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Anatomical plane multi-view learning for detecting spinal deformities with surface topography

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Abstract: Detecting functional and structural spinal deformities in children, such as rounded back and scoliosis, is essential to enable timely treatment and reduce the risk of reduced quality of life in adulthood. This study proposes a multi-view binary classifier based on anatomical planes for identifying postural deviations. Tested on 1,477 surface topographical measurements from school children, the model achieved 75% accuracy, 84% specificity, and 64% sensitivity. With further optimization and validation on broader cohorts, this approach shows promising as a scalable tool for school-based screening programs.

I. Introduction

Functional and structural spinal deformities in children are major risk factors for developing back pain later in life, but prevalence among children over 10 years old is high with up to 65.3% [1]. Functional deformities are posture-related abnormalities, such as rounded back or flat back, whereas structural deformities involve underlying vertebral changes, including adolescent idiopathic scoliosis (AIS) or Scheuermann's disease. At a young age, these deformities often remain unnoticed, although conservative treatments such as physiotherapy and bracing are particularly effective during this developmental period.

Research on non-ionizing imaging tools such as surface topography (ST) has focused primarily on school screening for AIS [3], [4], [5], whereas broader detection of postural deformities has received less attention. A major challenge is that different deformities manifest in different anatomical planes; rounded back primarily in the sagittal plane, AIS across multiple planes, while their symptoms may overlap. This complicates feature attribution for machine learning (ML) models. To address this, this paper proposes a multi-view ML approach that integrates anatomical planes for detecting postural deformities.

II. Material and methods

I.I. Data collection

A total of 1,477 ST measurements were collected in clinical settings, including 809 healthy children and 668 with structural or functional postural deviations. Participants were 6-19 years old (mean 10.9 ± 2.4 years) and 58% female. Measurements were obtained using the rasterstereography-based DIERS formetric 4D system (DIERS International GmbH, Wiesbaden, Germany) with DICAM software (v3.11.6.0).

I.II. Anatomical Multi-View

To model anatomical planes explicitly, the multi-view approach StaPLR by van Loon et al. [6] was adapted to use anatomical views instead of multiple measurement systems with views TP (transverse plane), SP (sagittal plane) and CP (coronal plane). Algorithm 1 outlines the full training procedure. Each view is specifically trained to distinguish between healthy measurements and those indicating spinal deviations. A meta-learner then integrates the outputs by assigning greater weight to the most informative views, optimizing the overall decision-making process.

Algorithm 1: Modified StaPLR to combine three sets of views into a meta classifier.

Input: Feature sets $X^{(v)}$, $v = 1, \dots, 86$, assigned to three anatomical views:
- View 1: TP (Transverse plane): $v = 1, \dots, d_{s_1}$
- View 2: SP (Sagittal plane): $v = d_{s_1+1}, \dots, d_{s_2}$
- View 3: CP (Coronal plane): $v = d_{s_2+1}, \dots, 86$

Output: Binary target variable $y \in \{0,1\}^n$, final classifier $\hat{f}_{final}(x)$

Step 1: Train base classifiers
For each view $s = 1, 2, 3$:
1. Extract view-specific feature matrix $X^{(s)} \in \mathrm{R}^{n \times d_s}$
2. Train logistic ridge regression model $\hat{f}_{inter}$ with cross-validated selection of λ
3. Generate 10-fold out-of-fold predictions $z^{(s)} \in \mathrm{R}^n$

Step 2: Train meta-learner (stacking)
1. Construct intermediate prediction matrix:
$Z_{inter} = [z^{(1)}, z^{(2)}, z^{(3)}] \in \mathrm{R}^{n \times 3}$
2. Train a logistic nonnegative lasso classifier constraint on (Z_{inter}, y) to obtain stacked model $\hat{f}_{stacked}$
3. Obtain 10-fold out-of-fold predictions of the stacked model, $z_{stacked} \in \mathrm{R}^n$

Step 3: Final prediction for a new sample x
1. Apply view-specific intermediate models:
$h_1 = \hat{f}_{inter}^{(1)}(\hat{f}_{1:d_{s_1}}), h_2 = \hat{f}_{inter}^{(2)}(\hat{f}_{(s_1+1):d_{s_2}}), h_3 = \hat{f}_{inter}^{(3)}(\hat{f}_{(s_2+1):86})$
2. Compute final stacked prediction:
$\hat{f}_{final}(x) = \hat{f}_{stacked}(h_1, h_2, h_3)$

In this implementation, each plane is modeled separately and then stacked using a logistic nonnegative LASSO classifier, with logistic ridge regression for feature selection and hyperparameter optimization. The 86 parameters extracted from the DIERS formetric 4D system were assigned to their respective anatomical planes, forming three distinct datasets (e.g., lateral deviation in the coronal view, kyphosis angle in the sagittal view, vertebral rotation in the transverse view). Model training used repeated cross-validation, repeated ten times with different random seeds to account for dataset variability.

III. Results and discussion

In distinguishing the classes healthy posture and postural deviations, the model achieved an overall accuracy of 0.746 with a specificity of 0.837 and sensitivity of 0.635 (Table 1). Variability among different fold compositions was low with up to 0.012. For the best-performing model from the hyperparameter optimization, the meta-model selected a regularization parameter of $\lambda = 0.1$. Feature selection resulted in 8 features for view 1, 13 features for view 2, and 23 features for view 3.

Table 1: Results of the multi-view approach.

Accuracy	0.746 ± 0.006
Specificity	0.837 ± 0.010
Sensitivity	0.635 ± 0.011
PPV	0.764 ± 0.012
F1-score	0.692 ± 0.009

The model achieved high specificity but comparatively lower sensitivity. In posture analysis, lower sensitivity is generally more acceptable than lower specificity, as progressive deviations can still be detected at subsequent screening rounds, whereas false positives lead to unnecessary and costly referrals. A key advantage of the multi-view approach is the improved interpretability of feature relevance across anatomical planes (Fig.1). Coronal parameters emerged as the most influential for the model's decision-making. This may indicate that ST, as a frontally oriented acquisition system, captures these features more reliably. Alternatively, it may reflect characteristics of the study population: although 25% of participants had AIS, only 7% presented with a rounded back.
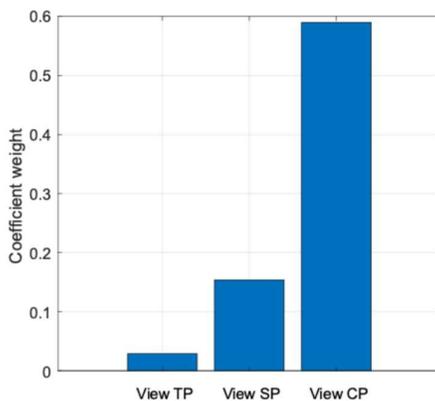

Figure 1: Bar chart representing the weight of each anatomical view in the decision making of the meta-model.

The selection of 23 features for view 3 compared with only 8 for view 1 aligns with the inherent feature distribution of the DIERS formetric 4D system. This pattern likely reflects differences in information density across anatomical planes, which is expected given that feature extraction relies on frontal images produced by the DICAM3 software. Accordingly, the predominance of view 3 is more plausibly attributed to technical factors and acquisition characteristics than to underlying biological variation. This study has several limitations. Although the dataset was balanced for the binary classification task, the underlying spinal conditions remain unevenly represented, which may affect model behavior and feature preferences. A multi-class model incorporating anatomical views might offer improved performance, as condition-specific view compositions could be jointly modeled within dedicated classes. Additional data are needed to balance these classes and evaluate this possibility.

IV. Conclusions

This paper adopted a multi-view approach to handle anatomical views in ST imaging for classifiying for postural deviations. Results showed good specificity with the need to improve false negatives. This could be achieved by creating a more balanced dataset of postural conditions. Overall, the multi-view approach paves the way for easy-access to postural screening programs.

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