Abnormality Diagnosis of Musculoskeletal Radiographs Combined with Shallow Texture Features

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Abstract. In this paper, a new algorithm for anomaly classification combined with shallow texture features is proposed for radioactive musculoskeletal images. The classification algorithm consists of three steps. The radioactive image is first preprocessed to enhance image quality. The local binary pattern (LBP) features of the image are then extracted and merged. Finally, the merged dataset is sent to the DenseNet169 convolutional neural network to determine whether it is abnormal. The method presented in this paper achieved an accuracy of 79.64% on the musculoskeletal radiographs (MURA) dataset, which is superior to the method that does not combine texture features. The experimental results show that the shallow texture features of the combined image can more fully describe the difference between the lesion area and the non-focal area in the image and the difference between different lesion properties.

Keywords: Local binary pattern (LBP) · Musculoskeletal radiographs (MURA) · DenseNet

1 Introduction

Work-related musculoskeletal disorder (WMSDs) refers to systemic muscle, bone, and nervous system disorders caused by occupational factors. During the work process, the musculoskeletal system needs to bear the ergonomic load such as posture load and strength load, because the operator needs to maintain repetitive movements or a compulsory position to carry or lift heavy objects. And, the musculoskeletal system of the limbs is damaged, and there are irritations such as acid, numbness, swelling, and pain [1]. More than 1.7 billion people worldwide are affected by musculoskeletal diseases, so it is important for the abnormal detection of musculoskeletal.

In recent years, deep learning has become a hot spot in the field of machine learning research. Image features extracted by deep convolutional neural networks (DCNN) have proven to be effective in image classification, segmentation, or retrieval applications. Based on its advantages in non-medical images, DCNN is beginning to be gradually applied to medical image classification and detection problems. For example, Spanhol proposed the use of DCNN to classify breast cancer pathology images [2]. Li proposed a DCNN-based pulmonary nodule classification system [3]; Roth proposed

an algorithm for developing a lymph node detection system using DCNN [4]. Based on the above successful experience of DCNN applied to medical images, we tried to use DCNN to classify radioactive musculoskeletal. However, the images currently used to train the DCNN model have the following drawbacks:

1. The quality of the training images is not high.
2. For radioactive image datasets, DCNN does not extract its texture features very well.

Therefore, this paper proposes to preprocess the image to improve the image quality, then fuse the shallow texture features and then send them into the Densnet169 network for classification, and compare the classification effects without using the shallow texture features.

2 Musculoskeletal Abnormality Diagnosis Based on Densenet

The method proposed in this paper is shown in Fig. 1 including image preprocessing, image fusion, and training depth neural network.
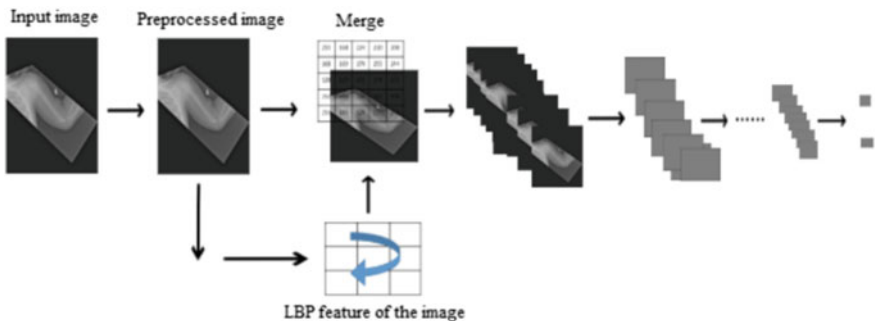
Fig. 1. The structure of the algorithm

2.1 Preprocessing

Histogram equalization is a method of enhancing image contrast (image contrast). In experiments, we used contrast limited adaptive histogram equalization (CLAHE) [5] for image enhancement. The histogram value of the CLAHE method is:

$$\text{Hist}'(i) = \begin{cases} \text{Hist}(i) + L & \text{Hist}(i) < T \\ H_{\max} & \text{Hist}(i) \geq T \end{cases}$$

where Hist(i) is the derivative of the cumulative distribution function of the sliding window local histogram, and H_{max} is the maximum height of the histogram. We cut off the histogram from the threshold T and then evenly distribute the truncated portion over the entire grayscale range to ensure that the total histogram area is constant, so that the entire histogram rises by a height L. The preprocessed image is shown in Fig. 2.

Fig. 2. The original image on the left and the preprocessed image on the right

2.2   DenseNet Neural Networks

In the field of imagery, deep learning has become a mainstream method. We chose DenseNet [6] as our model because it has better performance than ResNet in the case of less parameter and computational cost.

DenseNet's structure is to interconnect all layers, specifically each layer will accept all of its previous layers as its additional input, as shown in Fig. 3, and DenseNet directly merges feature maps from different layers, which can be achieved feature reuse to improve efficiency. We experimented with the DenseNet 169 layer network structure, adjusting the number of neurons in the last layer to 2.
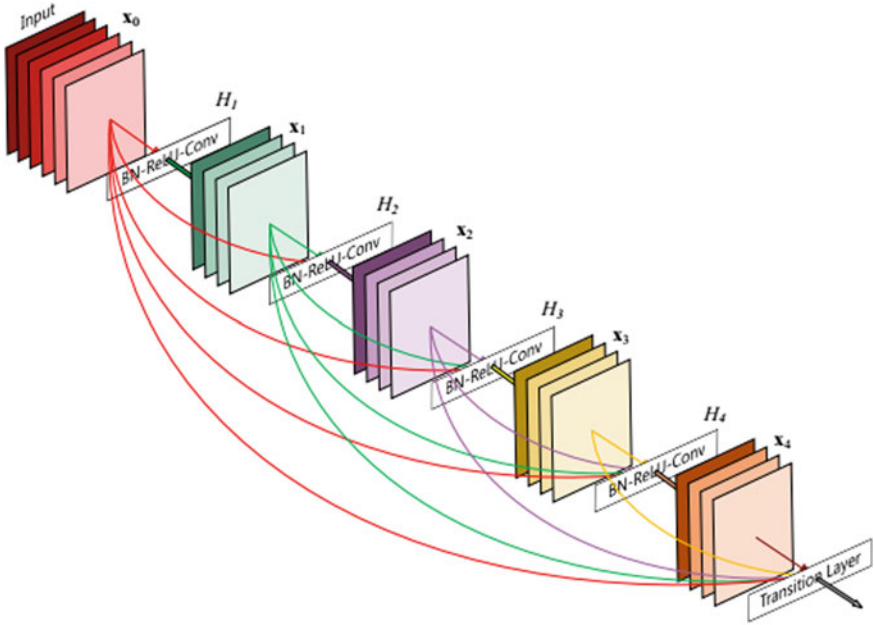
Fig. 3. DenseNet structure

2.3 Merge Texture Features

Deep neural network can directly classify images, but it does not use the underlying features of images. Considering that there are a large number of underlying features such as texture in medical images, this paper integrates the original image and texture features and then sends them into the deep neural network for classification.

2.3.1 Extract the LBP Texture Features of the Image

The local binary mode is a texture metric in the gray range. In order to improve the limitations of the original LBP, it is impossible to extract the texture features of large-size structures. Ojala et al. [7] modified the LBP to obtain the LBP value that uniquely represents the local texture features:

$$\text{LBP}_{P,R} = \sum_{i=0}^{P-1} s(g_i - g_c)2^i \tag{1}$$

where $S(\cdot)$ is defined as:

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{2}$$

2.3.2   Merging LBP Features

Performing mean variance normalization on the grayscale image and the corresponding LBP feature image, and then combining the grayscale image with the LBP image in the channel dimension, for example, the shape of the grayscale image is (h, w), the shape of the LBP image Also (h, w), the combined shape is (h, w, 2).

3   The Experiment

3.1   Experimental Dataset

MURA is a dataset of musculoskeletal radiographs, which contains a total of 14,863 studies of 12,173 patients and 40,561 multiview radiographs. Each was one of seven types of standard upper extremity radiology studies: fingers, elbows, forearms, hands, humerus, shoulders, and wrists [8].

MURA contains 9045 normal and 5818 abnormal musculoskeletal radiographic studies as shown in Table 1.

Table 1. Composition of the MURA dataset

Study	Train		Validation		Total
	Normal	Abnormal	Normal	Abnormal	
Elbow	1094	660	92	66	1912
Finger	1280	655	92	83	2110
Hand	1497	521	101	66	2185
Humerus	321	271	68	67	727
Forearm	590	287	69	64	1010
Shoulder	1364	1457	99	95	3015
Wrist	2134	1326	140	97	3697
Total No. of studies	8280	5177	661	538	14,656

3.2   The Experiment

We trained a 169 layer convolutional neural network to diagnose musculoskeletal abnormalities.

3.2.1   Parameter Settings

During training, we resize the image to 320×320, and we use a random horizontal flip and a random rotation of 30° for augmentation. All parameters of the network are randomly initialized. The optimizer chooses Adam, where β_1 is equal to 0.9 and β_2 is equal to 0.999. We trained the model using minibatches of size 16. The initial learning rate is chosen to be 0.00625. When iterating to the 60th and 80th, the learning rate is attenuated 10 times.

3.2.2 The Experimental Setup

To demonstrate the effectiveness of our proposed method, we conducted three sets of experiments:

- Experiment 1: Training with grayscale image
- Experiment 2: Training with grayscale + lbp (radius 1, sampling 8 points)
- Experiment 3: Training with grayscale + lbp (radius 2, sampling 8 points).

3.3 The Experimental Results

The performance of the experimental results on the validation set is shown in Fig. 4. We can see that combining LBP features when the model converges is better than using only grayscale images, which proves the effectiveness of the proposed fusion method between gray images and shallow texture features.
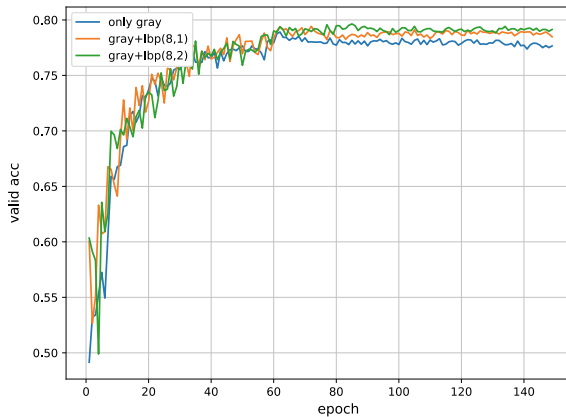
Fig. 4. The performance of the three experiments on the validation set

Table 2 shows the highest precision achieved in the validation set for Experiment 1, Experiment 2, and Experiment 3.

Table 2. The highest precision achieved by the three experiments on the validation set

Model	Only gray	Gray + LBP (8, 1)	Gray + LBP (8, 2)
Val_acc (%)	78.91	79.42	79.64

4   Conclusion

In this paper, a new classification algorithm based on deep convolutional neural network is proposed for radioactive musculoskeletal images. Adaptive histogram equalization with limited contrast was used to improve the training image quality, and the image texture features were merged and sent to DenseNet169 for training and classification. Experimental analysis shows that the proposed algorithm can effectively improve the classification accuracy of radioactive musculoskeletal images.

Further work in this paper is to continue to optimize the algorithm and expand the dataset to train a new depth neural network sensitive to radioactive musculoskeletal images.

References

1. Qin D, Wang S, Zhang Z, He L (2017) Advances in research on discrimination criteria for work-related musculoskeletal disorders. Chin Occupational Med (3)
2. Spanhol FA, Oliveira LS, Petitjean C, Heutte L (2016) Breast cancer histopathological image classification using convolutional neural networks. In: International joint conference on neural networks, IEEE
3. Wei L, Peng C, Dazhe Z, Junbo W (2016) Pulmonary nodule classification with deep convolutional neural networks on computed tomography images. Comput Math Methods Med 2016:1–7
4. Roth HR, Lu L, Seff A, Cherry KM, Hoffman J, Wang S et al (2014) A new 2.5 D representation for lymph node detection using random sets of deep convolutional neural network observations. Med Image Comput Comput Assist Interv
5. Pizer S (1987) Adaptive histogram equalization and its variations. Comput Vis Image Process 39(3):355–368
6. Huang G, Liu Z, Laurens VDM, Weinberger KQ (2016) Densely connected convolutional networks
7. Ojala T, Pietikäinen M, Mäenpää T (2002) Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal & Mach Intell
8. Rajpurkar P, Irvin J, Bagul A, Ding D, Duan T, Mehta H et al (2017) Mura: large dataset for abnormality detection in musculoskeletal radiographs