Classification of Markerless 3D Dorsal Shapes in Adolescent Idiopathic Scoliosis Patients Using Machine Learning Approach

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***Abstract*— Adolescent Idiopathic Scoliosis (AIS) is a musculoskeletal condition commonly seen in pediatric children that causes deformity of the spine. The study aims for early detection and diagnosis as these are the possible options to delimit the progression of the disorder. The work has explored the development of an algorithm that could detect the landmarks and extract the shape-based features from the markerless 3D surface data in AIS patients. An approach to classifying these extracted features using the machine learning algorithm, Support Vector Machine (SVM), has been investigated. The objectives of the work were divided into three frameworks. Framework-1 is aimed at classifying the data based on the asymmetry pattern observed in the spinal surface of the patients. The data corresponding to normal posture were considered as 'without deformity' and data with an asymmetry spinal curve were considered as 'with deformity' based on indicators extracted using the ScolioSIM tool. Framework-2 is aimed at classifying the AIS patients' data based on the three deformity levels namely, mild, moderate and severe. Framework-3 is aimed at classifying the shape orientation of the AIS condition as right or left based on the extracted shape features. The SVM algorithm was able to classify the asymmetry spinal surface pattern and the three deformity levels with accuracy values of 72.4% and 80%, respectively. Furthermore, an accuracy of 94.9% was obtained to classify the shape orientation either as right- or left-oriented. Hence, this non-invasive diagnosis and assessment study paves a new way of approach for the 2D and 3D shape classifications of AIS and expedites the treatment planning process.**

Keywords—3D Surface Scan, AIS, Classification, ScolioSIM, SVM, Machine Learning, Shape Features

I. Introduction

Scoliosis is a 3D condition of the spine that usually affects very young population, primarily adolescents [1]. As the reason for their development is mainly unknown, early detection and therapy would help in preventing progression of the deformity. Current diagnostic methods are mainly related to X-ray diagnosis and visual assessments which can lead to exposure to higher ionizing radiation and not precise diagnosis [2]. New approaches force non-invasive optical solution to allow fast screening and detection of adolescent idiopathic scoliosis (AIS) in early stages in children [3]. This also go in line with improvements in ICT technologies and emerging health sciences.

The sudden boom of artificial intelligence in data science has proven beneficial for solving complex problems in the fields of medicine, engineering and in other areas as well. The capacity of machine learning (ML) algorithms to handle larger datasets have made them a superior choice for solving high end complicated medical problems. The machine learning algorithms have been prominently used in the fields of computer vision [4], image processing [5], [6], brain-computer interfaces [7] and it mainly helps in the prognosis of disorders [8]–[10]. Here, one of the most powerful and flexible ML algorithms, Support Vector Machine (SVM), is used to classify the severity of AIS in patients using shape-based features extracted from the markerless 3D dorsal surface data. The challenges that lie in the prediction of AIS condition are the dearth of medical data pertaining to the various levels of severity and the need for an accurate and fast prediction algorithm to classify the condition. This would help the medical practitioners in identifying the AIS condition in patients leading to an early and timely intervention.

This paper elucidates the implementation of a fast and a computationally efficient prediction algorithm for the presence of AIS condition in individuals, for the classification of various levels of deformity and also to classify the orientation of the deformity. This work leverages a simple and an effective algorithm to predict AIS condition in patients that paves the way for an early prognosis of the disease and treatment by the physicians.

II. MATERIALS AND METHODS

A. Dataset Information

In this randomized controlled study, children with AIS condition participated and the analysis was done using retrospectively collected datasets from Clinical center Kragujevac (Serbia) which include 44 patients' back surfaces optically digitalized using non-invasive ARTEC Eva 3D optical scanner, out of which there were 8 cases with normal posture and 36 with AIS (18 males and 18 females). On every sample surface, 7 markers were placed on prominent anatomical landmarks around spine and scapulae (C7, S1, S2, M, Lb1, Lb2, V) and their 3D coordinates were extracted as shown in Fig. 1. As a primary inclusion criterion, subjects with

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fully digitalized back surfaces with normal standing posture and relaxed arms were considered. Exclusion criteria were subjects with improper 3D surfaces (scarfs, missing regions, deformed meshes, etc.), and adults.

B. Pre-Processing Steps

ScolioSIM is a tool that allows non-invasive detection of the key anatomical landmarks on the digitalized dorsal surface, its asymmetry line, prediction of the internal spinal alignment and calculation of various parameters of deformity. Surface features extraction is performed in PLM system CATIA and it is based on curvature analysis of the back surface. Based on the positions of key anatomical landmarks and internal spinal alignment, ScolioSIM calculates positions of vertebral and intervertebral centroids and axial vertebral rotations. These elements are of key importance for 2D/3D registration of 3D vertebral models and generating a patient-specific deformity. ScolioSIM tool is a part of the web- and ontology- based application - ScolioMedIS information system which allows internet-based diagnosis and visualization of 3D deformities in 3Dxml formats [11], [12].

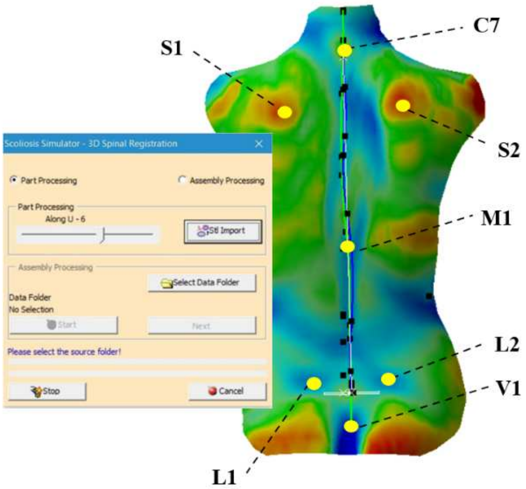

Fig. 1. Markers coordinates data taken for consideration for this shape-based classification using machine learning approach with the output image taken using the Scoliosis Simulator – 3D Spinal Registration tool (ScolioSIM)

1) Feature Extraction: The main indicators of the internal spinal status and parameters of the deformity were extracted by processing all the 3D surfaces of the subjects using ScolioSIM tool (version 1.0). Nine primary shape-based features of the deformity spinal alignment were extracted after complex curvature analysis [13] namely, MaxCobb Angle XY, MainThoracicFrontT3T12, ProximalThoracicFrontT1T3, ThoracolumbarLumbarFrontL4T12, SosortFrontT5T12, SosortFrontT2T5, SosortFrontT10L2, BaryCenter X, BaryCenterZ [14]. The sample data used in this study are tabulated in Table I.

Fig. 2 represents coordinates of barycentricity of the AIS in patient-specific model extracted using ScolioSim tool. Fig. 3 illustrates important parameter of AIS called Cobb angle which is considered as a gold standard in radiographic diagnostic. Depending on the number of curvature segments, AIS deformity can have multiple Cobb angles, but first two with highest values greater than 10 deg (primary and secondary) are used as significant.

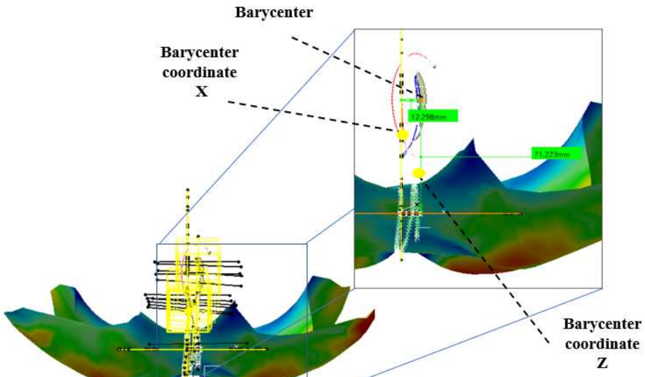

Fig. 2. Coordinates of barycenter point in AIS sample

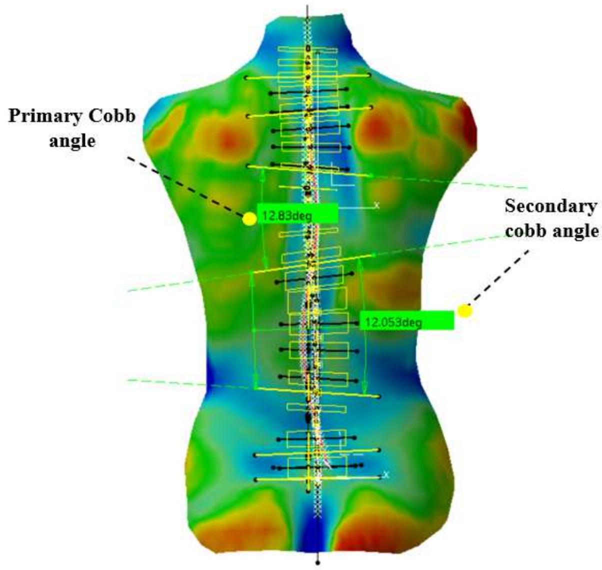

Fig. 3. Primary and secondary Cobb angles extracted automatically over internal spinal alignment predicted using ScolioSIM

TABLE I. SAMPLE DATA OF FEATURE VALUES EXTRACTED FROM AIS SUBJECTS USED IN THIS STUDY

Subjects	Features								
	MaxCobb Angle XY	*Bary Center x*	*Bary Center z*	*Proximal Thoracic FrontT1T3*	*Sosort FrontT2T5*	*Main Thoracic FrontT3T12*	*Sosort FrontT5T12*	*Sosort FrontT10L2*	*Thoracolumbar Lumbar FrontL4T12*
#1	36.035	15.976	-9.609	5.591	16.430	23.588	36.106	4.952	9.721
#2	27.869	-8.780	2.095	22.450	7.557	32.262	15.826	18.838	9.899
#3	49.349	-14.377	-4.201	27.082	10.044	46.738	45.506	4.047	25.760
#4	43.931	-12.117	4.379	17.732	18.134	32.176	8.480	14.521	2.265
#5	28.496	10.569	-4.481	9.073	5.980	23.245	24.790	16.839	19.270

Other parameters are recommended by SOSOR and SRS scoliosis societies, and they are always measured in the same range of vertebra.

C. Classification

The objectives of the work were specifically divided into three frameworks. All the objectives aimed to predict the presence of AIS condition using the shape-based features extracted from the markerless 3D surface data using the SVM algorithm. Framework-1 is aimed at classifying the data based on the asymmetry pattern observed in the spinal surface of the patients. The data corresponding to normal posture were considered as 'without deformity' and data with an asymmetry spinal curve were considered 'with deformity'. Framework-2 is aimed at classifying the AIS patients' data based on the three deformity levels namely, mild, moderate and severe. The patients were categorized based on the Cobb angle. Framework-3 is aimed at classifying the shape orientation of the condition as right or left based on the extracted shape features. These objectives are primarily helpful in predictive modelling and diagnosis of the scoliosis condition.

The classification algorithm adopted in this work is SVM that uses a linear kernel. It is a supervised machine learning algorithm that uses an optimal hyperplane to separate the classes, one being positive class and other is a negative class. It offers a high generalization capability [15]. SVM has been used for classification as well as regression problems [16]. The objective of the hyperplane is to maximize the margins between the classes that aids in separation.

SVM is trained on labeled data given as the input. The input used here is the shape-based features extracted from the markerless 3D dorsal surface data. SVM is chosen in the present study as it is known to offer a higher generalization performance, and are resistant to the curse-of-dimensionality. They are prominently exploited in pattern recognition problems [17]. Five-fold cross validation with ten repeats has been used to compute the classification accuracy value, which was used as the performance metric. This scheme is adopted for the work since the dataset taken for evaluation is small and to mainly avoid overfitting the model [18].

III. RESULTS

Classification of the subject either into normal or abnormal category is the foremost and important step to alleviate the delay in initiating the treatment for the concerned subject. Pertaining to this, the classification accuracy obtained using SVM is 72.4%. The algorithm has classified the extracted features into various levels of deformity with an average accuracy value of 80%. The 2D scatter plot of data corresponding to MaxCobb Angle XY and BaryCenter X is shown in Fig. 4.

The confusion matrix obtained using all the nine features is shown in Fig. 5. The efficacy of the same framework was investigated with only five features namely, MaxCobb Angle XY, BaryCenter X, BaryCenter Z, ProximalThoracicFrontT1T3, and SosortFrontT2T5, and the accuracy was found to reach up to 88% and the corresponding confusion matrix is shown in Fig. 6. These five selected features were based on the vertebrae angles since the clinicians are mostly interested in the specific angles to understand the asymmetry pattern in AIS. Finally, the data has been classified either into right or left oriented with a maximum accuracy value of 94.9%.

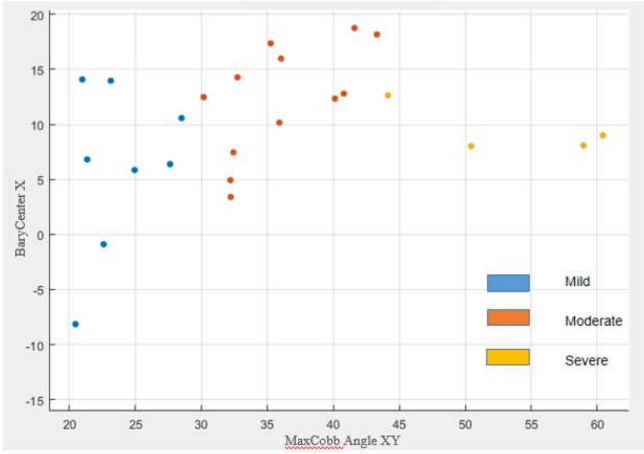

Fig. 4. 2D Scatter plot of the MaxCobb angle (deg) and BaryCenter X measured from the data belonging to the three deformity levels of scoliosis

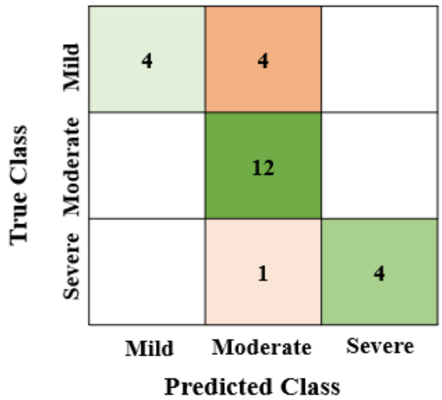

Fig. 5. Confusion matrix obtained by SVM to classify the scoliosis data into the three deformity levels namely, mild, moderate and severe using nine features

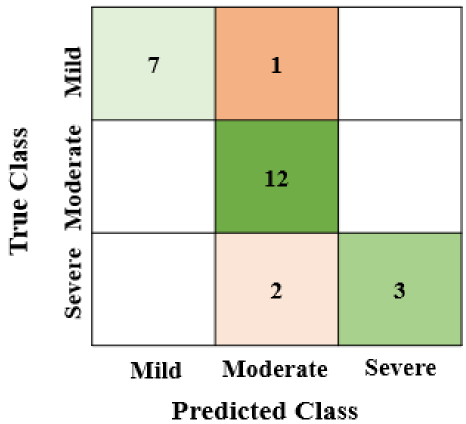

Fig. 6. Confusion matrix obtained by SVM to classify the scoliosis data into the three deformity levels namely, mild, moderate and severe using five features

The corresponding 2D scatter plot of datapoints belonging to two features namely, MaxCobb Angle XY and BaryCenter X is shown in Fig. 7. The confusion matrix obtained by SVM to classify the left and right oriented data is shown in Fig. 8.

Table II summarizes the performance of SVM classifier in the prediction of AIS condition based on the three objectives framed as a part of this work.

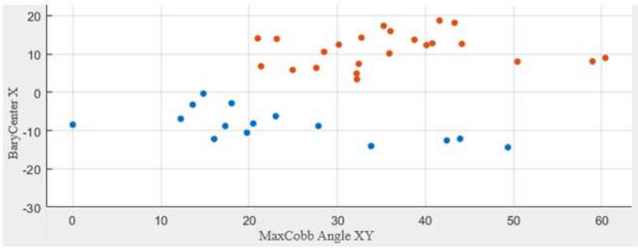

Fig. 7. 2D Scatter plot of the MaxCobb angle (deg) and BaryCenter X measured on left oriented (blue) and right oriented scoliosis condition (red)

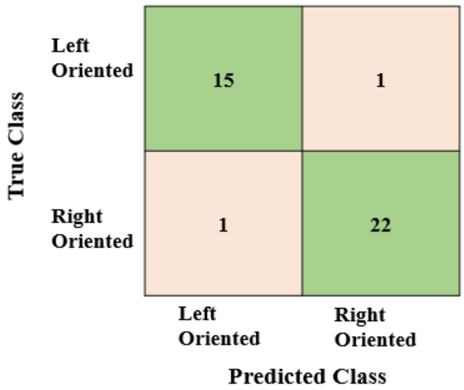

Fig. 8. Confusion matrix obtained by SVM to classify the left oriented and right oriented scoliosis data

TABLE II. CLASSIFICATION PERFORMANCE OF SVM FOR THE PREDICTION OF AIS CONDITION USING SHAPE-BASED FEATURES

Frameworks	Description	Accuracy (in %)
Framework-1	to classify the normal and scoliosis condition	72.4
Framework-2	to classify the three deformity levels	80
Framework-2 with 5 features	to classify the three deformity levels using five features	88
Framework-3	to classify scoliosis into left or right-oriented	94.9

IV. DISCUSSION

The 3D dorsal shapes in AIS patients were classified using a machine learning algorithm called SVM. The results show that the shape-based features extracted from the scoliosis patients' data can aid in determining the presence or absence of deformity. Also, the ability of the algorithm was shown to classify the deformity levels into mild, moderate and severe with an accuracy of 80%. However, not all the nine features were good enough to contribute towards the separation of the three classes. Furthermore, the clinicians are mostly interested in the specific angles to understand the asymmetry pattern in AIS. Hence, five features namely, MaxCobb Angle XY, BaryCenter X, BaryCenter Z, ProximalThoracicFrontT1T3, and SosortFrontT2T5 were selected based on the vertebrae angles. These features have been selected manually prior to classification and considered as the input to the classifier. No feature selection method has been adopted in this study. When the abovementioned features were considered for classification, the performance of the algorithm was improved to 88%. This suggests that selection of the discriminant features is beneficial in the identification of the contributors to good classification of the data. This also aids in reducing the time taken for the predictive model to get trained. Hence, future work would involve extraction of more significant deformity features from the data and adopting automatic feature selection methodologies to enhance the classifier's performance. Furthermore, classifying the deformity as right oriented or left oriented help the physicians in providing proper intervention.

The limitation of the current study is that there was a disparity in the sample size of mild, moderate and severe conditions. In such situations, there are chances that the developed model could be biased towards the class that has higher number of samples. Hence, future work would involve equalizing samples for all the classes of interest.

V. CONCLUSION

This work has manifested the use of an effective classification algorithm to classify the AIS condition using 3D markerless surface data. The objectives formulated in this research would pave the way to identify whether the subject has scoliosis or not. Secondly, it assesses the severity of the patient and aids in early intervention to treat the disease. Lastly, classifying the scoliosis patient into right or left oriented would benefit in the proper treatment planning. Hence, this non-invasive diagnosis and assessment study paves a new way of approach for the 2D and 3D shape classifications of AIS. This approach comparatively yields better outcome than the conventional methods applied in clinical practice.

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