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Classification of Lenke Scoliosis using GLCM Feature Extraction and Support Vector Machine

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Abstract Lenke scoliosis is a spinal deformity that is classified into six types by the Lenke classification system. Traditionally, clinicians undertake classification based on manual visual examination of X-ray images, which is time-consuming, requires high skill and is subject to errors caused by human fatigue. To overcome these constraints, the current work presents an automated and reliable classification system to boost the efficiency and accuracy of diagnosis. The method is based on the application of the Grey Level Co-occurrence Matrix (GLCM) for the feature extraction and of a Support Vector Machine (SVM) classifier. The main contribution is the optimisation of SVM kernel functions (Quadratic, Cubic and Coarse Gaussian) using advanced pre-processing methods to achieve very good accuracy while preserving compute efficiency suitable for clinical applications. The approach combines picture pre-processing (grey scale conversion, resize, contrast improvement by adaptive histogram equalisation, segmentation, augmentation) and GLCM-based feature extraction and classification using multiple SVM kernels. The model's performance is evaluated based on accuracy, precision, recall, F1 Score, and execution time. The testing results demonstrate that the Quadratic SVM has the best classification accuracy of 92.26% with a processing time of 20.44 seconds, which outperforms the Cubic SVM (90.97%, 19.30 seconds) and the Coarse Gaussian SVM (60.64%, 21.70 seconds). The results show that the quadratic SVM has the optimum compromise between accuracy and processing efficiency. In conclusion, the proposed GLCM-SVM approach has tremendous potential to support doctors in the automatic categorisation of Lenke scoliosis, improving the accuracy and speed of diagnosis without requiring large computational resources. In future work, we will aim to expand the dataset and include additional features to further improve the model's resilience and generalisability.

Keywords **Classification; Lenke scoliosis; GLCM; SVM**

I. Introduction

Adolescent idiopathic scoliosis (AIS) is a spinal condition with abnormalities of the coronal, sagittal, and axial planes and is defined as a coronal curvature >10° [1], [2]. This condition has been reported in persons between the ages of 10 and 18 years [3]. Abnormal lateral curvature indicates a spinal problem. Lenke's classification system is used to identify the characteristics of spinal curvature in patients with scoliosis [4], [5]. The Lenke classification identifies six types of curves (1-6) and lumbar spine modifiers (A, B, C) and sagittal modifiers (-, N, +) (-, N, +) [6]. There are 6 categories of the Lenke classification of scoliosis. Type 1 is a one-way curvature irregularity (main contour). Type 2 is distinguished by an abnormal angulation of two major curves, which are often opposite in direction (one lordotic and the other kyphotic). Type 3AN is a one-directional curvature deformity with some spinal rotation. Type 3BN is a unidirectional curvature deformity with moderate to extreme spinal rotation. Type 3CN represents a uniplanar deformity with significant spinal rotation. Type 4 is a curvature deformity in two or more directions with noticeable anomalies on both sides of the spine. Treatments for scoliosis, such as exercises or therapies like the Schroth technique, are meant to

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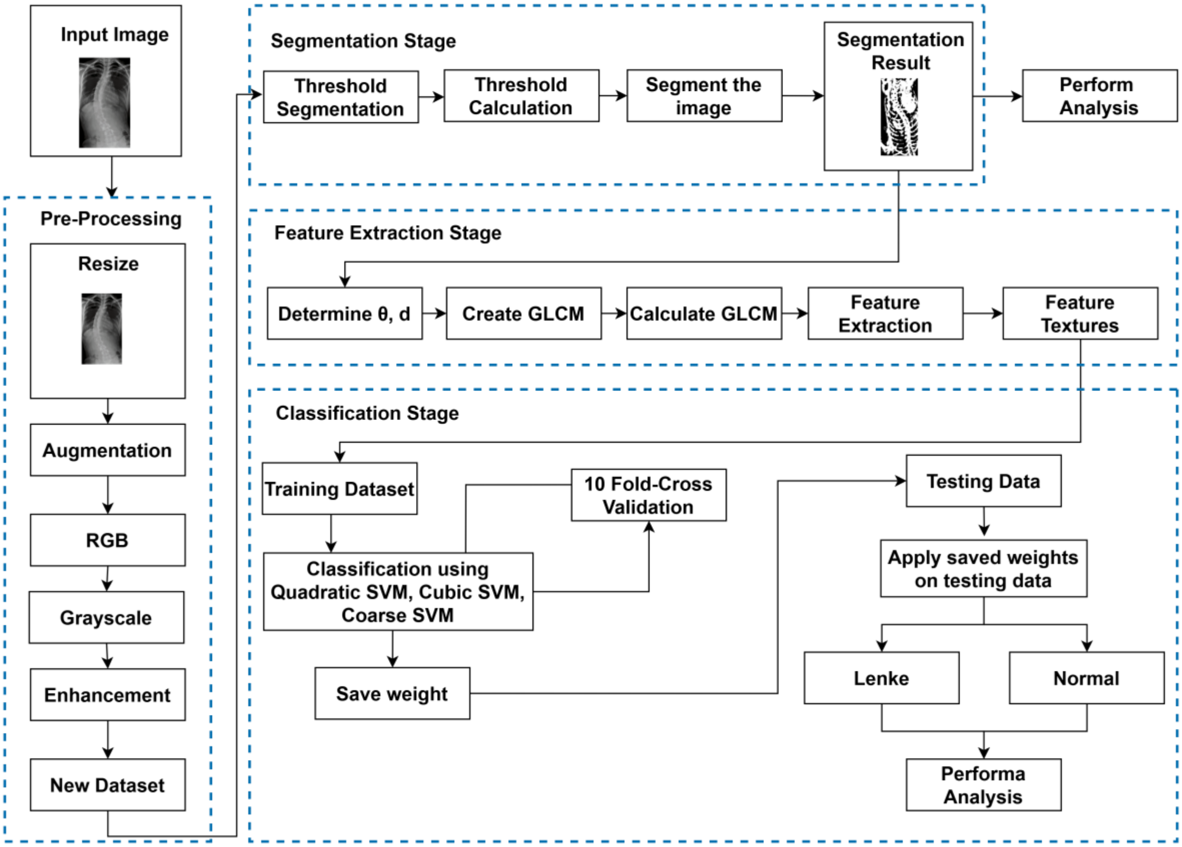

Fig. 1. Research Flowchart

change and move the spine to get a more "normal" physiological alignment. These techniques help improve posture, reduce curves, and promote spinal balance and stability [7], [8]. The development of automated scoliosis classification utilising machine learning techniques has been widely investigated [9], The texture features were extracted by the Gray-Level Co-occurrence Matrix (GLCM) technique. SVM has been successfully used to detect relevant texture patterns in medical images [10], and GLCM can extract unique texture features from X-ray images [11]. However, this strategy has several disadvantages, such as the relatively high computational cost, especially for large datasets, which may impact the efficiency of the method in clinical applications. In addition, different SVM kernel functions (Quadratic, Cubic, Coarse) lead to different classification results.

Other research has used other methodologies such as Convolutional Neural Network (CNN), deep learning and Random Forest, which show great accuracy when they are trained with huge data sets [12], [13], [14], [15]. However, these approaches are typically not interpretable and thus not ideal for clinical decision making, where transparency is necessary. Improving the accuracy of scoliosis classification has important implications for clinical practice, particularly for selecting appropriate treatment modalities [16]. An accurate automated categorisation system can reduce the errors in diagnosis, increase patient safety and assist in better treatment planning [17]. However, despite these advances, there is still a paucity of research that jointly addresses classification accuracy, computational efficiency and model interpretability in Lenke scoliosis classification [18], [19]. Existing approaches tend to focus either on achieving high accuracy or on reducing computational complexity, but rarely address both aspects in a balanced manner. Therefore, a more optimized method is needed to improve classification performance while maintaining efficiency and clinical applicability [20], [21]. The current methods tend to focus on either high accuracy or low computation. In this paper, a classification method for Lenke scoliosis is shown to solve this problem. Grey Level Co-occurrence Matrix (GLCM) is used for feature extraction and integrated with a Support Vector Machine (SVM) with multiple kernel functions: Quadratic, Cubic and Coarse Gaussian. Moreover, numerous preprocessing approaches are applied, such as greyscale conversion, scaling, contrast enhancement (adapthisteq), segmentation (thresholding), and image augmentation

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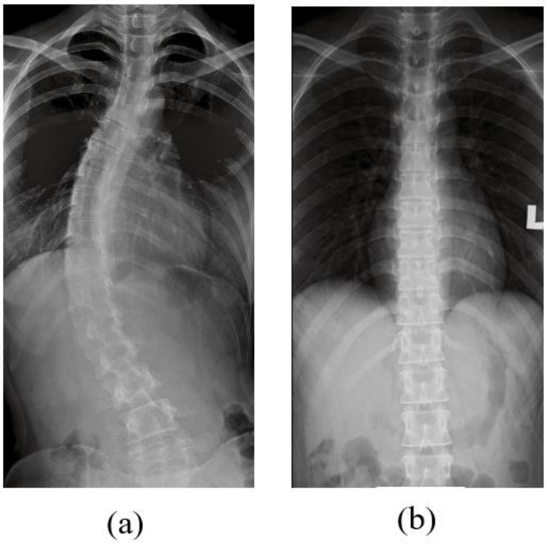

Fig. 2. Input Image (a) lenke **(b)** normal

to improve data quality and classification performance [22], [23]. This study fills a gap in the literature, especially the lack of research that combines computational efficiency and excellent accuracy in Lenke classification with a method that can be clinically interpreted. The present research attempts to fill this gap by optimising the utilisation of GLCM and SVM with different kernels to develop an accurate and clinically relevant scoliosis classification system. The main contributions of this work are mentioned below. First, a Lenke scoliosis classification system is proposed based on GLCM feature extraction and SVM with three kernel types: Quadratic, Cubic and Coarse Gaussian. Second, the suggested method achieved the greatest classification accuracy of 92.24% using the Quadratic SVM, which is a quite good method [24]. Third, the complete preparation pipeline is applied, which includes converting the images to grayscale, scaling the images, enhancing contrast (adapthisteq), segmenting by thresholding, and augmenting the images [25]. Furthermore, the performance of the proposed model is evaluated by using different statistical measures like accuracy, precision, recall, F1-score, standard deviation, and execution time [26]. Finally, a structured table is supplied to summarize the methodology and accuracy for a comparative study with past studies. Therefore, this study proposes a classification method for Lenke scoliosis using GLCM-based feature extraction and SVM classifiers with different kernel functions. The aim is to evaluate the performance of each kernel and to identify the most effective model for achieving accurate and efficient scoliosis classification.

II. Method

Fig. 1. Workflow for Lenke scoliosis X-ray classification using GLCM and SVM MATLAB R2022a was used to develop the system and was the main platform for image processing activities. By developing a flowchart, the model was validated for its normal and intended functioning. The first step is to obtain the Lenke scoliosis X-ray image data, as shown. The next step is image preprocessing, and the preprocessed pictures are passed via GLCM for feature extraction. Then the retrieved characteristics are given into the SVM classifier. Finally, the classification result decides whether the input image [27].

A. Dataset

This study used X-ray images of the spine from Lenke scoliosis and normal cases in JPG format. Examples of normal scoliosis and Lenke scoliosis images are presented in Fig. 2. A total of 288 images consisting of 129 Lenke scoliosis types 1–6(Class 1) and 159 images as normal (Class 2). The images obtained have varying sizes. These images were obtained from Universiti Sains Malaysia Hospital, which has passed ethical approval.

B. Preprocessing

In medical images, such as X-ray images, image pre-processing is used to prepare the images for subsequent processing and analysis [28]. In this research, the preprocessing consists of greyscale, resize and enhancement with adaphisteq. The original photos were transformed from RGB to greyscale to obtain simpler images and to minimise time and computational effort. The original images of different pixels need to be equalised so that they may be processed by the algorithm. The initial X-ray images were low-resolution, so their contrast and quality were enhanced using the adaptive histogram equalisation method (adaphisteq). In contrast, the Lenke scoliosis X-ray images were improved, and the spinal structures became more visible. An adaptive histogram equalisation was used for the image contrast enhancement as given in Eq. (1) [19]

$$T'(r) = \min\left[(L-1)\cdot\frac{CDF(r)}{1-C_{limit}},\ L-1\right] \quad (1)$$

The symbol r is the input pixel intensity; L is the number of grey levels in the image, and CDF(r) is the cumulative distribution function of the pixel intensities. The clipping limit, Climit, is utilised for contrast enhancement and to prevent over-amplification. This modification locally modifies the pixel intensities, which improves the visibility of the spinal structures in the X-ray pictures and provides a better segmentation and feature extraction. We enhance the amount of input photographs by augmenting the data with horizontally flipped images. The robustness of the classification model improves with increasing dataset size [29]. The segmentation is then performed using Otsu's

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thresholding to isolate the object of interest from the background [30].

C. Feature Extraction

Feature extraction is performed to obtain features for class discrimination, so this step is critical [31]. In this study, texture-based feature extraction using GLCM (Gray Level Co-occurrence Matrix) is chosen for normal and Lenke-type scoliosis spinal X-ray images. GLCM will provide characteristic information based on the X-ray images used. GLCM extracts 4 features from the image: contrast (C), homogeneity (H), energy (E), and correlation. The contrast feature can measure local intensity even when it varies, which is well-suited for observing variations in spinal shape. Homogeneity functions to assess the closeness of local area intensities, which can show a uniformly distributed texture shape in certain types of spines. Energy indicates a uniform texture size, capable of being consistently structured in area detection. Meanwhile, correlation describes the linear relationship between pixels, thus capable of depicting the orientation of texture patterns [32], [33]. The combination of these four features is expected to improve the accuracy in classifying normal and Lenke-type spines, according to the role of each texture feature in obtaining distinctive characteristics in scoliosis images. Each feature has a specific formula, allowing for a more in-depth analysis of the pixel intensity distribution patterns in spine images. The primary GLCM features were calculated using Eq. (2), Eq. (3), Eq. (4), and Eq. (5) [34]

$$C = \sum_{i=1}^{N}\sum_{j=1}^{N}(i - j)^2 \, P(i,j) \quad (2)$$

$$E = \sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j)^2 \quad (3)$$

$$H = \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{P(i,j)}{1+|i-j|} \quad (4)$$

$$Correlation = \sum_{i,j}\frac{(i-\mu)(j-\nu)P(i,j)}{\sigma_i\sigma_j} \quad (5)$$

N refers to the number of gray levels, determining the size of the matrix. Meanwhile, P denotes the probability at position (i, j), representing the normalized frequency of occurrence of the intensity pair of pixels i and j. μ and ν denote the mean values, σi and σj represent the standard deviations. Data was extracted into 16 GLCM texture features by calculating four texture features, namely contrast, energy, homogeneity, and correlation, with orientation variations of 0°, 45°, 90°, and 135° [35].

D. Classification

Here, we used an SVM as the classifier, a common machine learning technique for separating classes by finding the best hyperplane. Moreover, SVM uses Eq. (6) that gives the most efficient classification hyperplane f(x), which maximizes the margin Eq. (7)

$$f(x) = \omega^T x + b \quad (6)$$

$$Margin = \frac{2}{\|\omega\|} \quad (7)$$

where ω represents the weight vector, b is the bias term, and $\|\omega\|$ signifies the norm of the weight vector [36]. Support vectors were defined as the points that satisfy Eq. (8).

$$y_i\,(w^T x_i + b) = 1, \quad (8)$$

where y_i is the class label is (+1 or −1) and x_i indicates the feature vector of the data point. The optimization issue for SVM is defined by Eq. (9) subject to Eq. (10) [25].

$$\min_{w,b} \frac{1}{2}\|w\|^2 \quad (9)$$

$$y_i\,(w^T x_i + b) \geq 1, \ \forall i. \quad (10)$$

The final class prediction of SVM is determined using the decision function in Eq. (11). For non-linear data, a kernel function of Eq. (11)

$$\hat{}\{y\} = \mathrm{sign}(w\hat{}Tx + b) \quad (11)$$

The slack variable constraint is defined in Eq. (12) to allow a small classification error during optimisation.

$$\xi_i \geq 0 \quad (12)$$

The kernel mapping function is formulated in Eq. (13).

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad (13)$$

was used to transform the input space into a higher-dimensional space, where $\phi(x)$ is the feature mapping function. Eq. (14), Eq. (15), and Eq. (16) formulate the SVM kernel function [26].

$$\text{Quadratic} = K(x_i, x_j) \coloneqq (x_i^T x_j + 1)^2 \quad (14)$$

$$\text{Cubic} = K(x_i, x_j) \coloneqq (x_i^T x_j + 1)^3 \quad (15)$$

$$\text{Coarse} = K(x_i, x_j) \coloneqq \exp(-\gamma\,|x_i - x_j|^2) \quad (16)$$

Each model was trained 10 times using 10-fold cross-validation. The regularisation parameter C and slack variable $\xi_i$were used to balance the trade-off between margin maximisation and classification error. The soft-margin optimisation objective is formulated in Eq. (17), while the constraint condition is defined in Eq. (18).

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \quad (17)$$

$$y_i\,(w^T x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \quad (18)$$

The models were evaluated using the confusion matrix and metrics such as accuracy (ACC), precision (P), recall (R), and F1-score (F_1) as depicted in Eq. (19), Eq. (20), Eq. (21), and Eq. (22) [37], [38]

$$ACC = \frac{TP+TN}{TP+TN+TP+TN} \quad (19)$$

$$P = \frac{TP}{TP+TP} \quad (20)$$

$$R = \frac{TP}{TP+TN} \quad (21)$$

$$F_1 = \frac{2 \cdot P \cdot R}{P+R} \quad (22)$$

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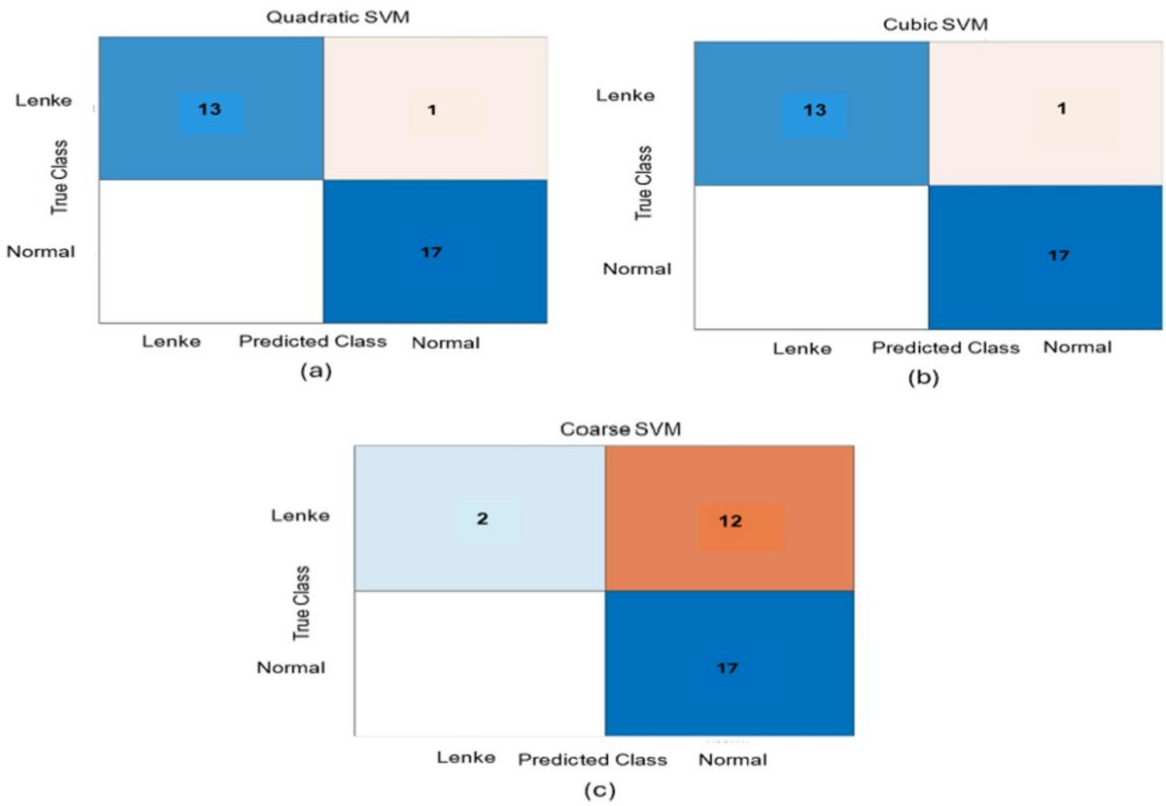

Fig. 3. **Confusion matrices (a)** Quadratic SVM **(b)** Cubic SVM **(c)** Coarse SVM

True Positive (TP) is a set of data that may correctly predict the positive class. True Negative (TN) is a set of data which is correctly predicted as the negative class. A False Positive (FP) is data that is incorrectly predicted as the positive class. A False Negative (FN) on the other hand, is a set of data that is projected wrongly as the negative class. [39].

III. Result

This study compares the performance of three SVM kernels for spinal classification. The experiment involves preprocessing, feature extraction, and classification, all implemented in MATLAB. The investigation uses X-ray image data of the spine with Lenke and normal types. The X-ray data are divided into 90% training data and 10% testing data. A total of 288 data is used, consisting of 257 training images, including 115 Lenke scoliosis types 1–6 (Class 1) and 142 images as normal (Class 2). Meanwhile, the testing data consists of 31 images, including 14 Lenke images (Class 1) and 17 normal images (Class 2). The image size was standardized to 512 × 512 pixels. The training phase consists of 10 runs and 10 testing processes using 10-fold cross-validation with the Classification Learner. Quadratic SVM, Cubic SVM, and Coarse SVM are classification algorithms that were used to tell the difference between Lenke and normal types. The results of the experiment show that the Quadratic and Cubic SVM kernels do a better job at classifying than the Coarse SVM kernel. Moreover, the classification results are evaluated using confusion matrices, as shown in Fig. 3. This figure presents an example of the best-performing confusion matrix from 10 runs for each of the three SVM kernel classifiers. Based on Eq. (11), Eq. (12), Eq (13), Eq. (14), the confusion matrix indicates that the Quadratic SVM and Cubic SVM can correctly classify 13 out of 14 Lenke test images, with one classification error in each class and all 17 normal images. The Coarse Gaussian SVM

Table 1. The Performance of SVM Kernels

Kernel	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Quadratic SVM	92.26	94.66	87.86	91.08
Cubic SVM	90.97	93.26	84.99	88.84
Coarse SVM	60.64	100.00	12.86	22.84

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Table 2. Performance Comparison of Accuracy and Computational Time of SVM Kernel Classifiers

Kernel SVM	Training	Running Time	Testing	Running Time
Quadratic	98.81	11.14	92.26	20.44
Cubic	99.24	19.31	90.97	19.30
Coarse	74.03	4.55	60.64	21.70

could only distinguish between 2 out of 14 Lenke test images, but it could distinguish between all normal-type images. The classification performance testing was conducted in 10 trials for each kernel, and the average was taken. The performance evaluation of the three SVM models in terms of accuracy, precision, recall, and the F1-score is shown in Table 1. In Table 1, the average results show that the Quadratic SVM achieves the highest performance on all metrics with an accuracy of 92.26%, precision of 94. 66%, recall of 87.86%, and an F1 score of 91.08%. Meanwhile, the Cubic SVM achieves an accuracy of 90.97%, precision of 93.26%, recall of 84.99%, and an F1 score of 88.84%. In contrast, the Coarse Gaussian SVM achieves the lowest values with an accuracy of 60.64%, precision of 100.00%, recall of 12.86%, and an F1 score of 22.84%. This study also presents a comparison of the average training and testing computation times across 10 trials in Table 2. From Table 2, the Cubic SVM gives the best training accuracy of 99.24%, testing accuracy of 90.97% with computation time of 19.30 seconds. The Quadratic SVM provided similar results with slightly lower accuracy scores of 98.81% and 92.26% for training and testing, respectively. It took 20.44 seconds to compute. In contrast, the Coarse Gaussian SVM achieved the lowest accuracy of 74.03% for training and 60.64% for testing, with a computation time of 21.70 seconds.

IV. Discussion

In this study, differences were observed among the three SVM kernel classifiers in terms of performance, including accuracy, precision, recall, F1-score, and computational efficiency. As presented in Table 1, the Quadratic SVM showed the best overall performance, achieving 92.26% accuracy, 94.66% precision, 87.86% recall, and 91.08% F1-score. These values indicate that the Quadratic SVM provides balanced classification performance. This model is also considered accurate in identifying Lenke cases. This is consistent with the confusion matrix shown in Fig. 3. , where the Quadratic SVM correctly classifies many Lenke and normal cases, with only a small number of misclassifications. Similarly, the Cubic SVM kernel showed relatively excellent performance, with 90.97% accuracy, 93.26% precision, 84.99% recall, and 88.84% F1-score, indicating that the model can correctly identify a large number of Lenke and normal cases. This model also exhibits a low number of false positives, resulting in relatively high precision. However, the slightly lower recall indicates that some Lenke cases were misclassified as normal, leading to an increase in false negatives. This observation is consistent with the confusion matrix shown in Fig. 3. .

Furthermore, the Coarse Gaussian SVM model exhibited relatively low performance, with an accuracy of 60.67%, despite achieving a perfect precision of 100%. With an FP value of 0, the model identified all normal classes and failed to predict any false positives (lenke). On the other hand, the recall value is relatively low at 60.66%, with a high number of false negatives, causing the model to fail to identify a considerable number of Lenke cases. This is consistent with the confusion matrix shown in Fig. 3. , where many Lenke images are classified as normal cases. From this understanding, the model tends to avoid identifying the Lenke class, resulting in an F1-score of 75.49% due to the imbalance between precision and recall. Table 2 illustrates how well Quadratic SVM works. It took 11.14 seconds to train, while Cubic SVM took 19.31 seconds. The time it takes to test is a little longer, but it's still close (20.44 seconds vs. 19.30 seconds). Given these time constraints, Quadratic SVM is the best choice since it strikes the best balance between performance and time. Coarse Gaussian SVM, on the other hand, has the fastest training time (4.55 seconds), but its performance is very low, thus it is not a good choice for clinical use. In addition to using the confusion matrix to measure the performance of the SVM kernel, the ROC curve was also used in this study. We achieve high AUC values in the training phase, indicating good separation between classes. The ROC curves (Fig. 4.) demonstrate that Quadratic SVM and Cubic SVM obtained AUC values close to 1.00, which means that they have excellent discrimination ability between the "Lenke" and "normal" classes during training. Meanwhile, the Coarse Gaussian SVM also got a relatively high AUC value of 0.97, but its classification performance on the test data is inferior. Therefore, the

Table 3. Comparison with Previous Studies

Author(s)	Method	Accuracy (%)
Chen et al. [11]	ResNet-50	94.00
Xu L et al. [40]	ResNet-50	95.60
Xie K et al. [41]	Artificial Intelligent	87.07
Chamim et al. (this study)	GLCM + Quadratic SVM	92.26
Liu D et al. [42]	Unet++ + S4 + KNN	78. 60

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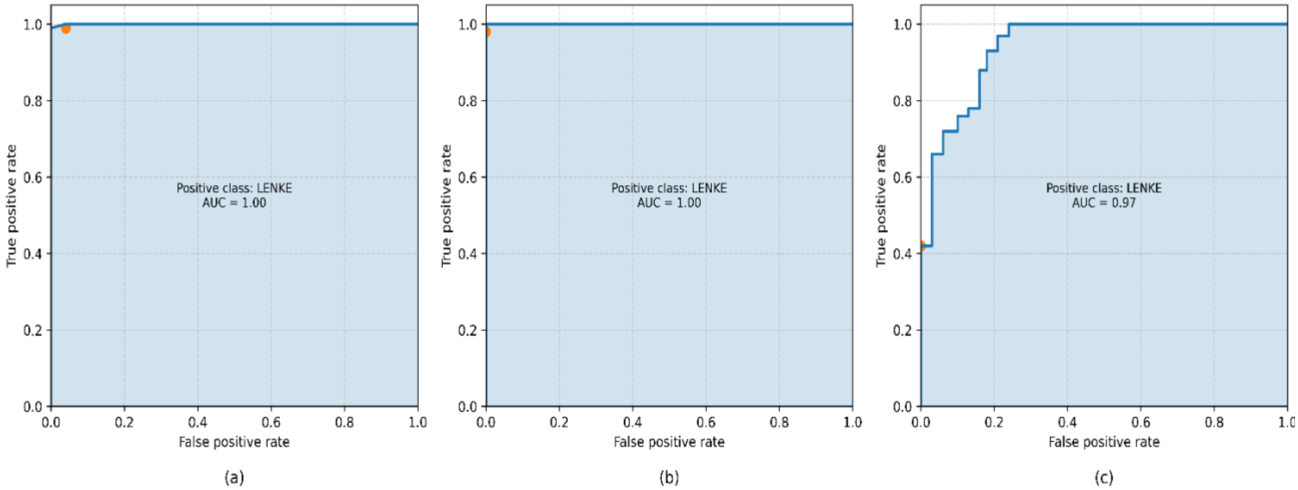

Fig. 5. ROC (a) Quadratic SVM **(b)** Cubic SVM **(c)** Coarse Gaussian SVM

performance of the final model is further analysed using test accuracy, recall, and precision and confusion matrix analysis to obtain a more reliable assessment of the model's generalisation.

Table 3. compares the performance of the proposed GLCM-based SVM classification method with some previous studies related to scoliosis and Lenke classification. Chen Y et al. (2026) [11] reported 94.00% accuracy in scoliosis classification using a ResNet-50. Xu L et al. (2025) [40], Deep learning method for Lenke classification, 95.6 % accuracy and 0.862 macro-average F1-score. Xie K et al. (2025) [41] built an AI-based automatic Lenke classification system with 860 spinal radiographs from AIS patients and achieved 87.07% accuracy for curve type classification and 92.59% accuracy for lumbar modifier and thoracic sagittal profile classification. Dong Liu et al. (2023) [42] used U-Net++ segmentation and adaptive shape descriptor with KNN classification on Lenke and obtained an accuracy of 78.60%. The combination of GLCM with Quadratic SVM proposed in the present study had the best performance in the Lenke classification, with an accuracy of 92.26%, precision of 94.66%, recall of 87.86%, and F1-score of 91.08%. These results indicate that the proposed method provides competitive performance compared with previous studies while using a relatively simpler machine learning approach. This study has certain limitations despite the good outcomes. First, the dataset employed in this study was restricted to the accessible X-ray pictures of scoliosis, which may influence the generalization capabilities of the model for broader clinical applications. Second, the classification performance was tested on a single data set and was not externally validated at other universities or in other imaging contexts. Besides, the classification results may be affected by fluctuations of image quality, patient posture and curve properties. Hence, more studies with bigger multicenter datasets and further validation are required to enhance the robustness and reliability of the proposed GLCM-SVM model for automatic Lenke classification.

This study has various major implications for medical image processing, especially in scoliosis and Lenke classification. The results suggest that feature extraction using GLCM and the Quadratic SVM classifier provides an efficient, and computationally affordable method that could be used in clinical decision support systems. Furthermore, the results show that traditional machine learning methods can still obtain competitive performances in relation to more sophisticated deep learning approaches, provided that proper feature extraction techniques are adopted. This is especially crucial when interpretability and computational efficiency are needed. Furthermore, the low calculation cost of the suggested method possibly allows for application in resource-limited healthcare facilities.

V. Conclusion

This paper proposes a computer-aided classification method for Lenke scoliosis based on Gray-Level Co-occurrence Matrix (GLCM) feature extraction and Support Vector Machine (SVM) classifiers with different kernel functions. The results of the evaluation indicate that the Quadratic SVM provided the best performance with 92.24% accuracy and 20.44 seconds of computation time, followed by the Cubic SVM with 91.98% accuracy and 19.30 seconds of processing time, while the Coarse Gaussian SVM showed substantially lower performance (60.66% accuracy). These results suggest that the choice of kernel function is important for classification performance, and the quadratic kernel

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provides a better trade-off between accuracy and consistency. The results also indicate that GLCM features can extract discriminative texture information that is relevant to scoliosis classification. Despite the encouraging conclusions, the study is constrained by the size of the dataset and the use of texture-based features only. Future work should include increasing the dataset and combining it with other feature representations or more advanced segmentation methods to increase the robustness and clinical usability of the model.

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Data Availability

The datasets used and/or analyzed in the current study are not publicly available due to ethical and privacy restrictions under the approval of the Human Research Ethics Committee Universiti Sains Malaysia (HREC-USM).

Author Contribution

Anna Nur Nazilah Chamim contributed to the conceptualization, study design, ethics, data collection, and data analysis and interpretation. Hasimah Ali supervised the study, contributed to the ethics submission, methodology development, and critically revised the manuscript. Yessi Jusman contributed to the study design and provided technical guidance on programming. Mohd. Imran Yusof contributed to data provision and data validation. Prasaca Pigama Priyanindhita contributed to programming and the manuscript. Asy-Syifa Febya Ananta assisted in data collection, processing, and documentation, as well as the manuscript. All authors reviewed and approved the final manuscript and agreed to be accountable for all aspects of the work.

Declarations

Ethical Approval

This study was conducted in accordance with ethical standards and was approved by the Human Research Ethics Committee Universiti Sains Malaysia (HREC USM) under protocol number USM/JEPeM/KK/23080587

Consent for Publication Participants.

Consent for publication was given by all participants.

Competing Interests

The authors declare no competing interests.

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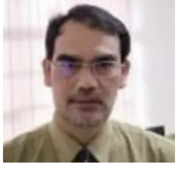

Mohd Imran Yusof is a distinguished academic and orthopaedic surgeon with more than 30 years of career experience. He graduated as a medical doctor from UKM in 1993, became an orthopaedic surgeon in 2001, and specialised in spine surgery. Promoted to associate professor in 2007 and professor in 2014. He served as the head of the Department of Orthopaedics and the chairman of the Malaysian Orthopaedic Association for many years. He is presently the deputy director (operations) of Sains Malaysia Hospital. He is an active academic reviewer, co-editor of the Malaysian Medical Journal and a professor. Beyond his clinical expertise, he is passionate about teaching and mentoring young orthopaedic surgeons and has published extensively on orthopaedic research and the development of new surgical procedures in spine surgery.

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