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A Robust Scheme of Vertebrae Segmentation for Medical Diagnosis

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ABSTRACT Precise and reliable segmentation of vertebral column is crucial for accurate computer aided diagnostic system (CADx). It assists the radiologists and doctors in identifying various pathologies in the vertebrae with better visualizations. Accurate segmentation of vertebral disks and bones from the medical images is a tough job and becomes more challenging when dealing with various deformities and pathologies. While remarkable success was achieved by deep convolutional neural networks (DCNNs) in medical image segmentation, it is still a difficult task for DCNNs to handle the medical image segmentation problems with various deformities and anatomical complexities. In this paper, we propose a novel and efficient framework to address the subject problem by integrating a parametric level set approach in deep convolutional neural networks. The proposed scheme utilizes the probability map of pre-trained deep network to initialize the level set and it refines the output iteratively under the action of various forces to fine-tune the training of deep network. Thus the learning of the network is improved and the network is able to accommodate high topological shape variations in the vertebrae. This proposed method was evaluated on two different datasets. The first one is 20 publically available 3D spine MRI dataset to perform disc segmentation and the second one is 173 computed tomography scans for thoracolumbar (thoracic and lumbar) vertebrae segmentation. The dice score was found to be 90.37 ± 0.9 percent for disks segmentation and 94.7 ± 1.1 with ASSD of 0.1 ± 0.04 mm for thoracolumbar vertebrae segmentation. The results reveal that our proposed method is robust over multiple segmentations and outperformed the recently published state of art methods.

INDEX TERMS Intervertebral disk, thoracolumbar vertebrae, computed tomography, vertebrae segmentation, deep learning, computer aided diagnosis.

I. INTRODUCTION

Vertebral column is an integral part of human skeleton. It is associated with versatile and numerous functionalities [1]. It extends from the skull region and elapses till the pelvis. It is comprised of 33 individual bones which are stacked from top to down in a decent sequence. The vertebral column is further classified into five subdivisions, i.e. cervical, thoracic, lumbar, sacral and coccyx [2]. The cervical spine is comprised of seven individual bones i.e. C1 – C7. It supports the head region and helps the skull to move in various directions. Thoracic spine is comprised of twelve individual bones i.e. T1 – T12. It supports the rib cage and protects various organs in the ribs. The lumbar spine is comprised of five individual bones i.e. L1 – L5 and it provides flexibility to the weight bearing low back. The last two parts i.e. sacral and coccyx are fused bones. The sacral connects the entire vertebrae to the hip region and also protects various organs in the pelvic and no main function is recognized by coccyx [2]. In addition to these vertebral bones, the intervertebral discs are present in-between every two vertebral bones. Thus these intervertebral discs are twenty three in number. The labeled diagram of vertebral column is presented in Figure 1.

Human vertebral column may encounter various pathologies like vertebral degeneration, scoliosis, osteoporotic vertebral fractures and vertebral injury cases like traumatic fractures. These deformities are globally common even in the developed countries. For instance, US national-wide impatient sample database revealed total of 63,109 cases with acute traumatic spinal cord injury for the years between 1993 and 2003 [3]. Figure 2 gives the graphical illustration of this study. The study reflects that injury cases were increased

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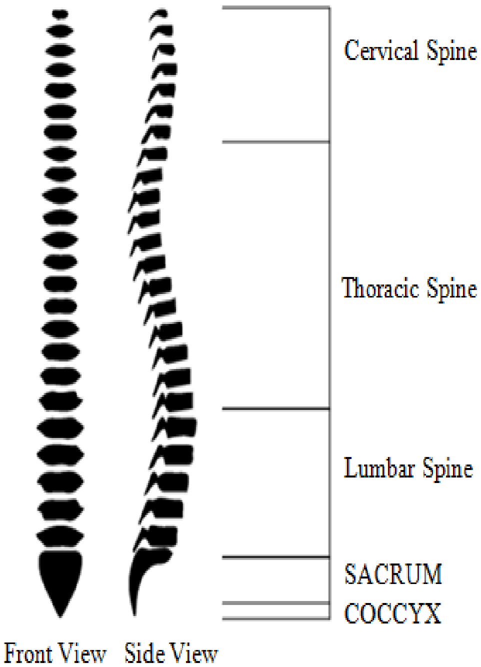


FIGURE 1. Labeled diagram of human vertebrae.

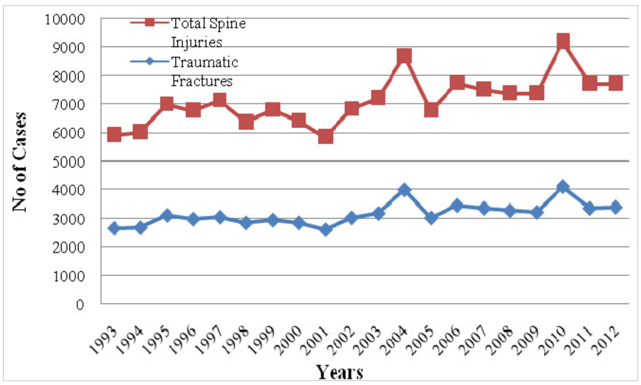


FIGURE 2. Trends of vertebral injuries in US.

with increase in population. While going from 1993 to 2012 the occurrence rate of traumatic spinal cord injuries were nearly stable.

In Europe [4], a study was conducted from twenty two countries using the data of 2012, total of 1840 deaths were recognized with traumatic vertebral injuries for which 59% were males. Similar studies were conducted in China [5], Japan [6] and other countries of the world. The main reasons of these injuries include accidents, motor vehicle crashes and unintentional falling. Accidents were recorded as an external cause of these injuries. Motor vehicle crashes are mostly common in low income countries and unintentional falling is dominated in elderly population.

In addition to traumatic injuries, osteoporotic vertebral fracture is also rapidly increasing worldwide. Osteoporotic vertebral fracture is occurred due to bone-osteoporosis in which vertebral bones are shirked as the bone mass is

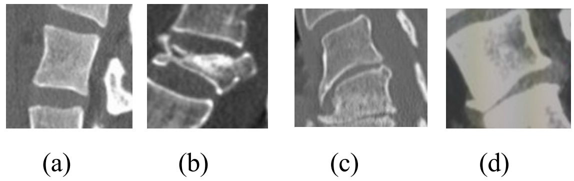


FIGURE 3. Vertebral pathologies are presented; (a) Normal healthy bone and disk (b) Bone with osteoporotic vertebral fracture (c) Degenerative bone (d) Vertebral herniated disc.

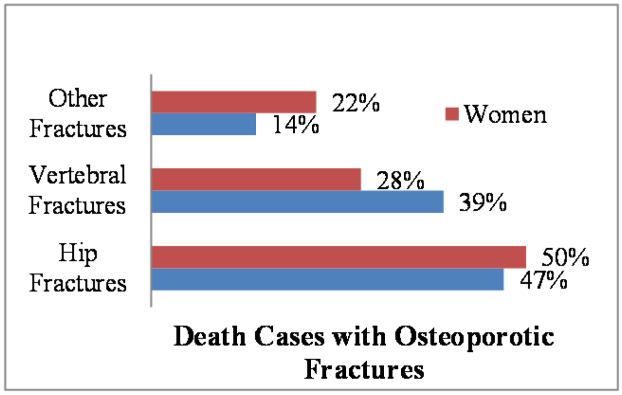


FIGURE 4. Plot of the death cases due to osteoporotic fractures on the basis of data from thirty countries of Europe in the year of 2010.

lowered. In vertebral osteoporosis, bones become narrow and weaken with osteoporosis that causes the fracture [8]. Statistics reveal that approximately eight point nine million fractures of vertebral column are caused due to osteoporosis on annual basis, which means that osteoporotic vertebral fracture is caused after every three seconds worldwide [9]. In Figure 3, vertebral column with various pathologies are illustrated, starting with the normal healthy bone with disc in (a), the bones with osteoporotic vertebral fracture, degeneration and herniated intervertebral disc are presented as (b), (c) and (d) in series.

Osteoporotic vertebral fractures should be identified at early stages. These fractures, if untreated, may lead to hip fracture [10]. Figure 4 presents a survey report of death cases in the year of 2010 from the data of thirty different European countries [11]. The ages of all the people were above fifty. In Figure 4, the percentage of hip fractures is larger as compare to the vertebral fractures and it is also observed that many of the hip fractures are caused by untreated vertebral fractures.

The vertebral fractures with osteoporosis are more common in elderly population. For this purpose, a survey was conducted worldwide to identify the increased risk of osteoporotic fractures in future [12]. Around 158 million patients above fifty years of age with osteoporotic fractures were identified in the year of 2010 from worldwide. The increase in probability till 2040 was estimated on the basis of this data. Figure 5 presents the probabilities in the form of graph [12].

Computer aided diagnosis presents a primary and initial tool for the doctors and radiologists in better visualizing the

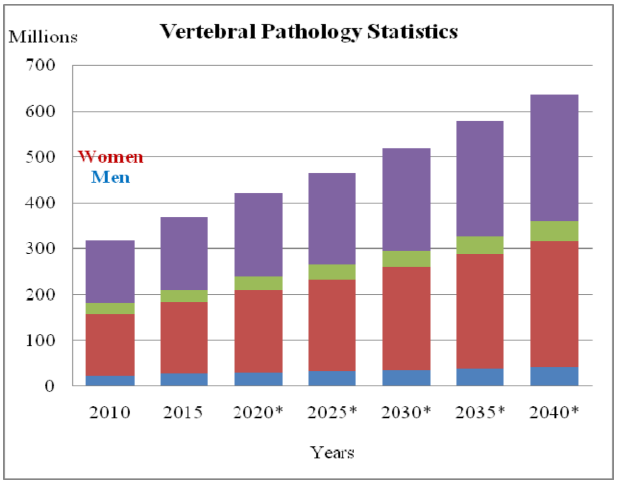


FIGURE 5. Estimated osteoporotic fracture cases worldwide.

radiological scans [13]. It improves the overall process of clinical diagnosis and also keeps this decision from false detection (also termed as medical error). Precise and accurate computer aided diagnostic system should be required as it has direct impact on the decision process. Development of a computer aided diagnostic system for vertebral deformities is a challenging task as there are high topological shape variations, poor contrast and various field of views in the radiological scans. In order to diagnose vertebral deformities efficiently, a robust and efficient vertebral segmentation algorithm is required to make an efficient computer aided diagnostic system. There are different kinds radiological scans which are used by the radiologists and doctors for the diagnoses of patients. These include computed tomography scans (CT scans), magnetic resonance imaging scans (MRI scans) and x-ray image scans [13], [14]. However, the patients subjected to various vertebral deformities are also referred to these kinds of radiological scans in order to diagnose them. In these cases computer aided diagnostic system provides assistance to clinicians while making the decision. In this way the process of diagnosis becomes more efficient, reliable and free from medical errors.

In the past decade, vertebral bones and disc segmentation problems were addressed by traditional imagery techniques, few of them are also discussed in our next section. Currently, deep learning techniques have proved state of the art performance especially in the field of medical image processing [7], [13], [14], [46]. For instance, U-Net architecture was originally presented by Ronneberger *et al.* [15] for biomedical image segmentation tasks. It has an ability to extract strong features that help to deal with the segmentation tasks very efficiently. However, when dealing with segmentation problems where high topological shape variations exist, U-Net architecture fails to perform and achieve appropriate segmentation performance. In these cases, a strong shape parameterization is required with U-Net architecture to achieve the desired segmentation results.

In this paper, we address the subject problem by integrating a novel level set based technique in deep network. The level set based techniques [16], [36] were traditionally employed by the researchers to deal with various medical imaging and other machine vision segmentation problems. These methods were based on traditional active contour models [17]. The main problem with these methods is their proper initialization. After properly initialized, they iteratively approach the desired segmentation level. Level set methods were initially proposed to solve the boundary extraction tasks. They successfully handled these problems but failed to solve region extraction problems. This limitation was removed by extending edge-based level sets to region-based level sets in which region based information was extracted in addition to boundary based information [16], [37].

We have performed a novel study of combining of parametric level set and deep convolutional neural network in a unified platform. This unification offered multiple advantages over a single framework. In this system we have extracted strong features from images using deep convolutional neural network i.e. U-Net architecture and its probability output is given as an input to the level set functional. Here, the level set performs its function to re-train the network after improving the output of deep network in iterations. The network was pre-trained with account to sensitivity of the level set initialization. The proposed framework produced competitive performance. The key highlights of our proposed framework are listed as:

- → We achieved vertebral bones shape parameterization on CT vertebral images using parametric level set approach accompanied with deep CNN.
- → We achieved intervertebral discs segmentation on MR vertebral images using the same novel approach.
- → We proved robustness on our proposed scheme on different image modalities and domains of segmentation.
- → We linked traditional level-set based method with deep learning approach to get double benefits.
- → We proposed a level set approach for accurate shape parameterization that is not achieved by original U-Net architecture alone and desired when dealing with complex shape variations in the segmentation regions.
- → We developed an algorithm that successfully handles multiple pathologies in a single framework.
- → We formulated a scheme that produced highly competitive results which are comparable favorably with the state of arts.

This paper is organized as: In section 2, we briefly summarize a few published researches to address the problem of vertebrae segmentation. Section 3 illustrates our proposed methodology and section 4 gives the experiments and implementation details. In section 5, we have presented our results and compared with state of the arts. Finally, section 6 presents the discussion section followed by conclusions and future directions.

II. RELATED WORK

Segmentation of vertebral bones has been a challenging problem from past few years. Various researches have been published using traditional imagery techniques to address the subject problem. For instance Klinder *et al.* [18] formulated a two scale model to segment out vertebral bones. It was shape based approach which worked in an automatic way to perform the segmentation task. Zhang *et al*. [19] applied thresholding based technique to obtain segmentation from CT vertebral images. Initially, image partitioning was performed to separate the region of interest i.e. bone region and then iterative correlation was applied to improve the segmentation. It was an adaptive thresholding technique that worked rapidly. Athertya and Kumar [20] automated active contour model with developing a contour initialization technique in order to perform vertebra segmentation. Mahmoudi *et al*. [21] worked on x-ray image dataset and initially extracted the contour of vertebral bones. Finally the contours were used and bone regions were extracted to get final segmentation.

Active appearance model (AAM) was employed by Roberts *et al.* [22] to address the problem of fractured vertebrae segmentation. The dataset was comprised of digital x-ray radiographs of lumbar spine (including fractured cases), collected locally from hospital. The proposed model was applied differently at various corners of vertebral bones in order to get segmentation of fracture vertebral bones. A dual mode was presented with dual application. Active shape model (ASM) was employed by Benjelloun *et al.* [23] in a semiautomatic way to get the segmentation of cervical vertebrae from x-ray image dataset. The initialization process was made manual with inserting two points on the bone in order to start the segmentation. In order to automate the initialization process of active shape model, Mysling *et al.* [24] proposed a framework that used a shape model sampling scheme to obtain shape samples. These samples were used to perform the final segmentation task.

The level set based techniques were also adapted in some previous researches to perform vertebrae segmentation tasks. These techniques were based on the concept of traditional active contour models (ACMs) [17]. For instance, level set method was adapted by [25] to perform CT vertebral image segmentation in various field of views. [26] Employed hybridized form of level sets to perform vertebrae segmentation. [27] Combined fuzzy cluster variation with region based level set to perform vertebrae segmentation from in-homogenous image dataset.

Recently, deep learning techniques have outperformed the traditional imagery techniques. A few works related to vertebrae segmentation have also been published in recent years with deep learning techniques. For instance, Sekuboyina *et al.* [28] employed fully convolutional network (FCN) to perform multi-class segmentation of lumbar vertebrae. Initially, lumber region was localized with multilayer perceptron, the final segmentation was obtained using fully convolutional network (FCN). Sekuboyina *et al.* [29] carried out another research to perform localization and segmentation of vertebral bones. 2D convolutional neural network was used for localization of low resolution vertebrae and 3D fully convolutional neural network was used to perform the segmentation. Lessmann *et al.* [30] added a memory component with fully convolutional neural network and adapted an iterative approach to perform vertebrae segmentation. In this framework, memory component was used by the network to analyze image patches in an iterative way to achieve appropriate segmentation results. In addition to them, intervertebral disks segmentation was performed by Dolz *et al.* [47] with multi model U-Net architecture termed as "IVD-Net". [47] added inception module in the U-Net architecture to improve the segmentation results. The results were compared with traditional architectures to demonstrate the significance of the scheme. Kim *et al.* [41] solved the problem of intervertebral disk segmentation with modified U-Net architecture. [41] employed various architectural schemes and all the results were presented to give the significance of the scheme.

Recently published works on vertebrae segmentation totally relied on deep learning techniques. Although they are very strong in features extraction and segmentation but they fail to handle high topological shape variations like in osteoporotic fractures. For instance, Al Arif *et al.* [31] performed cervical vertebrae segmentation with deep convolutional neural networks. [31] Added a shape based function in pixel wise loss layer while training the network for shape parameterization. This term was used to improve the accuracy of segmentation by taking euclidean distance between predicted and referenced shape. However, in order to get high level accuracy in the shape, a strong algorithm is still desired to combine with the deep learning network in order to handle various deformities in the segmentation.

In order to perform shape convergence or parameterization, level set techniques were previously used by the researchers. These techniques have an ability to extract boundary and shape from the images with high level of accuracy [16], [25]–[27], [35]–[37], [42]. Level set method was initially introduced by [32]. These methods are based on active contour models [17]. Once level set is proper initialized, it can independently extract the desired boundary or region. Recently, level set method was successfully combined with deep leering network by [33]. In addition to that, Ngo *et al.* [34] combined traditional level set with deep network and performed the segmentation of left ventricle of heart successfully.

III. PROPOSED FRAMEWORK

We have presented a novel framework of vertebrae segmentation which is capable of handling the complex shape variations in the vertebrae efficiently. This framework integrates deep convolutional neural network, i.e. U-Net architecture and the parametric level set in order to extract the shape of bones and disks accurately. Our framework is powerful and robust as it accommodates the advantage from multiple

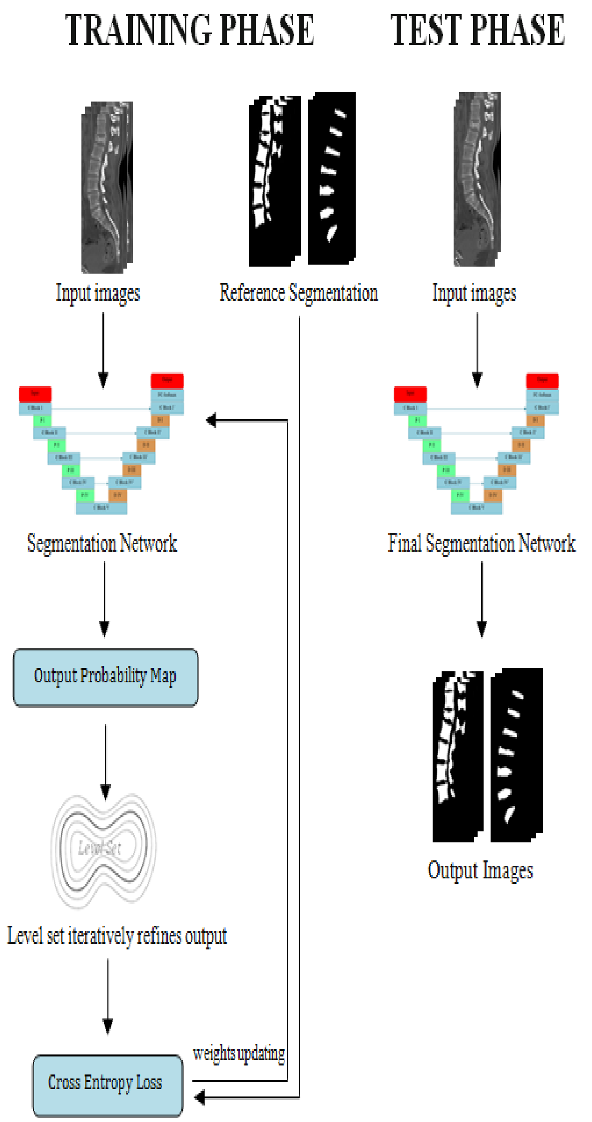


FIGURE 6. Proposed pipeline of our system.

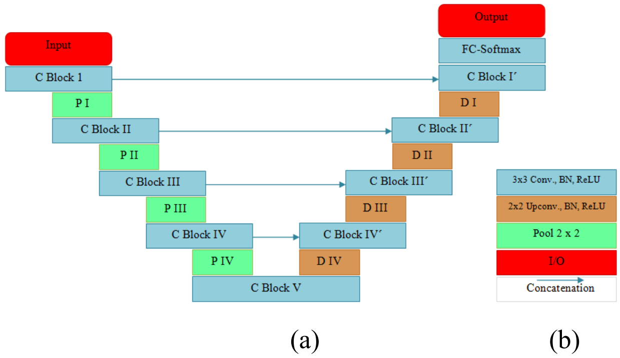


FIGURE 7. U-Net architectural diagram (a) Segmentation network (b) Labels.

algorithms used for biomedical image segmentation. The pipeline of our proposed framework has been demonstrated in Figure 6. In comparison with recently published methods on vertebrae segmentation, our proposed method performs segmentation with more accuracy and precision.

A. NETWORK ARCHITECTURE

U-Net Architecture was originally proposed by Ronneberger *et al.* [15] for biomedical image segmentation. It is a U shape curved network with contraction (left side) and expansion (right side). Inspired from [15], the segmentation network has been implemented with a little bit modification. The network diagram is presented in Figure 7. We have kept the dimensions of input and output image data constant by taking use of padding. On the left (contraction) side there are four convolution blocks. Each block is comprised of two 3×3 convolutions followed by batch normalization (BN) and rectified linear unit (ReLU). The spatial dimensions of the image data are reduced after each block with the use of 2×2 pooling. The final dimension of image data is reduced from 128×128 to 8×8 after the contraction path. The fifth convolution block at the bottom performs the same functions described above without pooling. On the right (expansion) side, four convolution blocks are employed in the similar fashion as in contraction side. Up sampling is performed with four deconvolutional layers and used after each convolutional block. In order to avoid the information loss, concatenation is performed across convolution blocks in contraction and expansion paths correspondingly. Our network takes a single channel input and predicts two channel probabilistic output of same dimension.

B. DEEP PARAMETRIC LEVEL SET INTEGRATION

This section gives the description of our level set formulation which has been integrated in the deep learning framework to improve the segmentation accuracy. Level set approaches were previously very common for the segmentation of various natural and medical imaging tasks. These techniques perform the subject tasks with an iterative curve evolution process provided by a good initialization. These approaches can perform image segmentation tasks efficiently under high topological variations in edges or regions to be extracted from the images.

Level set based method was initially presented in 1988 by Osher and Sethian [32]. It was a very effective contour evolution technique that was further divided into two sub categories, i.e. edge based techniques and region based techniques [37]. Initially, level set methods were used to solve edge detection problems. These methods used gradient based information of the images to perform the subject task using iterative curve evolution strategy. For instance, Caselles *et al.* [36] introduced geodesic active contours with level set approach. It was a very popular technique that was employed to solve various contour evolution tasks. However, edge based level set techniques take only edge related information to perform a segmentation task which leads to edge or contour leaking. In order to solve this boundary leaking problem, various solutions were proposed. For instance, a region based active contour model was proposed by [16]. Similarly geodesic active contour model was extended to geodesic active region model [37] to solve the subject issue. Boundary extraction problems can be solved using geodesic active contour models [36], [39].

$$E_b = \iint_{\omega} \delta_{\alpha}(\varphi) d(|\nabla I|)|\nabla\varphi| d\omega \quad (1)$$

where δ_a is the Dirac function [40], 'φ' is the level set and 'ω' is the image domain and d: $\mathcal{R}^+ \rightarrow [0, 1]$ is the decreasing function that attracts the boundary towards the desired curve. This function is expressed as the inverse of image gradient

$$d(\cdot) = \frac{1}{1 + |\nabla I|^2} \quad (2)$$

In order to accommodate region based information ϵ_r is introduced [37] that accounts object and background probabilities to approach the desired region.

$$E_r = \iint_{\omega} H_{\alpha}(\varphi(x)) \log \rho_o d\omega + \iint_{\omega} (1 - H_{\alpha}(\varphi(x))) \log \rho_i d\omega \quad (3)$$

$H(\cdot)$ is Heaviside function [40]. $\rho_o : \mathcal{R}^+ \rightarrow [0, 1]$ is the probability of object region and $\rho_i : \mathcal{R}^+ \rightarrow [0, 1]$ is the probability of background region. Here, calculus of variations is adapted to minimize this functional. In this way, new level set evolved with respect to time to drive the force to approach the desired segmentation [39].

After the development of region and edge based level set, consider the area of significance which optimizes the segmentation by maximizing the properties of the edge and region based level set [42]. Suppose 'ρ_o' is the probability of object region and 'ρ_i' is the probability of background region, 'ω' be the region inside this object region and 'ω' be the region outside this object. The energy functional for the area of significance for the segmentation optimization is given as

$$E_a = \iint_{\omega'} (M_b(x) - i(x))^2 \, dx + \iint_{\omega''} (M_b(x) - j(x))^2 \, dx \quad (4)$$

Here, 'x' implies all the points around the contour, i(x) and j(x) are calculated by arithmetic mean of the local-neighborhood points in the near-by area of contour of the segmentation objects. 'M_b' is the significance area coverage for the segmentation. It returns the output 'One' for the regions inside this significance area of coverage and outputs 'Zero' for the regions outside this significance area of coverage. Thus, this factor acts as blending parameter for edge and region based segmentation schemes. In Figure 8, the circle represents this significance area of convergence. The red segmentation part represents the corrected segmentation of vertebral disk and the pink shade represents the intersection area of object segmentation and the significance area of coverage.

After the description of various expressions, the final formulation is given as the minimization problem of form

$$E(\varphi, T) = E_a(\varphi, T) + u\,E_r(\varphi) v\,E_b(\varphi) \quad (5)$$

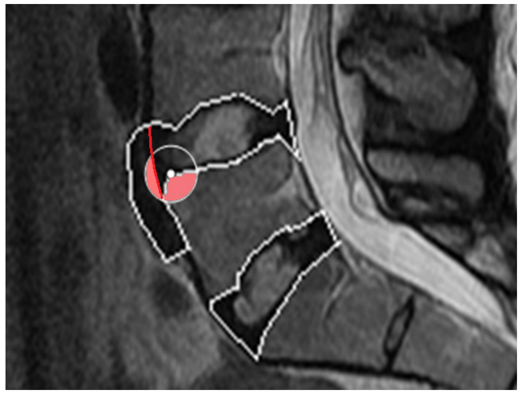


FIGURE 8. Illustration of area of convergence.

Equation 5 gives the final expression of our level set formulation. u & v are blending parameters which are constant tuned manually on experimental basis.

C. PROPOSED FRAMEWORK

Figure 6 presents our proposed scheme of vertebrae segmentation. We have incorporated parametric level set with deep network. Our deep segmentation network i.e. U-Net architecture extracts strong features from the images and this output is fed as input to the level set. In general, we have combined two different and powerful tools in single platform to achieve double benefit. As level set is sensitive to initialization, we have initially trained the network on training data and then used the output of this pre-trained network to input the level set. Our overall system takes an input vertebrae patch of size 128 × 128 and makes a prediction of binary segmented patch of uniform size output.

Integration of level set approach in deep learning network provides multiple advantages in the segmentation output. Equation 5 gives the final formulation of energy functional. The boundary convergence is achieved using Equation 1, region-based convergence is achieved using Equation 3 and significance area of convergence is used to enhance the effect of edge and region based segmentations using Equation 4. As we have given the output of pre-trained network to the level set, the level set is initialized in an effective way. The level set works in iterations and refines the segmentation output to the desired level. This output is further used to compute the cross entropy loss and weights were updated again to fine-tune the training of network.

Equation 1 deals with the boundary minimizing problem. Its lowest potential gives the attraction of geodesic curve with the boundary of interest. Similarly Equation 2 deals with the region partition problem. It works with the extraction of region of interest i.e. foreground region from the background part. This partition is defined by Heaviside function. In order to update the flow, calculus of variations [39] is applied which gives the optimum solution at the desired segmentation level. In this way boundary and region based optimization is performed. Equation 4 is based on the concept of supposition of a local neighborhood area for the precision

TABLE 1. Description of few CT Scans of our Dataset.

Cases	Gender	Age Yr	Machine	Manufacturer	Slice Thickness	No. of Slices	Abnormality
Case 1	M	21	16 slice CT Scan Machine	Toshiba	5 mm	512	No
Case 2	M	39	16 slice CT Scan Machine	Toshiba	5 mm	512	Yes
Case 3	F	13	16 slice CT Scan Machine	Toshiba	5 mm	512	No
Case 4	M	71	16 slice CT Scan Machine	Toshiba	5 mm	512	Yes
Case 5	F	66	16 slice CT Scan Machine	Toshiba	5 mm	512	Yes
Case 6	M	39	16 slice CT Scan Machine	Toshiba	5 mm	512	No
Case 7	M	42	16 slice CT Scan Machine	Toshiba	5 mm	512	No
Case 8	M	16	16 slice CT Scan Machine	Toshiba	5 mm	512	Yes
Case 9	F	69	16 slice CT Scan Machine	Toshiba	5 mm	512	Yes
Case 10	M	56	16 slice CT Scan Machine	Toshiba	5 mm	512	No

of the segmentation regions. The final energy minimization problem is given by Equation 5. This output is used by the loss function to find the cross entropy loss in order to update the weights and re-train the network.

This dual trained network is then tested on the test dataset. The vertebrae image patches from the test dataset were given to the trained network. The output segmented binary masks were obtained and evaluated on the ground truths to compute dice score and average surface distance.

IV. MATERIALS AND EXPERIMENTS

A. IMAGE DATA

We have used two different datasets for our experiment. The first dataset is publically available MR images of twenty patients collected from the datasets of spineweb [41], [48]. The size of pixels in the image dataset was 1.5 × 1.5 mm. The data was annotated and validated by the radiological experts and their details are listed in the acknowledgements.

The second dataset was one hundred and seventy three CT scans of thoracolumbar (thoracic and lumbar) vertebrae. These scans were acquired in the routine medical diagnosis by radiologists in the radiology department of POF's Hospital (Rawalpindi district) Pakistan between 2016 and 2018. There is a large variation in the ages of the patients. A few of them are illustrated in Table 1. All bones of the lumbar region and lower thoracic region are visible and few bones of upper thoracic region were visible in CT scans. The reference segmentations are obtained from the dataset which is explained in the implementation details. The dataset is rich in various deformities like osteoporotic vertebral fractures, traumatic injuries and other bone deformations and irregularities due to aging. The data is acquired with '16 slice CT Scan Machine' and CT scans were acquired with slice thickness of 5 mm. Further details of the scans are listed in Table 1.

B. EVALUATION METRICS

In order to evaluate our results, we have used two evaluation metrics i.e. the dice similarity score (DSS) and the mean absolute surface distance (MASD). This will help us in comparing with the state of art published works. These metrics were previously used by [13], [43], [44] for the evaluation segmentation performance. Dice score gives the similarity measure to evaluate the performance of segmentation and its expression is given as [43]

$$Dice\ Score = \frac{2\left|O_p \cap R_t\right|}{\left|O_p\right| + |R_t|} \tag{6}$$

In Equation 6, 'O_p' is the output predicted and 'R_t' is the reference segmentation, calculated on vertebral bones individually and then averaged. In addition to that, minimal average distance between two boundaries is calculated by mean absolute surface distance (ASD) and its expression is given as [38]

$$ASD = \frac{1}{O_p}\sum_{i=1}^{o_p} \left\| \partial_i \left(O_p, O_r\right)\right\| \tag{7}$$

In Equation 7, the output segmentation surface is given as 'O_p' the reference ground truth surface is given as 'O_r' is and minimum distance between the two surfaces calculated on the vertebrae in the same way as described above for the dice score.

C. IMPLEMENTATION DETAILS

Our proposed system pipeline is presented in Figure 6 and U-Net diagram is presented in Figure 7. We have implemented our framework in tensorflow (python), windows desktop system, Intel i7, 1080 GTX with 8 GB memory and GPU. The network training is done with 500 epochs and it was converged before. The other parameters include dropout of 0.2, momentum of 0.9 and decaying learning rate. The experiment was carried out on 2D slices in sagittal view. The dataset was divided into training and test sets. As the data augmentation is desired for proper network training and to achieve appropriate performance of deep network [15], we have applied various augmentation techniques [13], [31], [44], [45] like rotations on various angles, shifting, extraction of intra-slices etc to augment our training data up to several thousand images. The augmented data set is then used to extract reference ground truths. This is performed by using interactive live wire technique [35]. The obtained reference segmentation is also evaluated by clinical experts for validation. This is done to evaluate our reference segmentations specifically for the cases with shape deformations. After data preparation, we have trained the network initially with training data set on ground truths and then pre-trained network is trained with the level set output in order to enhance the learning of deep network. The level improves the output in an iterative way. These iterations follow calculus of variations. The output was converged at a very less number of iterations (less than one hundred) due to the use of deep network for

TABLE 2. Comparative results of dataset 1 with the state of the arts.

List of Techniques by	Segmentation Strategy	Dice Score (%)
Kim et al. [41]	U-Net	86.44± 2.44
Kim et al. [41]	Dilated U-Net	88.46± 2.63
Kim et al. [41]	BSU-Net	89.44± 2.14
Our Proposed Technique	U-Net + Parametric Level Set	90.37 ± 0.9

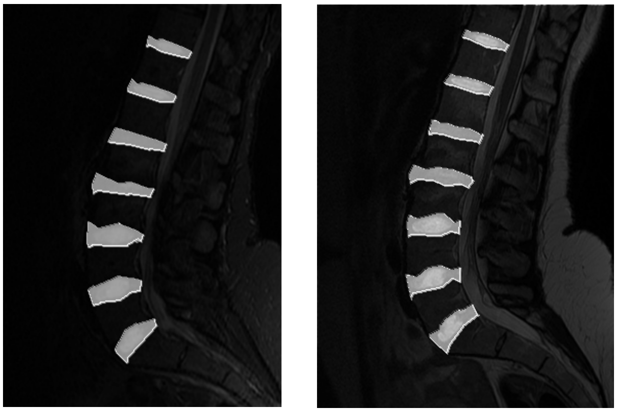


FIGURE 9. Segmentation results with our proposed method on dataset 1.

initialization and it was estimated on experimental bases. The final network was dually trained and learned complex features.

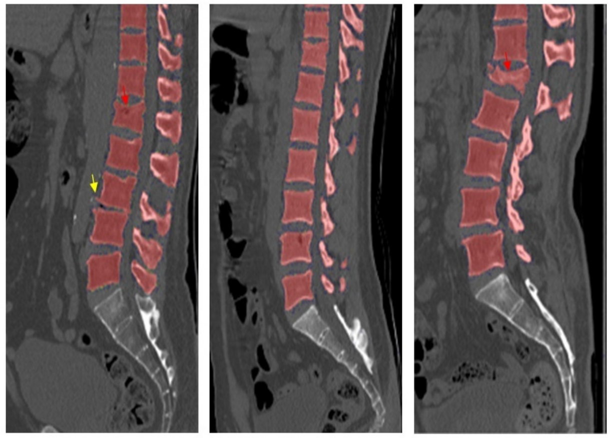
Our overall system is comprised of two components in which one is working under the other. The deep learning network i.e. U-Net architecture is used with a little bit modification in the original architecture. The parametric level set, which is working under the deep learning network, is based on contour and regional properties. The scheme worked well for the subject tasks and handled the deformities efficiently. In order to validate our system performance, we have made a comparison of our results with recently published state of art methods for vertebrae segmentation and they are presented in the next section.

V. RESULTS

A. SEGMENTATION PERFORMANCE

For the first dataset, we have made five fold cross validation in a similar fashion to [41]. This is performed in order to make the comparison with [41] and to evaluate our proposed method. We have obtained 90.37 ± 0.9 percent dice score for disks segmentation. The results with comparison have been presented below in Table 2. The segmentation results are presented in Figure 9.

For the second dataset, we have applied our proposed methodology on computed tomography scans of thoracic



(a) (b) (c)

FIGURE 10. Segmentation results with our proposed method on dataset 2, yellow arrow in (a) pointing the dilation in bones with aging and red arrows in (a) and (c) pointing the fractured bones.

and lumbar vertebrae and achieved promising results. As described above that deep learning techniques have proved state of art performance in medical image segmentation tasks. In addition to these techniques, the traditional level set methods are independently very strong in dealing with various medical image segmentation problems. The unification of these techniques has produced high quality results. The segmentation results are shown in Figure 10.

As level set is sensitive to initialization, we have used pre trained segmentation network to input the level set. Our proposed framework performed well for both healthy and non healthy cases. The dice score was found to be 94.7 ± 1.1 with U-Net and level set and 89.4 ± 1.8 with U-Net alone. In Figure 10(a), yellow arrows show the shape dilation in bones of aged patients. In Figure 10 (a) and (c), red arrows show the deformation in bones due to osteoporotic vertebral fracture. Comparing our proposed method with other techniques published on vertebra segmentation before, our deep level set framework outperformed the others on thoracic and lumbar computed tomography scan image data. The substantial improvement was produced with the use of pre trained segmentation network and the level set. The detailed results are presented in next section.

B. COMPARATIVE RESULTS

The segmentation results on our dataset are summarized in Table 3. Taking the advantage of shape based level-set under deep learning network, we have optimized the shape of vertebral bones and our proposed scheme achieved promising results. The dice score (DS) was found to be 94.7 ± 1.1 and average absolute surface distance (ASD) was found to be 0.1 ± 0.04. In Table 3, we have presented the results of the validation set of our thoracolumbar (thoracic and lumbar) vertebrae dataset.

To evaluate our segmentation performance, we have made a comparison of our results with recently published state of

TABLE 3. Comparative results on dataset 2 with the state of the arts.

List of Techniques by	Segmentation Strategy	Data Set	Dice Score (%)	ASD (mm)
Yao et al. [38]	Mean Shape Model	Thoracolumbar (Normal Healthy Bones)	94.7 ± 0.03	0.37 ± 00
Yao et al. [38]	Statistical Shape Model	20 CT Thoracolumbar (Including Fractured Bones)	89.7 ± 00	0.64 ± 00
Sekuboyina et al. [28]	FCN	25 CT Lumbar Vertebrae (Including Fractured Bones)	94.3 ± 2.8	- -
Lessmann et al. [30]	FCN + Memory	15 CT Lumbar Vertebrae (Normal Healthy Bones)	94.8 ± 1.6	0.3 ± 0.1
U-Net alone	U-Net	173 CT Thoracolumbar (Including Various Deformities)	89.4 ± 1.8	0.21 ± 07
Our Proposed (U-Net with level set)	U-Net + Parametric Level Set	173 CT Thoracolumbar (Including Deformities)	94.7 ± 1.1	0.1 ± 0.04

art techniques on vertebrae segmentation. Yao *et al.* [38] performed a milestone study on the challenge dataset of MICCAI CSI 2014. The datasets contain twenty CT thoracolumbar vertebrae, fifteen normal and five with osteoporotic fractures. Five challengers entered in the challenge and presented their algorithms with results. Out of them, the challenge winners for the segmentation of both healthy as well as osteoporotic fractured cases are listed in Table 3. The dice score was found to be 94.7 ± 0.03 for normal healthy cases using mean shape model and the dice score was found to be 89.7 for osteoporotic vertebral fractured cases using statistical shape model by the challenge winners. Moreover, Sekuboyina *et al.* [24] applied fully convolutional neural network on lumbar CT vertebrae and achieved dice score of 94.3 ± 2.8. Lessmann *et al.* [30] added the concept of instance memory in fully convolutional neural network and applied on 15 CT vertebrae of normal healthy subjects to achieve the dice score as 94.8 ± 1.6.

We have adapted two schemes to illustrate the superiority of our proposed framework. Initially, we have trained the segmentation network with the training dataset. The trained network is then tested on the test dataset and achieved dice score is listed in Table 3. In order to improve the segmentation performance, we have added parametric level set under this deep convolutional neural network. We have found a relative increase in the segmentation performance (more than 5% in dice score), the achieved dice score is listed in the Table 3. The proposed scheme shows that U-Net with level set can be robust, more accurate and outperformed the other segmentation techniques for the subject problem.

VI. DISCUSSIONS

In this research, we have combined parametric level set and deep convolutional neural network for vertebrae segmentation. Our approach incorporates boundary and regional information collectively with recent deep convolutional neural network to produce high-quality results for the subject task. We have got the advantages of the two different techniques in a single platform. The major issue with the level set methods is that they require a very good initialization. The probabilistic output of deep convolutional neural network provides a very good initialization for the level set to evolve the desired curve or region. In this way, the output of deep network is deliberately improved by the level set iteratively and network is able to learn complex features to handle high topological shape variations for segmentation. As the level set is sensitive to initialization, we have used the pre trained network with level set to achieve improved results.

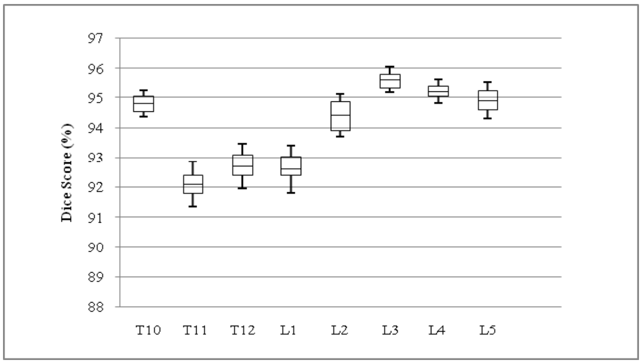


FIGURE 11. Box and whisker plot on our evaluation dataset.

As described earlier that vertebral bones lose their actual shape with aging. In addition to that, various other deformations may alter the actual shape of vertebral bones like osteoporotic vertebral fractures and traumatic injuries. Segmentation of these vertebral bones is challenging task and mostly neglected by recent researchers. We have included parametric level set approach in deep network as a strong shape predictor which is not possible to get from simple deep U-Net architecture. Level-set based deep learning network is capable enough of handling these cases efficiently. Parametric level set works in an iterative way in which boundary, region and convergence area were collectively used to improve the quality of segmentation. Hence, this framework performed substantially better than recently published methods of vertebrae segmentation.

Figure 11 represents the results with box and whisker plot on the evaluation dataset. The plot gives the achieved dice score drawn at bone level per vertebrae. The overall results are summarized in Table 3. From Figure 11, the obtained segmentations at T11, T12 and L1 are little bit lower than other. This shows that the segmentation was tough at these regions due to various deformities in bones. Additionally, we also found that the segmentation results at lower lumbar region are more accurate than upper lumbar and lower thoracic regions.

We have utilized a novel parametric level set to solve the problem of vertebrae segmentation especially for unhealthy subjects. The addition of our proposed level set provides us two way advantages in a unified framework. The dual

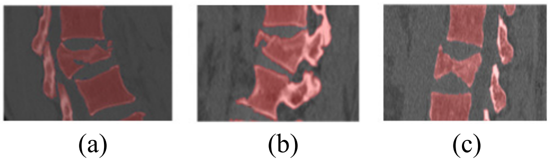


FIGURE 12. Segmentations on data with various deformities.

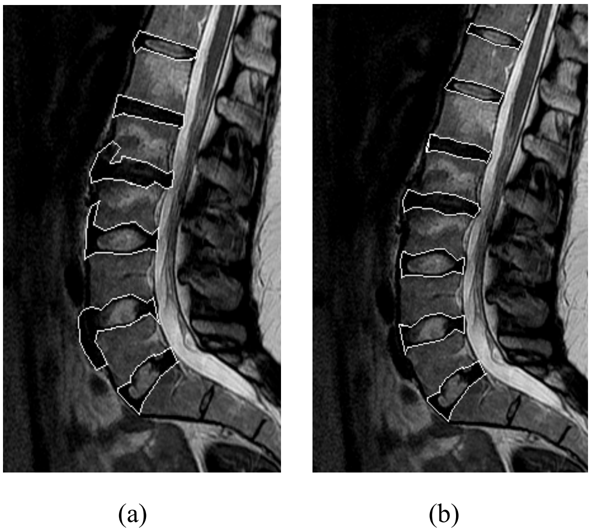


FIGURE 13. Comparing the results of U-Net alone with and U-Net with parametric level set.

trained network is capable of predicting vertebrae with high level of accuracy. It incredibly handles high variations in vertebral bones and disks shape effectively. The segmentation results with some deformed bones of the vertebrae have been illustrated in Figure 12.

Figure 13 presents the comparison of segmentation results obtained from U-Net architecture alone and U-Net architecture with parametric level set. Figure 13 (a) shows the wrong segmentations at third, fourth and fifth levels with U-Net architecture alone. Figure 13 (b) shows the correct segmentations with U-Net and parametric levels set. This shows that deep network alone fails to accommodate high intensity variations in medical image. The parametric level set accompanied with the deep network has great ability to handle the segmentations where high shape and intensity variations exist in the image data.

Precise segmentation of vertebral bones and disks from medical images allows us to perform automatic analysis of the vertebrae. An accurate vertebral analysis depends on the level of accuracy of segmentation. Parametric level set captures the shape of vertebral bones with high accuracy and gives us precise segmentation. Moreover, we have presented comparisons of our results with state of the arts. This helped us to validate our proposed method and to prove the superiority of using parametric level set with U-Net over simple U-Net. Our framework performed well without network overfitting and efficiently handled our dataset with high variation in field of views, intensities and with shape deformations. Although in few cases our method may performed slightly worse but overall, we have achieved highly promising and competitive results.

VII. DISCUSSIONS

We have formulated parametric level set based technique with deep learning framework. Our work is no doubt a bridge that links conventional imagery technique with recent deep learning approach giving double benefits. The method successfully addresses the vertebrae segmentation problem in 2D CT as well as MR image datasets. The parametric level set technique improves the vertebral bones segmentation obtained by deep convolutional neural network. This shape optimization outperforms, especially, when dealing with the deformed vertebral shapes. The results in different ways are evaluated and described along with the state of arts to show that our proposed framework is competitive over other methods.

In future, we can extend this work to multimodality images or datasets from different scanners in order to build a robust system. Another interesting future direction is the development of a simultaneous segmentation scheme that can perform cervical, thoracic and lumbar vertebrae segmentation over a single platform. In this way, it would be more useful to the radiologists for the diagnosis from multiple views. Moreover, the network training can be further enhanced with an increase in the training data. After successful implementation of our proposed scheme of vertebrae segmentation, the framework may also be employed to solve various other medical image segmentation problems where high topological shape variations occur. Finally we may also extend this work to classify different kinds of abnormalities in the vertebral column.

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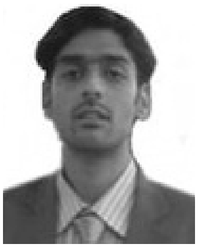

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