Computerized Classification of Pneumoconiosis on Digital Chest Radiography Artificial Neural Network with Three Stages

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Abstract It is difficult for radiologists to classify pneumoconiosis from category 0 to category 3 on chest radiographs. Therefore, we have developed a computer-aided diagnosis (CAD) system based on a three-stage artificial neural network (ANN) method for classification based on four texture features. The image database consists of 36 chest radiographs classified as category 0 to category 3. Regions of interest (ROIs) with a matrix size of 32×32 were selected from chest radiographs. We obtained a gray-level histogram, histogram of gray-level difference, gray-level run-length matrix (GLRLM) feature image, and gray-level co-occurrence matrix (GLCOM) feature image in each ROI. For ROI-based classification, the first ANN was trained with each texture feature. Next, the second ANN was trained with output patterns obtained from the first ANN. Finally, we obtained a case-based classification for distinguishing among four categories with the third ANN method. We determined the performance of

the third ANN by receiver operating characteristic (ROC) analysis. The areas under the ROC curve (AUC) of the highest category (severe pneumoconiosis) case and the lowest category (early pneumoconiosis) case were 0.89 ± 0.09 and 0.84 ± 0.12 , respectively. The three-stage ANN with four texture features showed the highest performance for classification among the four categories. Our CAD system would be useful for assisting radiologists in classification of pneumoconiosis from category 0 to category 3.

Keywords Computer-aided diagnosis (CAD) · Chest radiography · Artificial neural network · Pneumoconiosis · Texture feature

Introduction

Workers in the shipbuilding and metal goods manufacturing industry who inhale silica and/or coal dust are at an increased risk of developing pneumoconiosis. Therefore, they routinely undergo lung function tests and chest radiography. Specifically, according to the guidelines of the International Labor Organization (ILO) and the Ministry of Labor, Japan, radiologists subjectively classify radiolucencies on standard chest radiographs according to profusion, shape, and size [1–3]. Category 0 (normal case) refers to the absence of small opacities or the presence of small opacities that are less profuse than those in category 1 [2]. Profusion is determined by comparison with standard radiographs and recorded as one of the following categories: 0, 1, 2, or 3 [2]. However, it is difficult for radiologists to classify pneumoconiosis with small and irregular opacities [4]. Therefore, a number of researchers have developed computer-aided diagnosis (CAD) schemes for detecting pneumoconiosis on chest radiographs to assist radiologists as a “second opinion” in image interpretation.

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Table 1 Number of cases in the digital image database developed by the Ministry of Labor and ILO

Name of digital image database	Category 0	Category 1	Category 2	Category 3
The Ministry of Labor	7 cases	15 cases	10 cases	6 cases
The International Labor Organization	2 cases	5 cases	5 cases	5 cases
Total number of cases	9 cases	20 cases	15 cases	11 cases

Such CAD systems for detection of interstitial lung disease and pneumoconiosis on chest radiographs apply root mean square (RMS) variation, texture analysis based on the Fourier transform, geometric pattern feature analysis methods, and artificial neural network (ANN) methods [5–17]. Yu et al. segmented the lung field with pneumoconiosis using feature extraction based on the multi-scale difference filtering histogram and the gray-level co-occurrence matrix (GLCOM) [15]. Zhu et al. segmented the lung field using the combining Otsu's threshold method with morphological reconstruction followed by subdivision into six regions [16]. They developed a computerized scheme for classification between normal and abnormal regions with 22 wavelet-based energy texture features and a support vector machine (SVM) [16].

CAD systems for detection of diffuse lung disease on computed tomography (CT) images applied a gray-level run-length matrix (GLRLM), GLCOM, and a multi-scale filter bank [18–21]. Uchiyama et al. attempted to determine six physical measures with the mean and standard deviation of the CT value, air density components, nodular components, line components, and multi-locular

components [20]. Wang et al. developed an automated method with new texture features determined from GLRLM [21].

Many researchers have applied the ANN in classification of normal and abnormal or malignant and benign lesions on chest radiographs and CT images [22–26]. In addition, the ANN has been applied in differential diagnosis of interstitial lung diseases on chest radiographs [27] and CT images [28], hepatic masses on CT images [29], and hepatic fibrosis on magnetic resonance (MR) images [30]. Ashizawa et al. selected 11 interstitial lung diseases based on 10 clinical parameters (age, sex, duration of symptoms, temperature, etc.) and 16 radiological findings (distribution of infiltrates, characteristics of infiltrates, etc.) extracted by chest radiologists [27]. Fukushima et al. selected 10 clinical parameters and 23 CT features (extent of lesion, distribution of lesion, characteristics of lesion, nodular opacity, decreased lung opacity, etc.) extracted on chest CT images [28]. They developed the ANN for the differential diagnosis of 11 diffuse lung diseases (sarcoidosis, diffuse panbronchiolitis, non-specific interstitial pneumonia, lymphangitic carcinomatosis, interstitial pneumonia, etc.) on chest radiographs and CT images [27, 28].

Fig. 1 Architecture of the computerized classification method using three-stage ANN

Table 2 Number of ROIs per case defined as category 0 to category 3

The Ministry of Labor			
Category	No. of cases	Number of ROIs	
		Abnormal ROI	Normal ROI
Category 0	No. 1	0	48
	No. 2	0	75
	No. 3	0	47
	No. 4	0	99
	No. 5	0	128
	No. 6	0	98
	No. 7	0	19
Category 1	No. 1	6	90
	No. 2	17	141
	No. 3	135	40
	No. 4	21	44
	No. 5	113	50
	No. 6	207	40
	No. 7	202	44
	No. 8	218	36
	No. 9	244	23
	No. 10	242	3
	No. 11	138	30
	No. 12	478	4
	No. 13	312	0
	No. 14	418	104
	No. 15	77	23
Category 2	No. 1	303	24
	No. 2	333	20
	No. 3	169	39
	No. 4	416	18
	No. 5	713	0
	No. 6	1175	0
	No. 7	353	53
	No. 8	300	0
	No. 9	153	0
	No. 10	162	0
Category 3	No. 1	475	0
	No. 2	213	43
	No. 3	330	34
	No. 4	895	0
	No. 5	332	0
	No. 6	1266	0

The International Labor Organization

Category	No. of cases	Number of ROIs	
		Abnormal ROI	Normal ROI
Category 0	No. 1	0	101
	No. 2	0	96
Category 1	No. 1	240	21
	No. 2	324	22
	No. 3	96	33
	No. 4	255	30

Table 2 (continued)

Category 2	No. 5	31	96
	No. 1	302	61
	No. 2	346	0
	No. 3	316	27
	No. 4	215	14
Category 3	No. 5	219	16
	No. 1	356	23
	No. 2	341	24
	No. 3	481	0
	No. 4	495	0
	No. 5	289	0

For classification of two cases, such as normal vs. abnormal or malignant vs. benign lesions, ANN consisted of a number of input units and one output unit. We developed a CAD system to distinguish between normal (category 0) and abnormal (category 1, 2, or 3) regions of interest (ROIs) in pneumoconiosis using the ANN trained with the power spectrum (PS) values [31]. In addition, we developed a rule-based plus ANN method to distinguish between normal and abnormal ROIs using the window function, top-hat transformation, and GLCOM analysis [32]. The areas under the receiver operating characteristic (ROC) curves for category 3 (severe pneumoconiosis) and category 1 (early pneumoconiosis) were 0.93 ± 0.02 and 0.72 ± 0.03 , respectively [32].

Many groups have reported computerized schemes for higher classification between normal and abnormal regions on chest radiographs and CT images. However, because the diagnosis influences the recognition of the workers' handicap, it is necessary for the radiologist to correctly classify pneumoconiosis from category 1 (early pneumoconiosis) to category 3 (severe pneumoconiosis). In addition, ANNs have been useful for classification of a number of cases, such as the differential diagnosis of interstitial lung, hepatic masses, and hepatic fibrosis

Fig. 2 Gray-level histograms from four categories on 4-bit gray level

Fig. 3 Histograms of gray-level differences from four categories on 5-bit gray level

[27–30]. There have been no studies regarding the classification performance among four categories of pneumoconiosis with ANN. Therefore, we have developed a new

Fig. 5 PS values on the principal axis of the GLRLM feature image

CAD system based on a three-stage ANN with four texture features for case-based classification among four categories of pneumoconiosis on chest radiographs. We also investigated the effects of ROI-based classification with

Fig. 4 GLRLM feature image and PS obtained by Fourier transform of the GLRLM feature images for four categories (a–d). Trend-corrected images among the four categories (e–h). GLRLM feature images

among the four categories (i–l). PS images of the GLRLM feature images among the four categories

various parameters on four texture features with the first ANN.

Materials and Methods

Materials

As shown in Table 1, we used 38 posteroanterior (PA) chest radiographs developed by the Ministry of Labor. These included three normal cases, five cases of silicosis (category 1: three cases, category 2: one case, category 3: one case), five cases of asbestosis (category 1: two cases, category 2: two cases, category 3: one case), six cases of other pneumoconiosis (category 1: four cases, category 2: one case, category 3: one case), four cases of category 0 (normal case), six cases of category 1, six cases of category 2, and three cases of category 3 with pneumoconiosis [3, 33]. In addition, we used 17 PA chest radiographs developed by ILO. These included two cases of category 0 (normal case), five cases of category 1, five cases of category 2, and five cases of category 3 with pneumoconiosis [2]. The small opacities were classified into four categories, ranging from a completely normal case (category 0) to severe pneumoconiosis (category 3) [2]. These

Fig. 7 PS values on the principal axis of the GLCOM feature image

images were digitized with a pixel size of 0.175 mm, matrix sizes of 2468×2034 and 2034×2034 , and 12-bit gray level.

Overall Scheme of Pneumoconiosis Classification with Four Categories

Figure 1 shows the overall scheme of the classification with four texture features. An experienced radiological technologist manually selected approximately 100–1200

Fig. 6 GLCOM feature images and PS obtained by Fourier transform of the GLCOM feature images for the four categories (a–d). Trend-corrected images obtained from category 0 to category 3 (e–h). GLCOM feature

images among the four categories (i–l). PS image of the GLCOM feature images among the four categories

ROIs on the lung with a matrix size of 32×32 in the intercostal spaces and over rib spaces for each chest radiograph [5]. We eliminated overlap with ROIs. Table 2 shows the number of ROIs selected for each case. We obtained a background trend in all selected ROIs using a two-dimensional surface-fitting technique based on the least squares method [5]. After the number of gray levels in these ROIs was reduced by quantization level, we then obtained gray-level histograms, histograms of gray-level differences, GLRLM feature images, and GLCOM feature images. The first ANN was trained with each texture feature for the ROI-based classification of patterns among the four categories. Next, the second ANN was trained with combined patterns including output values obtained from the first ANN with each texture feature. Finally, we obtained the case-based classification performed for distinguishing among the four categories with the third ANN.

Four Texture Features

First, the gray-level histogram was applied to the trend-corrected images quantized to the 4-bit gray level. Compared with the images in category 3, the frequencies of pixel values 6 and 7 were higher for the images in the other categories (Fig. 2). The histogram of gray-level differences indicated the frequency of the difference of gray levels i and j at a specified distance d and specified direction θ . The histogram of the gray-level difference (distance level: 7 pixels and direction: 0°) was applied to the trend-corrected images quantized to the 5-bit gray level. Compared with category 3, the frequencies of the other categories were higher in the 0-pixel value (Fig. 3). The

effects of the number of gray levels and the distance levels on the gray-level histograms and histograms of gray-level differences in the ROI-based classification among the four categories will be discussed later.

A gray-level run-length was defined as a set of consecutive pixels of the same gray level in a given direction [21]. An element of a GLRLM measures the number of occurrences of a run with a specific gray level in a given direction [21]. In this study, the GLRLM feature images (direction: 0°) were applied to the trend-corrected images quantized to the 6-bit gray level (Fig. 4e–h). The horizontal and vertical directions of the GLRLM feature images were composed of the length of runs and the number of gray levels, respectively (Fig. 4e–h). These four categories showed quite different values in some parts of the GLRLM feature images. For example, as the profusion of small opacities was concentrated from category 0 to category 3, the GLRLM feature images for category 0 showed many long runs at the lower pixel values (Fig. 4e), whereas the GLRLM feature images for category 3 showed many short runs at the highest pixel values (Fig. 4h). We then determined the power spectrum (PS) images in these GLRLM feature images by fast Fourier transform (Fig. 4i–l). We used only PS values on the principal and secondary axes, which represent the maximum and next maximum PS values on the radial line from the central point, respectively [31, 32]. We used the PS values on the positive main and second axes representing spatial frequency, because they were symmetric with respect to the center of the PS image (Fig. 5) [31, 32]. Compared with category 3, the PS values of the other categories were lower at all spatial frequencies on the principal and secondary axes. The effects of the number of gray levels

Fig. 8 Architecture of training for the first ANN with gray-level histogram to classify the categories

on the GLRLM feature images on the ROI-based classification among the four categories will be discussed later.

An element at location (i, j) of the GLCOM showed that the joint probability density function indicated the possibility of gray level between the i pixel and the j pixel in a specified direction θ and a specified distance d [15]. In the same manner as for the GLRLM feature images, the GLCOM feature images (distance level: 3 pixels and direction: 45° , 225°) were applied to the trend-corrected images quantized to the 6-bit gray level (Fig. 6e–h). The horizontal and vertical directions of the GLCOM feature images were composed of the number of gray levels [32]. We calculated PS images by Fourier transform (Fig. 6i–l) and obtained only the PS values on the principal and secondary axes (Fig. 7) [32]. The PS values for each category were different at spatial frequencies of 0.5–1.5 on the principal and secondary axes. The effects of the

distance levels on the GLCOM feature images on ROI-based classification among the four categories will be discussed later.

First ANN with Four Texture Features

We used a feedforward ANN with a back propagation algorithm. On the first ANN for gray-level histograms, the ANN was composed of three layers consisting of input, hidden, and output layers. The ANN was composed of 16 input units, 9 hidden units, and 4 output units (Fig. 8). We used a total of 16 pieces (normalized frequency from 0 to 15 pixel values) on gray-level histograms as the input data (Fig. 2). The ANN was trained for the classification results (truth category = 0.9, other category = 0.1) [24]. In testing of ANN, when the output value was highest on the output unit of the truth category,

Fig. 9 Output values obtained from the first ANN for four texture features

the input data obtained from the ROI were considered as a truth category [24]. The first ANN for other texture features was composed of the same structure as the first ANN for gray-level histograms. As in the case of the first ANN for gray-level histograms, we used a total of 32 pieces (normalized frequency among ± 16 pixel values), 32 pieces (16 normalized PS values for each of the principal and secondary axes), and 64 pieces (32 normalized PS values for each of the principal and secondary axes) as input data on the first ANN in the histogram of gray-level differences (Fig. 3), the GLRLM feature images (Fig. 5), and the GLCOM feature images (Fig. 7), respectively.

Second ANN Combined with Four Texture Features

Figure 9 shows the output values obtained from the first ANN for each texture feature. On the output unit of category 0 (no. 0) on the gray-level histogram, the output value of category 0 was the highest of all categories (Fig. 9a). In addition, on the output unit of category 3 (no. 3) on the gray-level histogram, the output value of category 3 was the highest of all categories

(Fig. 9a). Therefore, the second ANN was trained with output patterns obtained from the first ANN for each texture feature (Fig. 10). The second ANN was composed of 16 input units, 9 hidden units, and 4 output units. The input data consisted of a total of 16 pieces (four output values obtained from the first ANN with four texture features). In the same manner as the first ANN, the ANN was trained for the classification results (truth category = 0.9, other category = 0.1) [24].

Third ANN

Figure 11 shows histograms of output values obtained from the second ANN for each case with four categories. Compared with the other categories, the histogram of category 1 was globally shifted to the right (Fig. 11b). In addition, the histogram of category 2 was globally shifted to the right (Fig. 11c). Therefore, for input data on the third ANN, we used a histogram of the output values obtained from the second ANN for each case (Fig. 12). The third ANN was composed of 40 input units, 21 hidden units, and 4 output units. Input data consisted of a total of 40 pieces (10 input values correspond to the 10

Fig. 10 Architecture of second ANN method for classification of pneumoconiosis category

Fig. 11 Histograms of the output values obtained from the second ANN for each case with (a) category 0, (b) category 1, (c) category 2, and (d) category 3

frequency values at 10 bins, from 0–0.1 to 0.9–1.0 [11]. In the same manner as the first and second ANN, the ANN was trained for the classification results (truth category = 0.9, other category = 0.1) [24].

Evaluation of Classification Performance

To investigate the effects of the number of gray levels and the distance level on each texture feature, we randomly divided the data into training data (category 0: 814 ROIs; category 1: 529 ROIs; category 2: 449 ROIs; and category 3: 544 ROIs) and non-training data (category 0: 813 ROIs; category 1: 528 ROIs; category 2: 449 ROIs; and category 3: 544 ROIs). We obtained averages of the ROC curves derived with the ten different pairs of non-training data sets. In addition, we calculated the statistical significance of differences between

ROC curves using the two-tailed paired t test with each non-training data set. As shown in the Fig. 13, in the case of the ROC curve in category 3, the output values of “category 3” on a certain texture feature were regarded as “true positives,” the output values of the “other category” on a certain texture feature were regarded as “true negatives” [28]. We obtained the area under the ROC curve (AUC) on each category in this manner [28].

For evaluation of the classification performance with the third ANN method, the original database (category 0: 9 cases; category 1: 20 cases; category 2: 15 cases; and category 3: 11 cases) was divided randomly into training data and non-training data for each category. We obtained the case-based averages of the ROC curves derived with the ten different pairs of non-training data sets.

Fig. 12 Architecture of third ANN method for classification of pneumoconiosis category

Results and Discussion

Effects of the Number of Gray Levels and the Distance Level of Texture Features

Figure 14 shows the effects of the number of gray levels and distance level on (a) the gray-level histogram, (b) the gray-level difference, (c) the GLRLM feature image, and (d) the GLCOM feature image in the first ANN. As shown in Fig. 14a, the classification performance with the gray-level

histogram of the 4-bit gray level was greater than with the previous method ($P < 0.05$). As shown in Fig. 14b, the classification performance with the histogram of the gray-level difference (distance level: 7 pixels) was larger than with the previous method ($P < 0.05$). As shown in Fig. 14c, the classification performance with the GLRLM feature image on the 5-bit gray level was larger than with the previous method ($P < 0.05$). Finally, as shown in Fig. 14d, the classification performance with the GLCOM feature image (distance level: 3 pixels) was larger than with the previous method ($P < 0.05$).

Fig. 13 Classification method of four categories on ROC analysis

Fig. 14 Effects of the number of gray levels and distance level on (a) gray-level histogram, (b) gray-level difference, (c) GLRLM feature image, and (d) GLCOM feature image in the first ANN

With regard to the effect of the gray level, as the number of gray levels increased, the pixel values were spread and ungraded, and the texture features were decreased among the four categories [7]. On the other hand, as the gray level decreased, the pixel values were focused on some pixel value: these texture features were increased among the four categories [7]. With regard to the effect of the distance level, for segmentation of the lung in severe interstitial lung disease and for detection of diffuse lung disease on chest CT images, the distance level of GLCOM ranged from 0.50 to 0.89 mm [21, 31]. Therefore, we selected the gray-level histogram of the 4-bit gray level, the histogram of the gray-level difference on the 5-bit gray level and 7-pixel (1.23 mm) distance level, the GLRLM feature image on the 5-bit gray level, and the GLCOM feature image on the 6-bit gray level and 3-pixel (0.53 mm) distance level.

Classification Performance By Overall Scheme

Figure 15 shows the ROC curves for (a) category 0, (b) category 1, (c) category 2, and (d) category 3 in the third ANN. Table 3 shows the AUC and specificity per case at 90% sensitivity obtained with the classification method using the third ANN for category 0, category 1, category 2, and category 3. On the non-training data, the AUC value and specificity for category 0 were 0.78 ± 0.10 and $34.2 \pm 28.7\%$, respectively. The AUC value and specificity for category 1 were 0.73 ± 0.08 and $38.3 \pm 11.7\%$, respectively. The AUC value and specificity for category 2 were 0.79 ± 0.06 and $52.5 \pm 11.3\%$, respectively. The AUC value and specificity for category 3 were 0.85 ± 0.09 and $60.1 \pm 24.9\%$, respectively. The AUC values for category 0, category 1, category 2, and category 3 were 0.72 ± 0.04 , 0.59 ± 0.05 , 0.51 ± 0.06 , and

Fig. 15 ROC curve on (a) category 0, (b) category 1, (c) category 2, and (d) category 3 in the third ANN

0.56 ± 0.05 , respectively, on ROI-based performance with second ANN combined with the gray-level histograms, histograms of gray-level differences, GLRLM, and GLCOM feature images. However, use the histograms of output values

Table 3 AUC and specificity per case at 90% sensitivity for third ANN in classifying among the four categories

	Training data		Non-training data	
	AUC	Specificity	AUC	Specificity
Category 0	0.94 ± 0.05	$80.7 \pm 20.2\%$	0.78 ± 0.10	$34.2 \pm 28.7\%$
Category 1	0.96 ± 0.02	$89.5 \pm 8.32\%$	0.73 ± 0.08	$38.2 \pm 11.7\%$
Category 2	0.94 ± 0.06	$88.4 \pm 14.2\%$	0.79 ± 0.06	$52.5 \pm 11.3\%$
Category 3	0.95 ± 0.03	$90.3 \pm 6.88\%$	0.85 ± 0.09	$60.1 \pm 24.9\%$

obtained from the second ANN for each case suggested that the case performance with the third ANN was increased.

In a database including 300 normal and 125 pneumoconiosis cases (category 1, category 2, and category 3), Yu et al. reported that AUC value, sensitivity, and specificity were 0.978, 92.0, and 87.7%, respectively [15]. In addition, in a database including 85 normal and 40 pneumoconiosis cases (category 1 and category 2), Zhu et al. reported that AUC value, accuracy, sensitivity, and specificity were 0.974 ± 0.018 and 0.929 ± 0.018 , 0.957 ± 0.021 , and 0.873 ± 0.024 , respectively [16]. However, the lower lung field of the right (AUC: 0.698) and left (AUC: 0.563) lungs that showed lower performance was not used [16]. Including our previous studies [31, 32], these CAD systems showed relatively high performance for detection of pneumoconiosis

on chest radiographs. However, as our study involved classification among the four categories with four texture features and ANN simultaneously, it was difficult to compare the performance of classification of a number of cases, such as in our study, with previous studies that involved classification between two cases, such as normal vs. abnormal.

In the case of ANN for classification of a number of cases, the performance of ANN for differential diagnosis of interstitial lung disease on chest radiographs and diffuse lung disease on HRCT showed AUC for ANN performance of 0.911 and 0.956, respectively [27, 28]. As these previous studies used patient information (sex, age, etc.) and patient interview information (incubation period for symptoms, etc.) instead of radiological findings determined by radiologists, we suggest that the performance of the ANN for differential diagnosis was higher than in our study.

Without analyzing and extracting features of the images, it was useful for recognizing images with a convolutional neural network (CNN). The CNN was used for classification of interstitial lung disease and lung nodules on chest CT images [34, 35]. The CNN required many training times for detection of specific texture features. The input data for first ANN consisted of 16, 32, 32, and 64 pieces on gray-level histograms (as shown in Fig. 2), histograms of gray-level differences (as shown in Fig. 3), GLRLM (as shown in Fig. 5), and GLCOM feature images (as shown in Fig. 7), respectively. Our computerized method was classified among the four categories with less training time than the CNN.

Wang et al. created five GLRLM features for detection of diffuse lung disease patterns based on new GLRLMs: (1) the number of short runs with relatively high CT values, (2) the number of long runs with relatively high CT values, (3) the number of short runs with low CT values, (4) the number of long runs with low CT values, and (5) the total number of runs [21]. These CAD systems for detection of pneumoconiosis and diffuse lung disease used a combination of GLRLM and GLCOM features [15, 21]. By obtaining different texture features from the gray-level histogram, the histogram of the gray-level difference, the PS values on GLRLM, and GLCOM feature images, wherever the texture patterns were placed within the ROI, were thought to obtain adequate texture features.

In the future, as training of the ANN depends on the number of cases and texture types on pneumoconiosis, for evaluating the clinical efficacy of this CAD system, we will obtain a comprehensive database including a wide distribution of patterns for each category.

Conclusion

We have developed a three-stage ANN method combined with gray-level histograms, histograms of gray-level differences, GLRLM feature images, and GLCOM feature images for classification among the four categories with

pneumoconiosis on chest radiography. Our computerized classification method will be useful in assisting radiologists in case-based classification of pneumoconiosis.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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