Comparison of Spine Curvature Images Classification using Support Vector Machine and K-Nearest Neighbors

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Abstract. The spine is one part of the human axial skeleton that serves as the body's primary support. Hence, the health of the spine must be considered. The most common spinal abnormality is scoliosis, with the shape of the spine forming the C and S letters. Along with technology development, spinal abnormalities can be identified using images from X-rays to be processed digitally to help health experts as a second opinion to carry out diagnostics of spinal disorders efficiently and accurately. This research was conducted by designing an image processing system for two spine types, normal and abnormal (i.e., scoliosis), by applying the Gray Level Co-occurrence Matrix (GLCM) feature extraction method and two classification methods: K-Nearest Neighbors (KNN) and Support Vector Machine (SVM). The design of this system aims to determine how effective the method is to classify the spine accuracy. The system accuracy in the KNN method reached 73% at a pixel distance of 100 and a quantization level of 16. For the SVM method, the system accuracy value of 90% was obtained at a pixel distance of 75 and a quantization level of 8. The SVM results achieved better than the KNN.

Keywords: Spine Curvature, X- Ray Images, Co-occurrence Matrix, KNN, SVM

INTRODUCTION

One of the most common spine abnormalities is scoliosis (the spine bends to the left or right). It can occur due to the wrong sleeping or sitting position, lack of calcium consumption, age, and genetic or hereditary factors. With the development of technology, especially in the medical field, image processing technology allows building a computer-based system for an automatic assessment process of images to efficiently obtain information or descriptions of an object contained in the image. Computer aided systems for biomedical images have been developed by many researchers due to the efficient and effective in term of time and accuracy. This system aided to minimize human errors in the crowded daily works.

Several related studies were used as references in conducting this research, such as Duong et al., who studied the automatic classification of spinal deformities using Support Vector Machines (SVM) [1]. Meanwhile, Birtane et al., in 2014, examined the detection of spinal abnormalities using image processing and enhancement technology and then proceeded to the classification process using the fuzzy method using the King-Moe approach. The results revealed that the fuzzy classifier achieved a success rate of 80% in the scoliosis model and 50% in X-Rays scoliosis [2]. In 2015, Kowalski et al. conducted an early detection of idiopathic scoliosis–analysis of three screening models [3]. Our previous studies about the classification of spine images employed the SVM for classification [4].

Studies have been conducted on an effective image retrieval scheme using color, texture, and shape features [5] and content-based image retrieval using color and texture fused features [6]. Some researchers have employed texture features to classify disease types from humans [7], [8], [9], [10], [11], [12]. One of which is the research on computer-extracted texture features to distinguish cerebral radionecrosis from recurrent brain tumors on

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Multiparametric Magnetic resonance imaging (MRI). Brain lesions on MRI were manually annotated by a neuroradiologist expert. A set of radiomic features was extracted for every lesion on each MRI sequence. Feature selection was applied to identify the top five most discriminating features for every MRI sequence on the cohort training. These features were then evaluated on the cohort test by an SVM classifier. On the cohort training, the area under the receiver operating characteristic curve became 0.79 [13].

Another study focused on differentiating brain metastases from different types of lung cancers using texture analysis of T1 Postcontrast MRI. Texture-based lesion classification was highly specific in differentiating brain metastases originated from different types of lung cancers, with misclassification rates of 3.1%, 4.3%, 5.8%, and 8.1%, respectively, for small cell lung carcinoma, squamous cell carcinoma, adenocarcinoma, and large cell lung carcinoma. The back-propagation artificial neural network (BP-ANN) model had a better predictive ability than the K-Nearest Neighbors (KNN) model. No texture feature could distinguish the four types of lung cancer [14].

In 2016, a study investigated the extracted magnetic resonance texture features to discriminate phenotypes associated with overall survival in glioblastoma multiforme patients. The study aimed to identify the three glioblastoma multiforme (GBM) phenotypes using a texture-based Gray-Level Co-occurrence Matrix (GLCM) approach and determine whether the texture features of phenotypes were related to patient survival. GBM phenotype discrimination based on texture features uncovered the best accuracy, sensitivity, and specificity of 79.31, 91.67, and 98.75 %, respectively. Among 22 features examined, three texture features could predict overall survival for GBM patients, demonstrating the utility of GLCM analyses in both the diagnosis and prognosis of this patient population [15]. Many other biomedical images are classified well by implementing GLCM to extract texture features [16], [17], [18], [19], [20].

Based on related research, the authors studied the design of a computer system to detect spine abnormalities, namely normal and abnormal spine (i.e., scoliosis), using the Gray Level Co-occurrence Matrix (GLCM) method to obtain feature extraction from the input images. Then, it utilized feature extraction data from the GLCM method as input for two classification methods (i.e. SVM and KNN). The two classification methods were employed to compare their performance in classifying spine images.

RESEARCH METHODS

The system design was carried using the GLCM feature extraction method to compare KNN and SVM classification methods in detecting spinal abnormalities. Figure 1 displays the block diagram of the system.

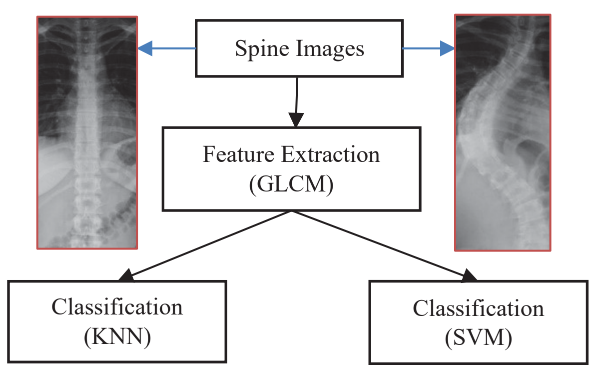

FIGURE 1. System block diagram.

Spine X-Ray Images

This study employed spinal image data from the Universiti Sains Malaysia Hospital [21]. The data obtained from the results of 40 x-ray images consisted of 20 normal spine images and 20 abnormal spine images. The data used in the testing were divided into four image datasets: dataset 1, dataset 2, dataset 3, and dataset 4. Each dataset consisted of two folders of training data and testing data with 75% training data, and 25% testing data. Hence, there were 30 images in the training data and 10 images in the testing data. The image data used were in grayscale and JPG format, with each image size of 200 x 500 pixels.

Feature Extraction

Feature extraction was a step carried out to obtain the uniqueness of each image used to distinguish one image from another during the classification process. This stage applied the pixel distance (d) as a parameter to determine the shift in the number of pixels taken in one GLCM calculation. The selection of a good pixel distance value was determined based on the pixel size of the images to be processed. The image size in this study was 200 x 500 pixels, divided into four and two parts to determine d values (i.e. 50 and 100). Furthermore, as a comparison of the d value, the median value of the two values was taken, namely 75. Therefore, there were three-pixel distance values: d=50, d=75, and d=100.

At this stage, GLCM also utilized quantization values to reduce the number of calculations to ease the process of computing the system. The quantization level changed the gray value (8-bit) of the image into a specific range of values determined according to system requirements. This spine abnormality detection system employed three different ranges of quantitation values of 8, 16, and 32. The output values of feature extraction (GLCM) taken in this study were contrast, correlation, energy, and homogeneity, with four correlation directions (angle) of 0º, 45º, 90º, 135º.

Classification

KNN is an instance-based learning group classification algorithm. It classifies new data by looking for groups of k objects in the training data closest to or similar to the new data or testing data. The KNN algorithm is included in the supervised learning algorithm, where the results of the query instance are classified based on the training data. The KNN algorithm works only based on the shortest distance from the query instance to the sample data, after that sorting the data with the shortest distance and then taking the closest K pieces of data. If the class is most commonly found in the KNN, the test data is included in that category. There are many ways to measure the distance between new data and old data (training data). The distance between query instance data and test data can be calculated using Euclidean distance presented by Eq. 1. Matrix D(a,b) is the scalar distance of both vectors a and b from a matrix with size d dimension.

$$D(a,b) = \sqrt{\sum_{k=1}^{d}(ak - bk)^2} \tag{1}$$

SVM has a strongest mathematical model for classification and regression. This powerful mathematical foundation gives a new direction for further research in the vast field of classification and regression. The calculation results of the feature extraction value processed in training are stored and will be processed later. SVM looks for the best hyperplane value from the training data, which will match the testing data. A study reviews the different computational model of SVM and survey on their applications for image classification [22].

RESULTS AND DISCUSSIONS

This stage presented results of two classification methods (i.e. KNN and SVM) to classify the spinal curvatures. To achieve the research goal, the results of the system accuracy was calculated. The accuracy of the spinal abnormality detection system using the KNN method at each distance and quantization value is presented in Table 1. The accuracy of the spinal abnormality detection system using the KNN method at each distance and quantization value is presented in Table 1 that:

- the highest accuracy value for a pixel distance of 50 is at the quantization value of 8, with an accuracy of 46%.
- the highest accuracy value for a pixel distance of 75 is at the quantization value of 16, with an accuracy of 72.50 %.
- the highest accuracy value for a pixel distance of 100 is at the quantization value of 16, with an accuracy of 73%.

Thus, the highest accuracy results obtained in testing the classification of spinal abnormalities using the KNN method are 73%, at a pixel distance of 100, and a quantization value of 16.

The accuracy of the spinal abnormality detection system using the SVM method at each distance and quantization is demonstrated in Table 2. Table 2 exhibits the overall accuracy data on the SVM classification method in each distance value and quantization value. It can be seen that:

- the highest accuracy value for a pixel distance of 50 is at the quantization value of 8, with an accuracy of 60%.

- the highest accuracy value for a pixel distance of 75 is at the quantization value of 8, with an accuracy of 90%.
- the highest accuracy value for a pixel distance of 100 is at the quantization value of 8, with an accuracy of 87.50%.

Therefore, the highest accuracy results obtained in testing the classification of spinal abnormalities with the SVM method are 90% at a pixel distance of 75 and a quantization value of 8.

TABLE 1. Accuracy value of the KNN method

d=50 n=8		**d=50 n=16**		**d=50 n=32**	
dataset 1	50%	dataset 1	50%	dataset 1	60%
dataset 2	30%	dataset 2	30%	dataset 2	30%
dataset 3	60%	dataset 3	50%	dataset 3	60%
dataset 4	50%	dataset 4	20%	dataset 4	30%
average	46%	average	38%	average	45%
d=75 n=8		**d=75 n=16**		**d=75 n=32**	
dataset 1	60%	dataset 1	90%	dataset 1	90%
dataset 2	60%	dataset 2	60%	dataset 2	60%
dataset 3	90%	dataset 3	80%	dataset 3	80%
dataset 4	50%	dataset 4	60%	dataset 4	50%
average	65%	average	72.50%	average	70%
d=100 n=8		**d=100 n=16**		**d=100 n=32**	
dataset 1	70%	dataset 1	70%	dataset 1	70%
dataset 2	70%	dataset 2	70%	dataset 2	70%
dataset 3	80%	dataset 3	80%	dataset 3	70%
dataset 4	50%	dataset 4	70%	dataset 4	60%
average	67.50%	average	73%	average	67.50%

TABLE 2. Accuracy value of the SVM method

d=50 n=8		**d=50 n=16**		**d=50 n=32**	
dataset 1	60%	dataset 1	70%	dataset 1	60%
dataset 2	60%	dataset 2	70%	dataset 2	60%
dataset 3	60%	dataset 3	60%	dataset 3	70%
dataset 4	60%	dataset 4	40%	dataset 4	40%
average	60%	average	60%	average	57.50%
d=75 n=8		**d=75 n=16**		**d=75 n=32**	
dataset 1	90%	dataset 1	80%	dataset 1	80%
dataset 2	100%	dataset 2	90%	dataset 2	90%
dataset 3	90%	dataset 3	90%	dataset 3	90%
dataset 4	80%	dataset 4	70%	dataset 4	70%
average	90%	average	82.50%	average	82.50%
d=100 n=8		**d=100 n=16**		**d=100 n=32**	
dataset 1	90%	dataset 1	90%	dataset 1	90%
dataset 2	90%	dataset 2	90%	dataset 2	90%
dataset 3	90%	dataset 3	90%	dataset 3	90%
dataset 4	80%	dataset 4	80%	dataset 4	80%
average	87.50%	average	88%	average	87.50%

Comparison of KNN and SVM Results

After testing the spine classification using the KNN and SVM methods, the system accuracy obtained between the two methods was compared. Table 3 demonstrates the comparison results.

TABLE 3. Comparison of KNN and SVM methods.

Method	Pixel Distance	Quantization	Accuracy
KNN	100	16	73%
SVM	75	8	90%

Table 3 displays the comparison of spine curvature classification based on the KNN and SVM methods. In the KNN method, the highest accuracy value is at a pixel distance of 100, with a quantization value of 16. Meanwhile, with a pixel distance of 75 and a quantization value of 8, the SVM method obtains a high accuracy value. In short, the SVM method can work better than the KNN method because it can classify well at small pixel distances and quantitative values. In contrast, the KNN method classifies with large pixel distances and quantization values. The highest accuracy value for a pixel distance of 50 is at the quantization value of 8, with an accuracy of 46%. The highest accuracy value for a pixel distance of 75 is at the quantization value of 16, with an accuracy of 72.50 %. The highest accuracy value for a pixel distance of 100 is at the quantization value of 16, with an accuracy of 73%. Thus, the highest accuracy results obtained in testing the classification of spinal abnormalities using the KNN method are 73%, at a pixel distance of 100, and a quantization value of 16. The result of SVM method is better than the KNN method that it can be obtained due to the texture features (i.e. contrast, correlation, energy, homogeneity) managed to find the best hyperplane value from the training data, which will match the testing data. Therefore, the classification performances is better than other technique.

CONCLUSION

Based on the results of the comparison study of spinal abnormalities detection systems with the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) methods, it can be concluded that the Gray Level Co-occurrence Matrix (GLCM) method could be used to determine characteristics of spine images with output in the form of four features: contrast, correlation, energy, and homogeneity, used as input for the classification stage. The KNN method could classify with an accuracy rate of 73% at a pixel distance of 100 and a quantization value of 16. In contrast, the SVM method could classify with an accuracy rate of 90% at a pixel distance of 75 and a quantization value of 8. Regarding the comparison between the two methods, the SVM obtained higher accuracy than the KNN. The SVM method could classify more quickly than the KNN method because, with a pixel distance of 75 and a quantization value of 8, the SVM obtained the highest accuracy.

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