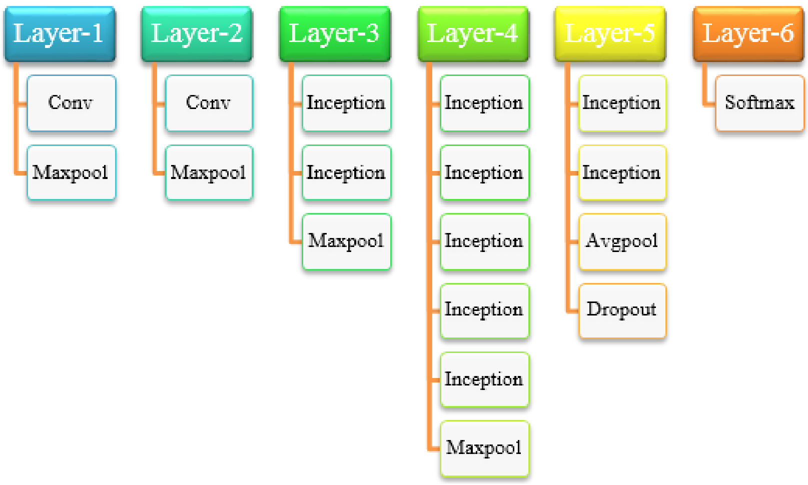

Figure 1: Proposed Architecture

MRI Image as a input vector to the initial layer is:

$$X = [x_1, x_2, \ldots, x_k] \tag{1}$$

K denotes the segmented image pixels. Then, to decrease the execution burden normalization of the data is carried out. In normalization data is mapped in between 0 and 1 [10],:

$$x = \frac{x - min}{max - min} \tag{2}$$

min and *max* is the minimum and maximum of respective data. This normalised data x is then converted to 2D matrix using reshaping operation and then this data is fed to convolution layer.

After covolution layer we got estimated the weight(w), bias (bj).

$$x_i^{l,j} = \sigma[b_j + \sum_{a=1}^{m} w_a^j x_{i+a-1}^{l-1,j}] \tag{3}$$

Activation function is indicated by the variable σ. Its nothing but ReLu,. ReLu function have higher efficiency and low execution time [22].

Max-Pooling Layer

Scale invariant property is preserved by Max-Pooling Layer by estimating aggregation statistics of the neighbourhood pixels. Thus they assist in dimensional reduction. Pooling have two types, max pooling and mean pooling . In our architecture we used max-Pooling. The max pooling layer find the maximum response i.e. maximum value of each block without compramixing feature loss [22]. Final response of max-pooling layer is given by:

$$x_i^{l,j} = max_{n=1}^{r} \left(x_{(i-1)*Tn}^{l-1,j} \right) \tag{4}$$

where n is pooling size and T is pooling stride.

Following equation models the Hidden layer to output .Proposed method have this capability

$$h_t = g(W_{xh^x t}) + W_{hh^h t-1} + b_h) \tag{5}$$

$$z_t = g(W_{hz^h t} + b_z) \tag{6}$$

here, g indicates elementwise nonlinearity(it can be sigmoid or hyperbolic tangent), x_t is the input $h_t \in R^N$ is the hidden state having hidden units equals to N. Output is denoted by Z_t at instant t.

pixel sequence $(x_1, x_2, \ldots, x_T)$ having T number of coefficient, then h1 (letting $h_0 = 0$), $z_1, h_2, z_2, \ldots, h_t, z_T$.

B. Time complexity of the proposed architecture

The time complexity is calculated as:

$$O(\sum_{l=1}^{d} n_{l-1}.s_1^2.n_1.m_1^2) \tag{7}$$

above equation calculate the time complexity of the convolutional layer. Layer index is indicated by l which is d in number. Total filter number is η_1 in lth layer and their spatial size is denoted by s_1. Channel number of is η_{l-1} at lth layer. Output have spatial size of m_1 . Initial Convolutional layer required 7% of the execution time.

This section details the conception of our implemented DDNN network approach for C1-C7vertebrae detection.

C. ROI region localization

The predicted ROI blob will assist to extract C1-C7 vertebrae from input MRI data. The purpose of this approach would be to extract each one of the individual vertebrae from cropped ROI . To this point, we have designed a segmentation to perform a multi-class segmentation of a ROI.

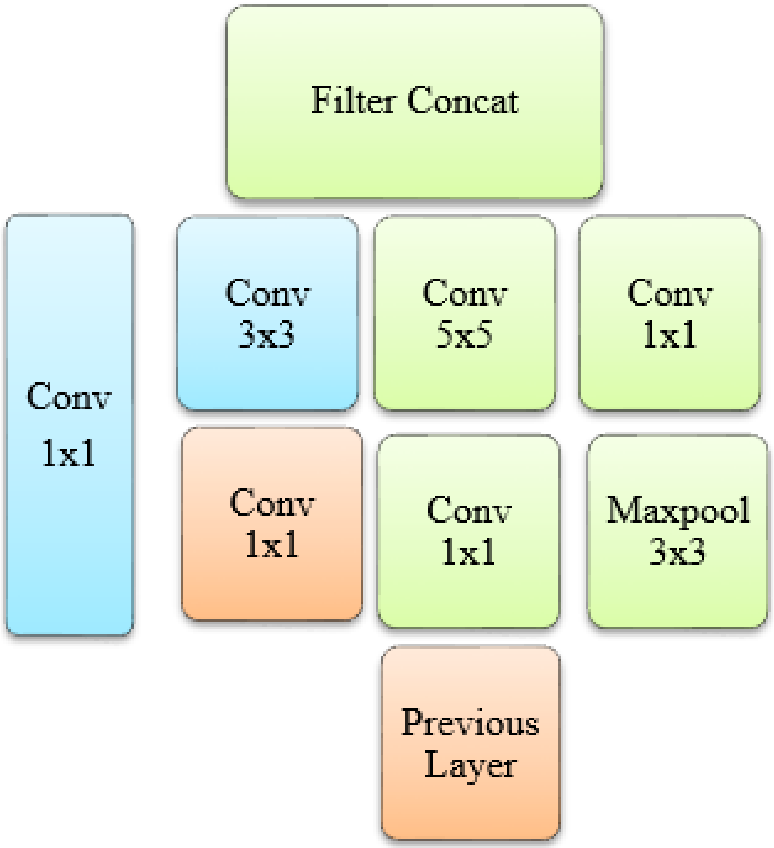

Figure 2: Inception layer

D. Dataset

In this study, cervical vertebrae CT data were collected from Hospital. Training set contain 700 images and testing set contain 150 images. For validation we keep 150 images. The testing data set are 300 subject, 221 of which are the CS patients and 79 of which are the healthy. The training set is made up of of spine MRI images obtained from aging between 32 and 58 years old. Image resolution is $1024x1024$.

5. Experiments

Proposed DDCNN is implemented using Matlab R2016b on Laptop with Intel core i52.50GHz CPUs, having 16GB. In terms of reducing computational cost, the image dimension of the input data is reduced to $512 * 512$ by binear interpolation.

Performance analysis

To validate the robustness of the proposed method, Proposed Deep Dense Auxiliary Inception Network is compared with well known techniques. This all techniques is implemented and tested on the same dataset with same folding. The summary of achieved results is shown below.

Proposed Deep Dense Auxiliary Inception Network achieves 95.33 % accuracy while other EasiCSDeep and PointNet++ achieves 92% respectively. Other method Such as FCM and CNN have 91% and 90 % accuracy respectively.

Table 1: Performance comparison of Proposed method and well known method

Method	Accuracy	Sensitivity	Specificity	Precision
Proposed	0.953333	0.990521	0.974684	0.945701
EasiCSDeep[27]	0.926667	0.980676	0.949367	0.918552
FCM[5]	0.91	0.970874	0.924051	0.904977
PointNet++[30]	0.923333	0.980583	0.949367	0.914027
CNN [6]	0.9	0.965854	0.911392	0.895928

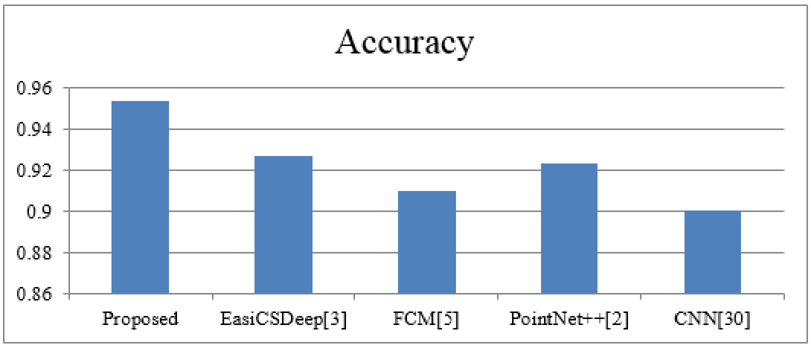

Figure 3: Accuracy comparison of proposed method

Proposed Deep Dense Auxiliary Inception Network achieves 99.05 % sensitivity while other EasiCSDeep and PointNet++ achieves 98% . Other method Such as FCM and CNN have 97% and 96 % sensitivity respectively.

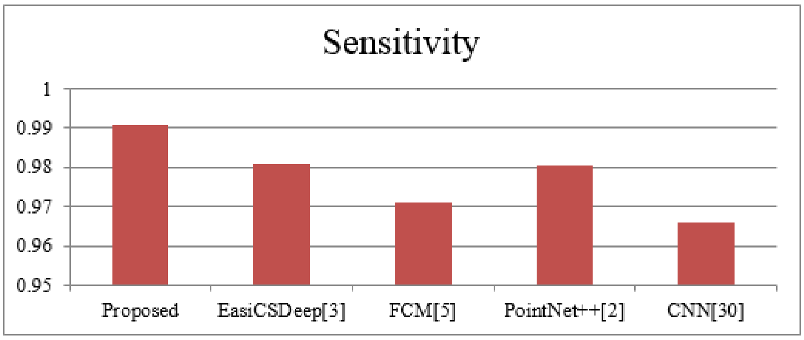

Figure 4: Sensitivity comparison of proposed method

Proposed Deep Dense Auxiliary Inception Network achieves 97.46 % Specificity while other EasiCSDeep and PointNet++ achieves 94% . Other method Such as FCM and CNN have 92% and 91 % Specificity respectively.

Proposed Deep Dense Auxiliary Inception Network achieves 94.57% Precision while other EasiCSDeep and PointNet++ achieves 91% . Other method Such as FCM and CNN have 90% and 89 % Precision respectively.

6. Conclusion

Also Strong correlations of the vertebrae makes the automatic detection procedure challenging. This paper showed a fully introduction to Deep dense CNN model. The proposed system can be

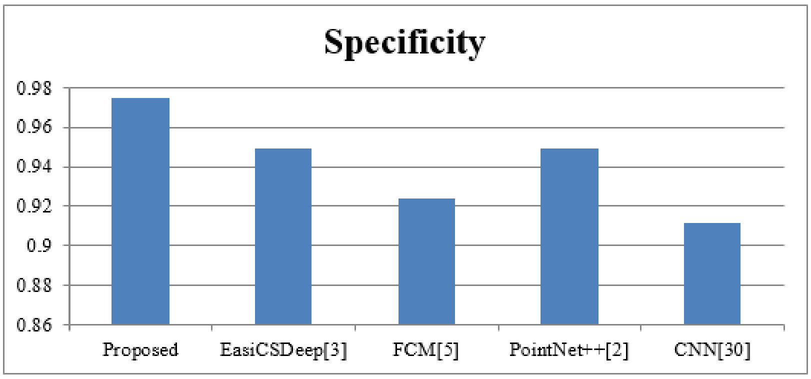

Figure 5: Specificity comparison of proposed method

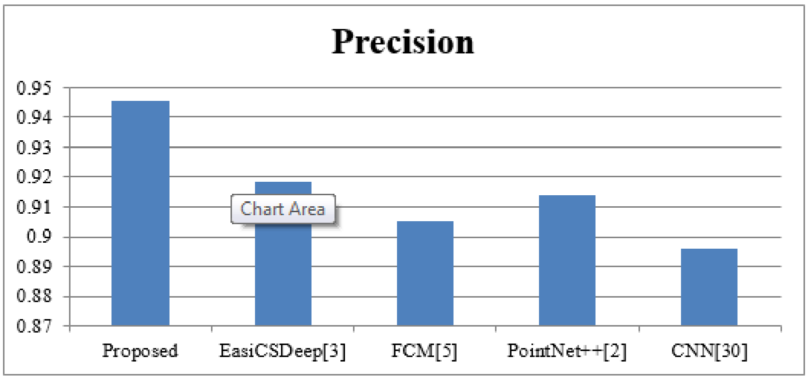

Figure 6: Precision comparison of proposed method

used to detect the onset of cervical spondylosis in early stages using deep learning techniques. The obtained results with proposed approach are superior to all of those reported by state-of-the-art techniques, although a direct evaluation of multiple techniques seems to be challenging, since not all of them are tested on a same given dataset. Hence all the Comparative methods are trained using given dataset and then test are carried out. From the experiments detailed quantitative and qualitative findings demonstrate that, in normal and abnormal situations, our suggested framework works more precisely than other state-of-the-art models.

7. Discussion

Cervical Spondylosis is a recurring spinal syndrome in which the spine progressively tightens and that can eventually become fully rigid. Cervical spondylosis causes intermittent pain in the neck of middle and elderly patients. These are induced often due to degenerative disk disease. Due to change in regular task, neck movement, irregular exercises, CS pain is noticed. The most severe and active state of this cervical spondylosis is the cervical spondylotic myelopathy. Early detection of cervical spondylosis can help to reduce the risk of disease. Early diagnosis is really an efficient way of improving the recovery rate and reducing costs. Automatic detection is challenging due to Strong correlations between the vertebrae , so segmentation of the vertebrae is of significant importance.

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