Computational Analysis of Vertebral Body for Compression Fracture Using Texture and Shape Features

Adela Arpitha, University of Mysore, India

Lalitha Rangarajan, University of Mysore, India

ABSTRACT

The primary goal in this paper is to automate radiological measurements of vertebral body (VB) in magnetic resonance imaging (MRI) spinal scans. It starts by preprocessing the images, then detecting and localizing the VB regions, next segmenting and labeling VBs, and finally, classifying each VB into three cases as being normal or fractured in Case 1; benign or malignant in Case 2; and normal, benign, or malignant in Case 3. The task is accomplished by extracting and combining distinct features of VB such as boundary, gray levels, shape, and texture features using various machine learning techniques. The class balance deficit dataset towards normal and fractures is balanced by data augmentation, which provides an enriched dataset for the learning system to perform precise differentiation between classes. On a clinical spine dataset, the method is tested and validated on 535 VBs for segmentation attaining an average accuracy 94.59% and on 315 VBs for classification with an average accuracy of 96.07% for Case 1, 93.23% for Case 2, and 92.3% for Case 3.

KEYWORDS

Augmentation, Boundary Features, Classification, Detection, Graylevel Features, Localization, Morphology, Segmentation, Shape Features, Texture Features, Vertebral Body Compression Fractures

1. INTRODUCTION

Imaging presents a window to peep into the patient anatomy. It may be very well utilized clinically to diagnose and select treatment for any abnormalities, in research to understand and devise new medicines for any abnormalities, and for routing during surgery planning. In this modern age, medical images are analysed for various automated tasks such as annotation, localization, labelling, segmentation, registration and classification all of which have become popular research topics. Computer Aided Diagnosis (CAD) acts as a practical tool to analyze any particular anatomical structure of a medical image to make better decisions in clinical diagnosis of pathologies, fractures, tumors, abnormalities and also for further planning of treatment, surgeries, post-surgical assessment and so forth (Rajaei et al., 2012). Medical institutions and hospitals produce immense medical images on a daily basis. Processing these images manually firstly requires proficiency / prowess in the field and secondly is an expensive and time consuming task to the professionals. This calls for the need of computerized image processing in this field.

DOI: 10.4018/IJCINI.20211001.0a21

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

In layman terms, a fracture is a break or crack in the bone. The human spine is built up of 33 vertebrae, which begins at the base of the skull: 7 cervical (C1- C, C7), 12 thoracic (T1 - T12), 5 lumbar (L1 - L5), 5 sacral bones welded forming the sacrum and 4 coccygeal bones which merge into one as coccyx. Every adjacent vertebra from cervical to lumbar is cushioned with an intervertebral disc in-between aiding flexibility to the spine. A vertebra is an irregular bone with a complex structure, divided into anterior and posterior parts. The posterior part of the vertebra, called the vertebral arch, which faces the back of a person, is formed by pairs of laminae and pedicles. Arising from the vertebral arch are four articular processes, two transverse processes and one spinous process. The vertebral forearm providing a passage for the spinal canal encloses and protects it. Vertebral Body (VB), the anterior part of the vertebra, is a cylindrical shaped portion that lies in front and provides majority of the structural support and stability to the spine.

Most of the Vertebral Fractures (VF) occur mainly in the VB section caused due to osteoporosis, injuries, infections and tumors, causing it to compress and is termed as compression fracture. Loss of height is eventually the result of multiple compression fractures. Compression fractures usually occur in the thoracolumbar spine (middle-lower) spine. In adults, VFs are commonly considered to be an indicator for osteoporosis and in pediatric cases its usually trauma related. Spinal fractures not only increase the risk of having another spinal fracture, but also of having other low-impact fractures in other parts of the body. All fractures cause deformities but the converse is not true. In clinical terms, a vertebral compression fracture subordinate to osteoporosis might be identified as a benign fracture, while if it's brought about by bone metastasis it is generally characterized as a malignant fracture. Both benign and malignant fractures may be identified with similar complaints but discriminating the etiology between them at a beginning stage is significant to decide the clinical course, treatment, and prognosis (Frighetto-Pereira et al., 2015a). Different instances of normal, benign and malignant VBs are shown in Figure 1.

Figure 1. Lumbar VB instances of normal, benign and malignant VBs

Medical images are well known to contain certain components which will affect the image contents such as unknown noise, artifacts, special markings (Rajaei et al., 2012), inhomogeneity, poor contrast, and weak boundaries. A coordinated computerized processing of spine will make the process of diagnosis progressively precise and consistent, further reducing the overall time, effort and

cost incurred (Shi et al., 2007). MRI is a very frequently used imaging modality to diagnose diseases and abnormalities of the spine, like VF and vertebral deformities, slipped vertebra, degenerated or herniated discs, bone marrow deformities (Barbieri et al., 2015). Compared to its other imaging counterparts like Computed Tomography (CT) and X-Ray imaging, MRI has additional advantages of lacking radiation during scan (Gawel et al., 2018) and adequately being able to deal with some pathologies like bone tumors and metastases (Broder, 2011). On the contrary, the performance of CAD systems in analyzing MRI spine is encountered with various challenges like arbitrary-field of view, image resolutions, similar signal intensity, bias field artifacts, partial volume effect, anatomically proximate tissues and unstable boundaries (Kim et al., 2018). Moreover, a standardized measurement unit like Hounsfield Units (HU) used in CT (Broder, 2011) is nonexistent in MRI.

Other than the imaging challenges, automatic detection, labelling and segmentation of individual vertebra is also challenging due to its complex structure, structural repeatability and structural variability among individuals (caused due to abnormalities or deformations like scoliosis, crushed vertebra, spondylolisthesis (Barbieri et al., 2015)). When there is varying Field-Of-View (FOV), for example the absence of first cervical or first thoracic vertebrae in the image which are used as anatomical reference landmarks (Rasoulilian et al., 2014), the task of labelling and segmentation (or vice-versa) becomes even more difficult.

Further of this paper is structured as follows: section 2 briefly recounts the literature, section 3 describes the materials used for the study, and section 4 unfolds the method step by step in detail followed by experimental results in section 5. Section 6 analyses and discusses the results and the last section brings the paper to an end with a conclusion and suggestions for possible extensions.

2. LITERATURE REVIEW ON SEGMENTATION AND CLASSIFICATION OF VCFS

It is very well known that segmentation plays a significant role in extracting the anatomical part of interest in medical images. The segmented output can be further processed for classification of fractures, deformities and computer assisted surgeries. Rich medical imaging literary works exists on segmentation of VB and its classification into different kinds of fractures. Back in the earlier days, VF was assessed by manually placing six points on each VB at four corners and mid points on the superior and inferior endplates. Then the anterior, mid and posterior VB heights were measured (Shi et al., 2007). This was evidently time consuming and tiresome and at times subjective.

Genant et al's. (1993) proposal of a semi-quantitative method for the evaluation of vertebral fractures related to osteoporosis, till date is considered a gold standard for fracture classification which combines numerical classification with visual inspection. Authors in (Shi et al., 2007) concluded that a vertebral deformity does not always indicate a vertebral fracture, but that a vertebral fracture is always accompanied by vertebral deformity.

The segmentation of grayscale medical images has been extensively researched in the past decades. Methods based on histograms apply a threshold to segment the images by using only pixel intensity. Region growing, a semi-automatic method starts with placing a seed which grows based on the neighboring pixel similarity. Edge detection approaches, for example Canny edge detector works by obtaining gradients using different kernels. Another most widely used method is clustering which generally starts with initial values and repeats its calculation until the data converges. Graph cut algorithm is another efficient method that transforms the image into a graph with nodes and edges. Based on the values of nodes and edges, the graphs can be transformed into a similarity matrix to perform segmentation. A few of the most recent studies proposing computer-aided methods for the detection and analysis of VBs are as follows. In (Kim et al., 2018), a semiautomatic method is employed, keeping the Region of Interest (ROI) placement to just one which included a VB. A correlation algorithm identified the remaining VBs to facilitate segmentation process via graph-based and line based segmentation algorithms. Tested on sagittal MR lumbar spine they achieved a Dice Similarity Coefficient (DSC) of 90%. With minimal user assisted initialization, authors of (Hille

et al., 2018) suggested intensity correction step to deal with bias field artifacts. Hybrid level set segmentation guided by appearance based VB probability maps were used for segmentation which achieved a DSC of 86.0%. Random forest based approach is proposed in (Kulkarni et al., 2017) to segment VBs followed by a biomarker evaluation framework that extracts vertebral heights and widths from the segmentations obtained. They obtained an average DSC of 72.5% for their dataset. The most recent approaches for segmentation are the deep-learning-based methods, which exhibit superior performance over existing mathematical algorithms. In (Lessmann, van Ginneken, & Išgum, 2018), an automatic method is proposed based on iterative convolutional neural networks which utilized the inherent order of the vertebral column to train the network with as little as ten manual reference segmentations. Vertebrae are segmented and identified one by one in sequential order, using an iterative procedure which correctly identified all vertebrae. A mean DSC of 94% was obtained. In (Lessmann, van Ginneken, de Jong et al, 2018), a fully convolutional neural network combined with an instance memory that retains information about already segmented vertebrae is used. The segmented vertebra is classified as completely or partially visible, so that partially visible vertebrae can be excluded from further analyses. The method achieved an average DSC of 95.8% and 92.1% on a vertebra segmentation challenge and on low-dose chest CT scans respectively. A method based on cascaded 3D Fully Convolutional Networks (FCNs) is executed in (Lessmann, van Ginneken, de Jong et al, 2018). A localization FCN found the bounding box of the lumbar region and a segmentation FCN performed pixel-wise multi-class segmentation to map a cropped lumbar region volumetric data to its volume-wise labels. The method achieved an average DSC of 95.77%. However, the deep neural networks are known to require large amount of data and use large amount of memory, which are key limitations. Furthermore, repeated heavy training processes may be required for the segmentation of different types of images (e.g., use of different contrasts, sequences, or different MR scanners). On the other hand, mathematical algorithms do not require a large amount of training datasets and can be applied to large sized images. Unlike common optical images, the acquisition of a large amount of data is a key limitation in medical imaging.

Recent works on vertebral fracture classification is mentioned ahead. Authors in (Janssens et al., 2018) proposed an automated method to detect and classify vertebral fractures from 3D CT lumbar spine images using convolution neural network. Each vertebra is processed into 100×50 2D 3-channel grayscale images in 3 anatomical planes which are fed into the 152 layer Residual Network. Of the 13,400 images generated, 12,700 are used for training and the remaining for testing with 100 images for each of the seven vertebra fracture classification. The network achieved 93.29% testing accuracy. An automated method is presented in (Bar et al., 2017) to detect spine compression fractures by first segmenting the spinal column and extracting the sagittal patches which are subsequently binary classified using a Convolutional Neural Network (CNN). In the end, a Recurrent Neural Network (RNN) is utilized to predict whether a vertebral fracture is present in the series of patches. The method resulted in 89.1% accuracy, 83.9% sensitivity and 93.8% specificity. Using the median sagittal planes of lumbar spine MRIs in (Frighetto-Pereira et al., 2016), statistical features of gray levels, texture and shape features are extracted to analyze the contours of the VBs from the manually segmented VBs. The k-nearest-neighbor method, a neural network with radial basis functions, and a naïve Bayes classifier are used with feature selection that resulted in an area under the Receiver Operating Characteristic (ROC) curve of 97% in distinguishing between normal and fractured vertebral bodies, and 92% in discriminating between benign and malignant fractures.

In the work of (Frighetto-Pereira & Metzner, 2016) using manually segmented VBs, the principal axis of each VB is identified using moments and then statistical features of height and width measured perpendicular and parallel to the principal axis is computed. The same set of classifiers as in (Frighetto-Pereira et al., 2016) are used that obtained ROC accuracy of 96% in the recognition of VCFs as compared with normal vertebral bodies and 73% for the classification of benign versus malignant VCFs. A total of 17 contrast and texture features are extracted from manually segmented VBs in (Frighetto-Pereira et al., 2015a) and the classification of malignant vs. benign VCFs is

performed using the k-nearest neighbor (KNN) classifier ($k=3$) with the Euclidean distance and 10-fold cross-validation. They obtained 91.3% classification accuracy with ROC curve. Spectral and fractal features are extracted from manually segmented VBs in (Azevedo-Marques et al., 2015). They performed classification of malignant vs. benign VCFs using the k-nearest neighbor classifier with the Euclidean distance. Combinations of features derived from Fourier and wavelet transforms, together with the fractal dimension, are able to obtain correct classification rate up to 95%. This backdrop shows that there is still a need and scope for the development of automatic segmentation and classification methods and we are proposing one in this paper.

The motivation for this work is that the VB surface appearance, shape measurements and positional angles of neighboring anatomies are necessary for good segmentation, labeling and fracture classification that will boost a clinician's diagnostic output. In a clinical scenario, since the number of cases of fractures / abnormalities is lesser than normal, the objective of this work is to build a durable system that incorporates various Machine Learning techniques at different stages of our work to procure accurate and reproducible results for diagnostic decision making for VFs. Though the present approach is not a seminal work or entirely in its own right, it weaves from the cognizance of important practices and successful approaches in the past. It follows a simple and easy to understand pattern that results in successful segmentation and classification of VCFs much needed in a clinical scenario that is computationally less expensive and time saving. The choice of features and their combination mainly contributes to the success of this work.

3. MATERIALS

This work is evaluated using the dataset obtained from (Frighetto-Pereira et al., 2016), where 63 patients (37 women, 26 men, mean age 62.25 ± 14.13 years) are diagnosed with at least one VCF; some patients have more than one VCF. The images of each patient used for segmentation and classification are T1-weighted median sagittal slices with varying Field of View (FOV). They are in 8 bits/pixel TIFF format (256 gray levels) collected from 62 different exams. For the current study, 535 thoracolumbar VBs are segmented and 315 lumbar VBs are classified into 3 different cases. The classification set contains 107 VBs with VCFs, of which 55 are benign (osteoporosis) and 52 are malignant (bone metastasis) VCFs, and the remaining are normal VBs. The ground truths of ROIs used in the present study are labeled and diagnosed results of consensus between two in-house observers and one external observer for the ground truth.

4. METHODOLOGY

This work describes a segmentation and classification framework designed to separate bone from soft tissue in MR images. The workflow from a raw MRI scan to radiological measurement for vertebral fracture classification has three steps with each step automatically initializing the next. The steps are described in detail in the following subsections as: (i) pre-process, detect and localize the vertebral region; (ii) segment and label the thoracolumbar VBs and (iii) extract image features from lumbar VBs to classify each VB into normal, benign and malignant fractures. Figure 2 displays the method workflow.

4.1 Pre-Process, Detect and Localize VB Region

Malignant vertebral fractures (present in the dataset) in a general sense are known to display low signal intensity across the whole VB involved in T1-weighted MRI. This, together with the background noise in MR images makes it hard to differentiate between spine tissues and its background. For this reason, as a preprocessing step, the original sagittal MR images in the database are normalized before extracting the VBs. As a preprocessing step, the original sagittal MR images are normalized by first picking eight images with suitable contrast and homogeneity. Next, their histograms are computed

Figure 2. Method workflow

and averaged (reference histogram). The cumulative distribution function is computed for the reference and target histograms. Using grayscale transformation (histogram mapping), for each gray level in $\text{Reference}_{\text{gray}} \in [0, 255]$, gray level in $\text{Target}_{\text{gray}}$ is found and matched. Unlike histogram equalization, histogram mapping maps to a specific histogram shape than bringing uniformity to the image histogram. Figure 3 shows histograms of a sample image before and after histogram mapping. The purpose of this step are: (i) it helps overcome image inhomogeneity which could hamper the classification between malignant fractures and the rest during extraction of texture features, (ii) visualization of fractured bony structures is better and (iii) eases extracting VB edges to compute features for classification.

Figure 3. Before and after histogram mapping

Before segmenting only the VBs of interest, first only the spine region needs to be localized to confine the Region Of Interest (ROI). This is done so by slicing the histogram mapped image into eight bit planes. Planes seven and eight contain most of the spine region in the image along with some background. Hence, planes seven and eight are added to get the complete spine region (Figure

4(a)). In order to confine to the ROI and remove the background, the binary image is subjected to morphological operations shrink and open with different structuring elements. This is followed by filling object holes after removing areas that touch the image boundaries (not part of vertebra) and removing island areas that are smaller and more eccentric than the vertebral bones (Figure 4(b)). A criterion to retain only the VB region is set by fetching the centroids of all the components and retaining only those components whose centroid x-coordinates lie within a threshold. The thoracolumbar VBs are localized at the end of this step (Figure 4(c)).

4.2 Segment and Label The VB Region

Computer valuation of a VB is of restricted clinical value if that anatomical structure cannot be precisely identified and segmented (Shi et al., 2007). As the current dataset contains VBs that are both normal and fractured, regions that are highly compressed and seem fragmented fall into the background category and gets removed during some of the processes performed as described in subsection 4.1. To redress this error, a convex hull of the localized output (Figure 4(d)) is superimposed on the histogram mapped gray image which fetches the missing VBs (Figure 4(e)).

It is known that the foreground surface contours of the anatomical structure are known to display more texture. That is, the foreground pixels of the medical images have higher irregularity and thus have higher range values (Rajaei et al., 2012). Hence to this superimposed output, range filter is applied to rightly segment VBs that is normal, benign and malignant. This can detect pixel intensity values of the edges within a window of size 3x3. Furthermore, to improve the extracted edges from the output of range filtered image, the image is multiplied by a constant value. This constant is empirically obtained as the mean contrast values of all the images that visibly provide strong edges. This is thresholded by a value which extracts only the VB boundaries of individual VBs (Figure 4(f)). Subsequently, morphological operations to remove island areas and object filling are done that is further considered for labeling thoracolumbar VBs.

Prior to the automatic diagnostic classification, the labeling of the VBs is pivotal as the fracture results are reported along with VB labels (Oktay et al., 2014). The spinal curve is known to be larger around the Lumbar vertebrae but this information helps only when all the VBs are normal. The segmentation for around 4% cases (fractures) in the dataset results in a single VB divided into two or three fragments (Figure 4(g)). This error might result in wrong and extra numbered labeling of the VB. This multiple fragment error of a single VB is rectified by merging the bounding box of smaller fragment to the bounding box of bigger fragment. Only those fragments are merged whose smaller fragment bounding box coordinates are within the coordinate values of the bigger fragments.

Consider $[x, y, \text{width}, \text{height}]$ the parameters of Bounding Box (BB) where (x, y) is top left corner of BB. Using these parameters, we can find two diagonal corners of BB (top right and bottom left) of BB as $[x, y, x + \text{width} - 1, y + \text{height} - 1]$. The reason for using -1 is because BB starts half a pixel outside the actual pixel. Follow the logic below to merge two or more closely detected BBs.

$\forall$ BB, where $x' = x + \text{width} - 1$ and $y' = y + \text{height} - 1$, the new BB coordinates is determined as:

$$x = \min(x), y = \min(y), \text{width} = \max(x'), \text{height} = \max(y').$$

The outcome is a single VB with connected fragments and a single label. The segmented VBs are labeled using the connected component labeling. The number labeling starts from the last visible VB in the image as L5 and decrements till L1 and again restarts from T12 and decrements until the first visible VB. The end of this step gives well segmented appropriately labeled VBs (Figure 4(h)).

The segmented output is overlaid on the input image to extract only VBs (Figure 4(i)) for gray level and texture features extraction discussed in the following section.

Figure 4. Stages of segmentation

(a) combined bit planes 7 and 8 from bit plane slicing (b) after morphological operations (c) centroid x co-ordinate based VB detection (d) convex hull selection of thoracolumbar spine (e) convex hull region overlay on original image (f) range filter output (g) mis-segmentation of VBs (h) well segmented and labeled VBs (i) segmented output overlaid on the input image for texture feature extraction

4.3 Classification

The purpose of an automated medical image classification framework is to develop a model that is able to classify images precisely and quickly into normal or abnormal classes (Rajaei et al., 2015). In this paper, we attempt to classify MRI spine images into normal or fractured and their types. The irregularities impacting the vertebrae are for the most part described in the VB. Benign fractures causes more changes in the VB shapes but have more surface similarity with normal VB, whereas malignant fractures cause more variations in the VB surface textural intensities but are more structurally similar to normal VB. For the purpose of making diagnosis, this work considers only VBs labelled L1-L5 and the machine learning framework considers several elements of the VB comprising gray level values, textures, shapes, and boundaries. All these features put together or on their own are used in various medical applications ranging from localizing a ROI, detecting abnormalities with a particular pattern, segmenting a particular anatomical structure, differentiating between healthy and pathological instances and more. The upcoming features are computed for each VB and its extent is normalized between 0 and 1.

4.3.1 Statistical Texture Features

Gray texture features are effective since these are known to provide better information content in medical images. Texture analysis separates significant data using an ensemble of mathematical computations executed on the images (Athertya et al., 2019). All texture functions work in a similar manner. A neighbourhood is defined around the pixel of interest and the neighbourhood statistics is computed which is then used as the value of the pixel of interest in the output image ().

From the gray level histogram of each VB, the following features are derived.

Ratio of the standard deviation of the intensity to the mean intensity (Equation (1)).

$$I\left(\frac{\sigma}{\mu}\right) \quad (1)$$

Ratio of the minimum intensity to the mean intensity (Equation (2)).

$$I\left(\frac{\min}{\mu}\right) \quad (2)$$

Ratio of the maximum intensity to the mean intensity (Equation (3)).

$$I\left(\frac{\max}{\mu}\right) \quad (3)$$

Ratio of the variance to the mean intensity (Equation (4)).

$$I\left(\frac{\sigma^2}{\mu}\right) \quad (4)$$

Other first and second order texture features computed are contrast (measures difference in intensities), entropy (measures randomness of intensity), skewness (measures asymmetry around the mean), kurtosis (measures oddity of a distribution's outliers), correlation (measures relationship among pixels), homogeneity (measures closeness of distribution), directionality (measures directional gradients), coarseness (measures roughness or granularity), maximum probability (estimates of parameter counts) and dissimilarity energy (measures non uniformity).

Local Binary Pattern (LBP) is an operator to describe images that is built upon the differences made between the centre pixel and its neighbours. Here, the two-dimensional surface textures are described by two scales: local spatial patterns and gray scale contrast (Ojala et al., 1994). Labels are formed for the image pixels by thresholding a neighborhood (3x3 which can be varied) for each pixel with the center value and considering the result as a binary number. The different labels obtained from these $28^2 = 256$ histograms is then used as a texture descriptor. This approach is relatively quicker to process and is found to be invariant to variations in monotonic gray scales and is a good pointer for variations in image textures in a ROI (Athertya et al., 2019). The definition of LBP for a given pixel (x_c, y_c) for pixel neighbourhood (P,R) with P sampling points around a circle of radius R is given using Equation (5):

$$LBP_{P,R} = \sum_{P=0}^{P-1} S(g_p - g_c) 2^P, \text{ } g_c \text{ and } g_p \text{ are the gray levels of center pixel} \quad (5)$$

$$S(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

Edge co-occurrence matrix (ECM) (Brandt et al., 2000): a similar concept as Gray Level Co-occurrence Matrix (GLCM), but with a difference. Here, the edge image obtained from the gray image is considered as input instead of gray image as in GLCM. The image is first filtered with an edge extractor, in this case using a Prewitt operator. The edges are found in 8 directions and the direction of the strongest edge is used as pixel location. The edge image is thresholded to retain only those edge pixels with strongest edge values. As a result, ECM is formed from the pairs of edge pixels separated by a given displacement. Equation (6) defines ECM as,

$$ECM_{ij} = N \{x | I(x) = i, I(x + d) = j\} \quad (6)$$

where, I is the edge image, d is the displacement vector (d_x, d_y) , ECM_{ij} is the edge co-occurrence matrix for $(i, j)^{th}$ component where the number of presences of edge directions i and j in I in the distance and direction determined by d for each other, N is the number of elements in the set and $x_{x,y}$ stretches through I . Since edges are detected in 8 directions, the size of ECM is 8×8 . The entries in the ECM are then used as components in the feature vector.

4.3.3 Shape Features

The shape of a ROI can be determined by analysing its boundary, the deflections and curvature all of which constitutes the information to be evaluated. The most widely recognized measurements made are those that characterize shape. In this work, shape features are addressed in two aspects: object area features and object boundary features.

Moments and functions of moments have been exploited in many applications as they capture global information about the image without the need for closed boundaries. Of the many moment functions, Zernike moments have been employed in this work. For a given image, the image center is considered the origin and pixel coordinates are mapped to the range of unit circle, i.e., $x^2 + y^2 = 1$. Pixels falling beyond the unit circle are not selected for computation (Khotanzad & Hong, 1990).

Following are the shape measurements used most relevant to VB analysis for fractures.

Compactness (Equation (7)) with VB perimeter as $\tilde{n}$, VB area as $\tilde{A}$ and $\tilde{\delta}$ as the ratio of the length of a circumference to the diameter w.r.t a circle.

$$C = \frac{4\pi \tilde{A}}{\tilde{n}^2} \quad (7)$$

Ratio of perimeter ($\tilde{n}$) of the VB's convex hull to the perimeter of VB (Equation (8)). This is called Convex Perimeter or simply as Convexity. Convexity is a cavity in an object that does not belong to the object but is located inside its outer boundary (Convex Hull) which can be segmented out from an object.

$$\frac{ConvexHull_{\bar{n}}}{VB_{\bar{n}}} \quad (8)$$

Ratio of the difference between the VB's convex hull perimeter and VB perimeter to the VB perimeter (Equation (9)).

$$\frac{ConvexHull_{\bar{n}} - VB_{\rho}}{VB_{\rho}} \quad (9)$$

Ratio of the convex hull area to the VB area, termed as Convex Area. It helps quantify the size and amount of concavities (Equation (10)).

$$\frac{ConvexHull_{\bar{A}}}{VB_{\bar{A}}} \quad (10)$$

Ratio of the difference between the VB's convex hull area and VB area to the VB area (Equation (11)).

$$\frac{ConvexHull_{\bar{A}} - VB_{\bar{A}}}{VB_{\bar{A}}} \quad (11)$$

Ratio of the VB perimeter to the VB's minimum enclosing BoundingBox perimeter (Equation (12)).

$$\frac{VB_{\bar{n}}}{MBB_{\rho}} \quad (12)$$

Ratio of the VB area to the VB's minimum enclosing BoundingBox area termed as Rectangularity (Equation (13)).

$$\frac{VB_{\bar{A}}}{MBB_{\bar{A}}} \quad (13)$$

Ratio of the length of minor axis to the length of major axis of VB, termed as Eccentricity (Equation). $\frac{Axislength_{minor}}{Axislength_{major}}$ (14)

Ratio of standard deviation of major axis to minor axis lengths (Equation (15)).

$$\phi \left(\frac{\text{Axislength}_{\text{minor}}}{\text{Axislength}_{\text{major}}} \right) \quad (15)$$

Ratio of minimum length between two boundary points of VB perpendicular to the major axis to the major axis length (Equation (16)).

$$\text{BD}_{\text{mm}} = \frac{\text{Minimumlength} \perp \text{majoraxis}}{\text{Majoraxislength}} \quad (16)$$

Chain code is a compact depiction of all the information in an object boundary by a connected sequence of straight line segments of specified length and direction referred to as Freeman chain code (Freeman, 1961). It consists of an initial location, here the boundary co-ordinate closest to the origin is chosen as the initial location, followed by a list of directions $d_1, d_2 \dots d_n$. The directions d_i are the estimates of boundary slopes based on 8-connectivity in clockwise direction.

Contour curvature, a local shape descriptor, is an important feature to judge similarity between shapes. Convex shapes yield positive curvatures whereas negative curvatures result from concave shapes. A point perpendicular to the centroid is chosen which traverses and computes the curvature in clockwise direction. The mean absolute curvature is used for normalization (Mokhtarian & Mackworth, 1992) and is given as in Equation (17)

$$\frac{K(p)}{\frac{1}{N} \sum_{p=1}^N |K(p)|} \quad (17)$$

Average bending energy denotes the average energy stored in a shape and is computed as the sum of squares of the boundary curvature $K(p)$ over the boundary length BL. Definition by (Young et al., 1974) is given by Equation (18)

$$\frac{1}{N} \sum_{p=1}^N K(p)^2 \quad (18)$$

where, $K(p)$ is the sum of squares of boundary curvature, p is the boundary length and N is the number of points on the contour.

Ratio of average distance of all boundary points of VB from the VB centroid termed as average radial distance/shape signature (Equation (19)).

$$\mu_{RD} = \frac{\sum_{i=1}^n D_i}{n} \quad (19)$$

here, D_i is the distance between VB centroid and i^{th} pixel on the VB boundary computed as $\sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$.

Ratio of average distance of all boundary points of VB from the VB centroid to the standard deviation of distances of all boundary points of VB from the VB centroid (Equation (20)).

$$\frac{\mu_{RD}}{\sigma_{RD}} \text{ where, } \sigma_{RD} = \sqrt{\frac{\sum_{i=1}^n (D_i - \mu_{RD})^2}{n}} \quad (20)$$

Ratio of average angles of all boundary points of VB from the VB centroid (Equation (21)).

$$\mu_{RA} = \frac{\sum_{i=1}^n \angle_i}{n} \quad (21)$$

Chord distribution calculates the lengths of all linearly collinear chords i.e., pairwise distances between boundary points of a shape and builds a histogram of their lengths (Kwiat, 1982). This work computes horizontally collinear (Eq (22)) width-wise and vertically collinear (Equation (23)) length-wise chord lengths.

$$C_h = \text{hist} \left(\sum_{i=1}^n HL_i \right) \quad (22)$$

$$C_v = \text{hist} \left(\sum_{i=1}^n VL_i \right) \quad (23)$$

Projection profile is the projection of a shape in a particular direction, measured as the sum / mean of pixel values. This work uses projection profiles in horizontal (Equation (24)), vertical (Equation (25)), left diagonal (Equation (26)) and right diagonal directions (Equation (27)).

$$PP_H = \sum_{j=0}^n f(i, j) \quad (24)$$

$$PP_V = \sum_{i=0}^n f(i, j) \quad (25)$$

$$PP_{LD} = \sum_{(i,j) \in \text{leftdiagonalline}}^n f(i, j) \quad (26)$$

$$PP_{RD} = \sum_{(i,j) \in \text{rightdiagonalline}}^n f(i, j) \quad (27)$$

An object's Feret properties (Eddins, 2017) are estimated by using boundary points on the antipodal vertices of the convex hull that encases that object. Minimum Feret diameter is measured as the minimum distance between any two boundary points on the antipodal vertices of the convex hull that encloses the object. Maximum Feret diameter is measured as the maximum distance between any two boundary points on the antipodal vertices of the convex hull that encloses the object.

Ratio of minimum Feret diameter to maximum Feret diameter (Equation (28)).

$$\frac{\text{Feretdiameter}_{min}}{\text{Feretdiameter}_{max}} \quad (28)$$

Ratio of Feret min angle to Feret max angle (Equation (29)).

$$\frac{\text{Feretangle}_{min}}{\text{Feretangle}_{max}} \quad (29)$$

Directional angle of the minimum and maximum Feret diameters are estimated with respect to the horizontal axis of the image.

Tortuosity refers to the degree of “twistedness” of vertebral endplates. The reason for measuring tortuosity in this work is it shows the depth of fracture, more so in case of benign fracture. The presented automated approach calculates tortuosity by calculating relationships between path lengths and end point distances (Shoelson, 2012). To start with, the VB contour is extracted using Prewitt (1970) edge detection. The detected edges are dilated and skeletonized with well pruned spurs. Next, the branch points are detected, dilated and used to break VB edges into different non-branching segments. The tortuosity is better measured with reasonably long unbranched segments. The intension here is to measure tortuosity of 4 different VB edges, superior endplate edge, inferior endplate edge and the 2 connecting edges of superior and inferior endplates on either side. The segments shorter than a threshold are appended to the nearest unbranched segment. This process is followed until it results in only 4 segments. The simplest mathematic method to find tortuosity is by the arc-chord ratio given in Equation (30) which is the ratio of the length of the curve to the distance between endpoints.

$$\text{tortuoisity} = \frac{\text{curvelength}}{\text{distancebetweenendpoints}} \quad (30)$$

This measure of tortuosity should result in 1 for a straight line and infinite for a circle, regardless of the orientation. The endpoints of each segment are found and the distance between them is

approximated by using half the perimeter length. Finally, the tortuosity of each of the 4 segments of a VB is individually evaluated against a threshold to decide for a fracture or normalcy.

4.4 Augmentation

For the purpose of classification, each segmented VB is considered as a single entity and the features are extracted. Machine learning algorithms have difficulty in learning when one class dominates the other. Moreover, in general, medical images are always few in number and hence difficult to differentiate between normal and abnormal. It is a common scenario in the medical domain to have fewer numbers of abnormal cases than the normal ones. The occurrence of normal, benign and malignant fractures in the lumbar spine for the current dataset is as shown in Figure 5, which clearly indicates data imbalance and calls for the need of data augmentation. Data augmentation will supply an enriched set of data for the learning system and captures data invariances. It significantly increases the diversity of available data without actually having to collect new data. The type of data augmentation chosen is quite significant in the classification process. Improper selections of data augmentation might lead to the augmented samples being ineffective on the robustness of the classifiers. Of the many data augmentation methods, this work employs Synthetic Minority Over-sampling Technique (SMOTE) (Chawla et al., 2002) which is instance based, to synthesize insufficiently available data. Benign and malignant fractures being the minority classes are sampled and increased. This augmented set of data is further augmented with horizontal flip, vertical flip, rotations at -15° , 15° and 35° , horizontal flips of data rotated at -15° , 15° and 35° , and lastly scaled by factors 0.8 and 1.2.

Figure 5. Occurance of normal, benign and malignant fractured vertebrae in the Lumbar region

5. EXPERIMENTAL ANALYSIS AND RESULTS

The segmentation performance is evaluated using leave-eleven-out cross validation, where each time eleven out of the 63 cases are sequentially taken out for testing and the remaining taken in for training. In order to avoid bias in results, the process is repeated for 6 folds with the last fold having three lesser cases. In each fold, the segmented results of the test data are compared with the respective ground truth segmentation. For each case in a test data, quantitative metrics such as accuracy (Equation (31)), sensitivity (Equation (32)), Dice Similarity Coefficient (DSC) (Equation (33)) and Jaccard

Figure 6. Segmentation performance (a) at each individual level of lumbar (b) for each type of VB i.e., normal, benign and malignant fractures.

Coefficient (JC) (Equation (34)) are analyzed. All implementations of section 4 have been carried out using MATLAB (MATLAB, 2018) on a 64 bit operating system with Intel® Core™ i7-5500U CPU @ 2.40GHz.

Accuracy of segmentation (A_{seg}) determines the degree of correctness of a segmented region to the object of comparison.

$$A_{seg} = \frac{TP + TN}{TP + FP + TN + FN} \% \quad (31)$$

Sensitivity (S_{seg}) measures the proportion of the actual ROI that is correctly identified as such.

$$S_{seg} = \frac{TP}{TP + FN} \% \quad (32)$$

DSC of segmentation (DSC_{seg}) quantifies the region overlap between the automatic and manual segmentation

$$DSC_{seg} = \frac{2TP}{2TP + FP + FN} \% \quad (33)$$

Jaccard Coefficient of segmentation (JC_{seg}) gauges the similarity and dissimilarity between the automatic and manual segmentation

$$JC = \frac{TP}{TP + FP + FN} \% \quad (34)$$

where, TP stands for True Positive (correctly segmented ROI), TN for True Negative (correctly segmented non-ROI), FP for False Positive (incorrectly segmented ROI) and FN for False Negative (incorrectly segmented non-ROI). To achieve accurate segmentation results, the DSC metric should be near to unity. The segmentation results for the above metrics are depicted in Figure 6.

This work performs classification in 3 cases: in case 1 it differentiates between normal and fracture VBs, in case 2 it differentiates between benign and malignant VBs and in case 3 it differentiates between normal, benign and malignant VBs. The original 315 MRI images obtained from (Frighetto-Pereira et al., 2016), as described in section 4.4, is augmented in almost equal ratios to a total of 6996 images. The case-wise augmented distribution of lumbar VBs is given in Table 1.

Table 1. Case-wise distribution of lumbar VBs before and after augmentation.

	Number of lumbar VBs					
	Before Augmentation			After Augmentation		
Case	Normal	Benign	Malignant	Normal	Benign	Malignant
1	208	55	52	2288	1210	1144
2	-	55	52	-	2420	2288
3	208	55	52	2288	2420	2288

The original and augmented data are classified using Random Forest after the parametric examination on the classification performance in connection with efficiency. The classification performance evaluation metrics used are accuracy (Equation (35)), precision (Equation (36)), recall (Equation (37)), and f-score (Equation (38)). 10-fold stratified cross-validation is used for training and testing with each fold having the same class distribution as the complete dataset for both the cases. The performance measures are averaged over all folds and are shown in Figure 7 for all 3 cases.

Accuracy (A_{cls}) indicates the fraction of results that came out right.

$$A_{cls} = \frac{\text{trueclassification}}{\text{overallclasses}} \% \quad (35)$$

Precision (P_{cls}) indicates how useful the classification results are.

$$P_{cls} = \frac{|(\text{trueclassification}) \cap (\text{obtainedclassification})|}{|(\text{obtainedclassification})|} \% \quad (36)$$

Recall (R_{cls}) indicates how complete the classification results are.

$$R_{cls} = \frac{|(\text{trueclassification}) \cap (\text{obtainedclassification})|}{|(\text{trueclassification})|} \% \quad (37)$$

F-score (F_{cls}) is a measure of classification accuracy.

$$F_{cls} = 2 * \frac{P_{cls} * R_{cls}}{P_{cls} + R_{cls}} \% \quad (38)$$

6. DISCUSSION AND DEFENSE

The segmentation results attained by our method are in norm with the results obtained by other methods in the literature and better than the results obtained on the same dataset using semi-automated methods (Barbieri et al., 2015). The preprocessed uniformity of gray level in all the images helps in better processing for detection and localization. The application of range filter over the localized output segments each VB almost precisely with nearly negligible TNs. When segmentation at each lumbar level is analyzed, the TPs are all on the better side of 90% except at the second lumbar level. When different types of VBs such as normal, benign and malignant are considered the TP segmentation of normal is almost 99%. The level of segmentation aids in providing a final well labeled diagnosis of the VB. The missed segmentations are mostly in cases of fragmented VBs with more than 2 fragments occurring in benign and malignant fractures.

As formerly stated, the distribution of the T1 signal intensity over a VB is a significant league to identify between normal and fractured VCFs in MRI. The presence of low-intensity T1 signal can be identified by the gray- level features, and the spatial distribution of low-intensity signals is characterized by the texture features. Shape features are also well known to increase the classification performance. With this understanding, the present work has adapted the most suitable VB texture and shape features for better classification. The graphs in Figure 7 show the results of before (column 1) and after (column 2) data augmentation for the three defined cases using the combined features. When the data is augmented, there is approximately an increase of 10% in accuracy, and 5% increase in precision, recall and f-score. Data augmentation seems to have a better effect in increased classification of fractures than normal VBs. From the features point of view, the shape features seem to have an

Figure 7. Classification performance graphs before and after augmentation for all 3 cases.

upper hand in differentiating fractures from the normal. The texture features are better utilized in identifying malignant fractures from the rest. Overall, the combined features work better for better discrimination for the three cases. Figure 8 shows the effect of texture and shape features on various VB types using boxplot. Comparative analysis of classification performance is given in Table 2.

Table 2. Comparative analysis of classification performance

Literature	Classification Accuracy		
	Case 1	Case 2	Case 3
Frighetto-Pereira et al., 2015	90.58%	80.39%	-
Azevedo-Marques et al., 2015	95%	94.7%	-
Frighetto-Pereira et al., 2015	-	91.3%	-
Frighetto-Pereira et al., 2016	96%	73%	-
Frighetto-Pereira et al., 2016	97%	92%	66.82%
Arpitha, A., & Rangarajan, L. 2020	94.17%	91.38%	91.07%
Present method	96.07%	93.23%	92.30%

Figure 8. Effect of texture and shape features on various VB types using boxplot

Compared to the works of (Azevedo-Marques et al., 2015; Frighetto-Pereira et al., 2015a; Frighetto-Pereira et al., 2015b; Frighetto-Pereira & Metzner, 2016) as seen in Table 2, that have used the same dataset, the performance of the present work compared to the highest stated performance is less than 1% for case 1, greater than 1% for case 2 and far greater for case 3. To justify, the present work has used the results of its automated segmentation for classification, while the former method has used the results of manual segmentation by experts. Experts always have a better hand on marking the best area for classification. As a bonus, the present work differentiates between 3 classes which only one of the earlier methods has attempted. The present work focuses on extracting information from the given medical images without converting it into any other form or other representations. When it comes to fractures, the shape of the VB is catchier to even an untrained person to differentiate between fractured and normal VBs and hence this work extracts every possible and relevant shape feature measurements in a simple and understandable fashion to differentiate VCF. The overall results obtained indicate better CAD performance to identify and diagnose compression fractures of VB.

Threats that may affect the validity of findings in this proposed model is discussed here. Only the poor contrast and non-homogeneity present in the considered dataset has been addressed with

histogram mapping in the present work. Other approaches recorded in the literature to rectify this error could be used to check the validity of the proposed approach. Other challenges applicable to Magnetic Resonance (MR) imaging could be externally applied to check the model's validity. A dataset free of any kind of scanner implicit noise or outliers could be used to expand the better performance of the model on such clear and clean images. Our experimentations are performed only to diagnose normal, benign and malignant fractures in MR images and hence could not be tested for validity on other datasets of different modalities as such fractures are better identified in MR images. The scope of vertebral fracture classification can be extended to the thoracic region as vertebral compression fractures most likely occurs in the thoracolumbar spine. The model could on the other hand be tested for validity to diagnose other vertebral compression fracture types and grades in other modalities which has been considered a task for further work. Lastly the class imbalance persistent in any medical image for fractures/disease diagnosis has been a limitation which needed augmentation for better discriminating performance of the model.

The limitations of the present study are the usage of only the lumbar spine for classification and the analysis being restricted only to the central sagittal plane which may cause some loss of information. But the vantage points are that the segmentation is fully automated and is performed for all the five lumbar and all the completely visible thoracic VBs. Both during segmentation and classification there is no use of templates or training set and the testing set do not overlap. No deep learning based approach is used that requires large training dataset and can be applied to images of any size.

CONCLUSION AND FUTURE OUTLOOK

The present work includes almost all the required machine learning steps to computationally analyze a medical image for diagnosis. It preprocesses the image to ward off image inhomogeneity, detects and localizes the thoracolumbar VB region, segments and labels each VB and finally classifies normal and fractured VBs using VB relevant texture and shape features. Data is augmented to retaliate the bias on the dominating normal samples over the abnormal ones. This improved the performance of various classification metrics used which promotes the confidence of diagnosis. Though the work has only been tried on lumbar VB it can be extended to thoracic VB. The future outlook is to improve the overall segmentation performance by applying semantic and instances based segmentations and introduce classification performance improving automated feature selector. Extension of the present work's concept for 3D images is also intended.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of Interests

All the authors of this paper declare that there is no conflict of interests regarding the publications of this manuscript.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent

Statement of informed consent is not applicable since the manuscript does not contain any participants' data.

ACKNOWLEDGMENT

The first author would like to thank the University Grants Commission's (UGC) Maulana Azad National Fellowship (MANF) for funding the present work.

MANF award no. F1-17.1/2014-15/MANF-2014-15-CHR-KAR-46275/(SA III/Website) dated Feb 2015

REFERENCES

- Arpitha, A., & Rangarajan, L. (2020). Computational techniques to segment and classify lumbar compression fractures. *La Radiologia Medica*, 125(6), 1–10. doi:10.1007/s11547-020-01145-7 PMID:32067163
- Athertya, J. S., Kumar, G. S., & Govindaraj, J. (2019). Detection of Modic changes in MR images of spine using local binary patterns. *Biocybernetics and Biomedical Engineering*, 39(1), 17–29. doi:10.1016/j.bbe.2018.09.003
- Azevedo-Marques, Spagnoli, Frighetto-Pereira, Menezes-Reis, Metzner, Rangayyan, & Nogueira-Barbosa. (2015). Classification of vertebral compression fractures in magnetic resonance images using spectral and fractal analysis. In *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE.
- Bar, A., Wolf, L., Amitai, O. B., Toledano, E., & Elnekave, E. (2017). Compression fractures detection on CT. Proc. SPIE 10134, Medical Imaging 2017: Computer-Aided Diagnosis, 1013440.
- Barbieri, P. D., Pedrosa, G. V., Agma, J. M. T., & Nogueira-Barbosa, M. H. (2015). Vertebral body segmentation of spine MR images using superpixels. In *2015 IEEE 28th International Symposium on Computer-Based Medical Systems* (pp. 44–49). IEEE. doi:10.1109/CBMS.2015.11
- Brandt, S., Laaksonen, J., & Oja, E. (2000). Statistical shape features in content-based image retrieval. *Proceedings of the 15th International Conference on Pattern Recognition*. doi:10.1109/ICPR.2000.906258
- Broder, J. (2011). *Imaging of Non traumatic Abdominal Conditions*. Diagnostic Imaging for the Emergency Physician.
- Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16, 321–357. doi:10.1613/jair.953
- Eddins, S. (2017). Accessed on April 15, 2019 <https://blogs.mathworks.com/steve/2017/10/24/feret-diameters-and-antipodal-vertices/>
- Freeman, M. H. (1961). A graphical method of objective forecasting derived by statistical techniques. *Quarterly Journal of the Royal Meteorological Society*, 87(373), 393–400. doi:10.1002/qj.49708737310
- Frighetto-Pereira, L., Menezes-Reis, R., Metzner, G. A., Rangayyan, R. M., Azevedo-Marques, P. M., & Nogueira-Barbosa, M. H. (2015a). Semiautomatic classification of benign versus malignant vertebral compression fractures using texture and gray-level features in magnetic resonance images. In *28th International Symposium on Computer-Based Medical Systems*. IEEE. doi:10.1109/CBMS.2015.37
- Frighetto-Pereira, L., Menezes-Reis, R., Metzner, G. A., Rangayyan, R. M., Nogueira-Barbosa, M. H., & Azevedo-Marques, P. M. (2015b). *Classification of vertebral compression fractures in magnetic resonance images using shape analysis*. In *2015 E-Health and Bioengineering Conference (EHB)*. IEEE.
- Frighetto-Pereira, L., & Metzner, G. A. (2016). Recognition of vertebral compression fractures in magnetic resonance images using statistics of height and width. *International Symposium on Medical Measurements and Applications (MeMeA)*, 1–5.
- Frighetto-Pereira, L., Rangayyan, R. M., Metzner, G. A., Mazzoncini de Azevedo-Marques, P., & Nogueira-Barbosa, M. H. (2016). Shape, texture and statistical features for classification of benign and malignant vertebral compression fractures in magnetic resonance images. *Computers in Biology and Medicine*, 73, 147–156. doi:10.1016/j.compbmed.2016.04.006 PMID:27111110
- Gawel, D., Glówka, P., Kotwicki, T., & Nowak, M. (2018). Automatic spine tissue segmentation from MRI data based on cascade of boosted classifiers and active appearance model. *BioMed Research International*. PMID:29854791
- Genant, H. K., Wu, C. Y., van Kuijk, C., & Nevitt, M. C. (1993). Vertebral fracture assessment using a semiquantitative technique. *Journal of Bone and Mineral Research*, 8(9), 1137–1148. doi:10.1002/jbmr.5650080915 PMID:8237484
- Hille, G., Saalfeld, S., Serowy, S., & Tönnies, K. (2018). Vertebral body segmentation in wide range clinical routine spine MRI data. *Computer Methods and Programs in Biomedicine*, 155, 93–14. doi:10.1016/j.cmpb.2017.12.013 PMID:29512508

- Janssens, R., Zeng, G., & Zheng, G. (2018). Fully automatic segmentation of lumbar vertebrae from CT images using cascaded 3D fully convolutional networks. In *15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE. doi:10.1109/ISBI.2018.8363715
- Khotanzad, A., & Hong, Y. H. (1990). Invariant image recognition by Zernike moments. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(5), 489–497. doi:10.1109/34.55109
- Kim, S., Bae, W., Masuda, K., Chung, C., & Hwang, D. (2018). Semi-automatic segmentation of vertebral bodies in MR images of human lumbar spines. *Applied Sciences (Basel, Switzerland)*, 8(9), 1586. doi:10.3390/app8091586 PMID:30637136
- Kulkarni, A., Raina, A., Sarabi, M. S., Ahn, C. S., Babayan, D., Gaonkar, B., Macyszyn, L., & Raghavendra, C. (2017). Automatic segmentation of lumbar vertebrae in CT images. In *Medical Imaging 2017: Computer-Aided Diagnosis* (Vol. 10134). International Society for Optics and Photonics.
- Kwiat, D. (1982). The Calculation of the Chord Distribution Function. *Nuclear Science and Engineering*, 80(3), 469–473. doi:10.13182/NSE80-469
- Lessmann, N., van Ginneken, B., de Jong, P. A., & Išgum, I. (2018). *Iterative fully convolutional neural networks for automatic vertebra segmentation*. arXiv preprint arXiv:1804.04383.
- Lessmann, N., van Ginneken, B., & Išgum, I. (2018). Iterative convolutional neural networks for automatic vertebra identification and segmentation in CT images. In *Medical Imaging 2018: Image Processing* (Vol. 10574). International Society for Optics and Photonics.
- MATLAB. (2018). r2018a ed. Mathworks Incorporated.
- Mokhtarian, F., & Mackworth, A. K. (1992). A Theory of Multiscale, Curvature based Shape representation for planar curves. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(8), 789–805. doi:10.1109/34.149591
- Ojala, T., Pietikäinen, M., & Harwood, D. (1994). Performance evaluation of texture measures with classification based on Kullback discrimination of distributions. *Proceedings of the 12th IAPR International Conference on Pattern Recognition (ICPR 1994)*, 1, 582–585. doi:10.1109/ICPR.1994.576366
- Oktay, A. B., Albayrak, N. B., & Akgul, Y. S. (2014). Computer aided diagnosis of degenerative intervertebral disc diseases from lumbar MR images. *Computerized Medical Imaging and Graphics*, 38(7), 613–619. doi:10.1016/j.compmedimag.2014.04.006 PMID:24972858
- Prewitt, J. M. S. (1970). *Object Enhancement and Extraction*. In *Picture processing and Psychopictorics*. Academic Press.
- Rajaei, A., Dallalzadeh, E., & Rangarajan, L. (2012). Segmentation of Pre-processed Medical Images: An Approach based on Range Filter. *International Journal of Image. Graphics and Signal Processing*, 4(9), 8–16. doi:10.5815/ijigsp.2012.09.02
- Rajaei, A., Dallalzadeh, E., & Rangarajan, L. (2015). Symbolic representation and classification of medical X-ray images. *Signal, Image and Video Processing*, 9(3), 715–725. doi:10.1007/s11760-013-0486-6
- Rasoulilian, A., Rohling, R. N., & Abolmaesumi, P. (2014). Automatic labeling and segmentation of vertebrae in CT images. In *Medical Imaging 2014: Image-Guided Procedures, Robotic Interventions, and Modeling* (Vol. 9036). International Society for Optics and Photonics.
- Shi, R., Sun, D., Qiu, Z., & Weiss, K. L. (2007). An efficient method for segmentation of MRI spine images. In *2007 IEEE/ICME International Conference on Complex Medical Engineering* (pp. 713-717). IEEE. doi:10.1109/ICCME.2007.4381830
- Shoelson, B. (2012). Accessed on July 2, 2019 <https://blogs.mathworks.com/pick/2012/04/27/calculating-arclengths-made-easy/>
- Young, I., Walker, J., & Bowie, J. (1974). *An analysis Technique for biological shape*. In *Information and Control*. Elsevier.

Adela Arpitha is presently a Research Scholar at the Department of Studies in Computer Science, University of Mysore, Mysuru from where she received her MCA degree. She has earlier worked at the same department as well as in Teresian College, Mysuru as an Assistant Professor of Computer Science. She has seven papers in international conferences and journals. Her research interests include Medical Image Analysis, Image Processing, Pattern Recognition and Deep Learning.

Lalitha Rangarajan is a Professor at the Department of Studies in Computer Science, University of Mysore, Mysuru. She has over 35 years of teaching and 20 years of research experience with 100+ publications in peer-reviewed journal proceedings and conferences and has contributed to the field of image processing, pattern recognition and bioinformatics. She has served the University in various capacities. She has also served as a Teaching Assistant at Purdue University, West Lafayette, Indiana, USA.