Abnormality Detection in Lumbar Discs from clinical MRI with a Probabilistic Model

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Purpose: This paper proposes a technique for the detection of abnormal intervertebral discs from clinical T2-weighted MRI to aid the radiologist, as well as subsequent CAD methods, in diagnosis of lower back pain (LBP). Intervertebral disc abnormality is a main reason for lower back pain [1]. Lower back pain is the second most common neurological ailment in the United States after the headache according to the National Institute of Neurological Disorders and Stroke (NINDS). Americans spend at least $50 billion each year on lower back pain and over 12 million Americans have some sort of Intervertebral Disc Disease (IDD) [2]. Fig. 1 shows a sample sagittal MRI with labeled lumbar disc levels. Abnormal discs are labeled as well as samples of abnormal discs are shown.

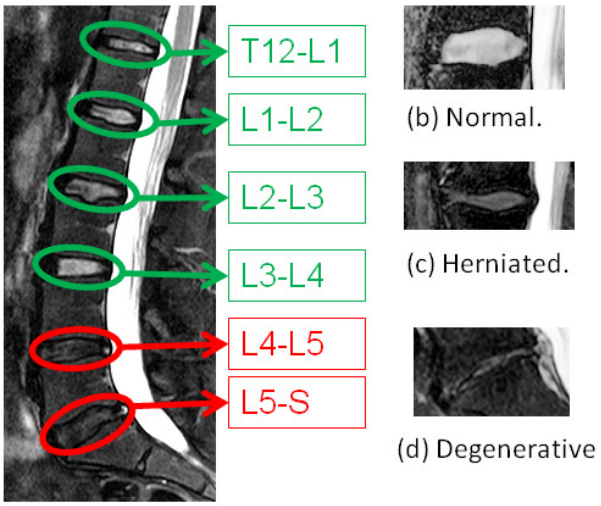
Methods: We propose a probabilistic method for detection of abnormality of intervertebral discs n_i in the lumbar area at each disc level i (Fig. 1(a)):

$$n_i^* = \arg\max_{n_i} P(n_i \mid d_i, \sigma_{I(d_i)}) \qquad (1)$$

And we capture the abnormality condition n_i with a Gibbs model:

$$P(n_i \mid d_i, \sigma_{I(d_i)}) = \frac{1}{Z[n_i]} \exp^{-E_{n_i i}(d_i, \sigma_{I(d_i)})} \qquad (2)$$

where n_i is a binary random variable stating whether it is a normal or abnormal disc and $n_i \in N = \{n_i : 1 \le i \le 6\}$, $d_i \in D = \{d_i : 1 \le i \le 6\}$ is the location of each lumbar disc, and $\sigma_{I(d_i)}$ is the intensity of a neighborhood surrounding the disc level i. $E_{n_i}(d_i, \sigma_{I(d_i)})$ is the energy function identified by disc location d_i and the intensity of a pixel neighborhood $\sigma_{I(d_i)}$.



(a) Lumbar disc levels labels.
Lower two levels are abnormal (red).

Fig. 1 Labeling of lumbar area discs and sample abnormalities.

We use three potentials, namely (i) the appearance I, (ii) the location d_i, and (iii) the context between discs $(i \sim j)$ which concludes our energy function $E_{n_i}(d_i, \sigma_{I(d_i)})$ to:

$$E_{n_i}(d_i, \sigma_{I(d_i)}) = \left[\beta_1 \sum_{d \in D} U_I(d_i, \sigma_I(d_i)) + \beta_2 \sum_{d \in D} U_D(d_i) + \beta_2 \sum_{d \in D} V_D(d_i, d_j) \right] \qquad (3)$$

where $\beta_1, \beta_2, \beta_3$ are the model parameters that control the effect weight of features on the inference. U_I is the appearance potential which is a model of both the location of each disc $d_i \in D$ and the intensity of the pixel neighborhood $\sigma_{I(d_i)}$ of that location. U_D is the location potential which is a model of the location of these discs D. V_D is the context potential which is a model of the distance between neighboring discs $(i \sim j)$.

Our model requires two inputs, the locations of the discs $D = \{d_i : 1 \le i \le 6\}$, and the intensity of a neighborhood surrounding every location $\sigma_{I(d_i)}$. The first input is the outcome of the labeling problem which we produce from our previous work [3]. The second input is obtained from the image intensity $I = \{Intensity : 0 \le Intensity \le 2^b - 1\}$ for the disc location and a defined neighborhood $\sigma_{I(d_i)}$ where b is the bit depth of the images, which is 12 bits for our dataset.

We use a dataset of 80 clinical MRI volumes containing normal and abnormal cases. Abnormalities include disc herniation, disc desiccation, degenerative disc diseases and others. We use the T2-weighted volumes for training and testing our proposed model for abnormality detection as disc intensities have better discrimination from other structures in

the image [4]. We pick the middle slice from every volume to represent that case and use it in our model training and testing.

We perform ground truth annotation for our dataset by selecting a point inside every disc that roughly represents the center for that disc d_i, and then determining whether the disc is normal or abnormal n_{d_i}. We train our model to learn the parameters of the three potentials representing the models for the appearance I, the location $D = \{d_i : 1 \le i \le 6\}$, and the context between discs $(i \sim j)$ using the ground truth (D, N) and the corresponding training images I.

Results: We perform a cross-validation experiment using the 80 cases to train and test our proposed method. In every round, we separate thirty cases and train on the rest 50 cases. We perform 10 rounds and every time the cases are selected randomly as shown in the table below. Dr. Gurmeet Dhillon provided the ground truth for all the 80 cases to automatically check classification accuracy which we define by:

$$Accuracy_i = \left(1 - \frac{1}{K}\sum_{j=1}^{K}\left|g_{ij} - n_{ij}\right|\right) * 100\% \qquad (4)$$

where $Accuracy_i$ represents the classification accuracy at the lumbar disc level i where $1 \le i \le 6$, the value K represents the number of cases in every experiment, g_{ij} is the ground truth binary assignment for disc i, and n_{ij} is the resulting binary assignment for disc i from the inference on our model. The binary variables g_i and n_i are assigned binary values the same way where they take the value 1 for normal and 2 for abnormal.

Set	E6	E5	E4	E3	E2	E1	Accuracy
1	27	25	27	29	29	28	91.7%
2	26	26	29	29	28	28	92.2%
3	26	26	27	27	26	26	87.8%
4	28	25	26	27	29	29	91.1%
5	27	27	29	28	27	27	91.7%
6	25	26	26	27	29	28	89.4%
7	25	27	28	26	28	29	90.6%
8	28	28	27	28	29	28	93.3%
9	27	26	28	27	29	29	92.2%
10	27	28	28	28	28	28	92.8%
%	88	88	91	92	94	93	-
Average Accuracy							91.3%

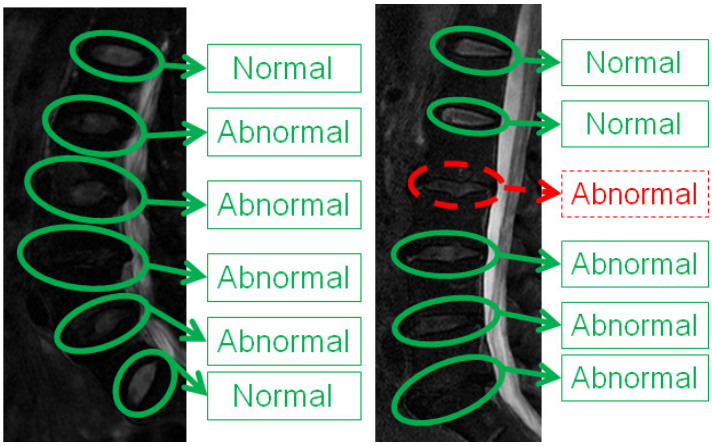


Fig. 2. (a) (Left) successful classification for all discs. (b) (Right) False negative disc at L2-L3 (dotted).

Incorporating a shape model might enhance our detection accuracy. For example, the misclassified disc at level L2–L3 appears more compact in shape than the other normal discs in the same case.

Conclusion: We achieve over 91% abnormality detection accuracy using our proposed model that incorporates disc appearance, location, and context. Our proposed model is extensible for subsequent diagnosis tasks specific to each intervertebral disc abnormality such as desiccation, stenosis, and herniation.

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