Anna Maria Becker*, Matthias Schaufelberger, Reinald Peter Kühle, Christian Freudlsperger, and Werner Nahm

Multi-Height Extraction of Clinical Parameters Improves Classification of Craniosynostosis

https://doi.org/10.1515/cdbme-2023-1050

Abstract: *Introduction:* 3D surface scan-based diagnosis of craniosynostosis is a promising radiation-free alternative to traditional diagnosis using computed tomography. The cranial index (CI) and the cranial vault asymmetry index (CVAI) are well-established clinical parameters that are widely used. However, they also have the benefit of being easily adaptable for automatic diagnosis without the need of extensive preprocessing.
Methods: We propose a multi-height-based classification approach that uses CI and CVAI in different height layers and compare it to the initial approach using only one layer. We use ten-fold cross-validation and test seven different classifiers. The dataset of 504 patients consists of three types of craniosynostosis and a control group consisting of healthy and non-synostotic subjects.
Results: The multi-height-based approach improved classification for all classifiers. The k-nearest neighbors classifier scored best with a mean accuracy of 89 % and a mean F1-score of 0.75.
Conclusion: Taking height into account is beneficial for the classification. Based on accepted and widely used clinical parameters, this might be a step towards an easy-to-understand and transparent classification approach for both physicians and patients.

Keywords: Craniosynostosis, Classification, Clinical Parameters, Cranial Index, Cranial Vault Asymmetry Index

1 Motivation

Craniosynostosis is a congenital defect caused by premature ossification of one or more cranial sutures in infants. This may result in increased intracranial pressure and can impair the neurological development of the brain [1]. The most common types of craniosynostosis are sagittal suture fusion (scaphocephaly), metopic suture fusion (trigonocephaly), and coronal suture fusion (anterior plagiocephaly). Dictated by Virchow's law, growth is blocked in the ossified direction and compensated by growth in the perpendicular direction, leading to specific deformations of the head for each type of suture fusion [2]. Since the bones of small children are still very soft, an early diagnosis increases the chances of successful treatment.

In clinical practice, the use of the cranial index (CI) and the cranial vault asymmetry index (CVAI) is a widely practiced method for diagnosing cranial deformities. In addition, the head is usually palpated by a physician and a computed tomography (CT) scan can be consulted as the gold standard. However, this exposes the children to ionizing radiation and sometimes requires them to be put under general anesthesia. To assist physicians in their diagnosis and to make the examinations more patient-friendly, there are some successful and radiation-free classification approaches based on neural networks [3, 4] and statistical shape models [5]. However, they are computationally expensive and require preprocessing during application. For facilitated clinical usage, an automated method using currently used clinical parameters might be desirable.

In this study, we introduce a multi-height-based approach using the two clinical parameters CI and CVAI as features that are easy to extract and do not require a lot of preprocessing. By using multiple height measurements we expand on similar approaches using CT scans for skull assessment that have been explored for shape analysis [6] and circumference-based analysis [7]. In contrast, we employ a four-height measurement setup on clinically established measurements. The proposed method uses 3D surface scans and classifies each subject based on the clinical parameters determined in different heights. This way, we ensure easy clinical applicability in contrast to heavy deep-learning-based approaches.

2 Methods

In the following sections, we provide an overview of the dataset, as well as the necessary preprocessing steps. We ex-

***Corresponding author: Anna Maria Becker,** Institute of Biomedical Engineering, Karlsruhe Institute of Technology, Kaiserstr. 12, Karlsruhe, Germany, publications@ibt.kit.edu
Matthias Schaufelberger, Werner Nahm, Institute of Biomedical Engineering, Karlsruhe Institute of Technology, Kaiserstr. 12, Karlsruhe, Germany
Reinald Peter Kühle, Christian Freudlsperger, Department of Oral and Maxillofacial Surgery, Heidelberg University Hospital, Im Neuenheimer Feld 400, Heidelberg, Germany

plain the algorithm of the multi-height approach and define how the corresponding feature points can be extracted.

2.1 Dataset and Preprocessing

The dataset was provided by the Department of Oral and Maxillofacial Surgery from the Heidelberg University Hospital and was collected between 2011 and 2022. Each sample consisted of a 3D triangulated mesh of the patient's head and torso. The created meshes had been annotated with ten cephalometric landmarks by medical personnel and were labeled corresponding to the physician's diagnosis.

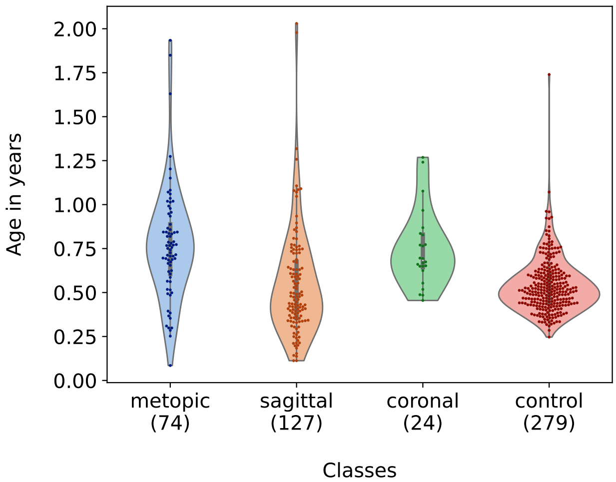

Fig. 1: Class and age distribution within the dataset. Parenthesis indicate the total number of samples.

According to the fused suture, the samples were categorized into one of the three pathologies "sagittal", "metopic" and "coronal" suture fusion (see Fig. 1). The control group consisted of healthy subjects and non-synostotic patients of plagiocephaly who later were treated with helmet therapy. In contrast, all craniosynostosis subjects underwent surgical remodeling of the skull. To prevent data leakage (in this case using different scans from the same subject in training and test data), we removed duplicate scans of the same patients and only kept the scan closest to the therapy start date. Rare diagnoses with less than ten samples were excluded from the study. This resulted in the final dataset of 504 patient samples. All patients were of an appropriate age for diagnosis (see Fig. 1).

2.2 Feature Extraction

As a comparison baseline, we used classification based on CI and CVAI values alone, which were computed on the largest expansion of the heads as

$$\mathrm{CI} = \frac{\mathrm{width}}{\mathrm{length}} = \frac{\mathbf{f}_3 - \mathbf{f}_7}{\mathbf{f}_1 - \mathbf{f}_5} \tag{1}$$

and

$$\mathrm{CVAI} = \frac{\mathrm{diag}_{-30^\circ} - \mathrm{diag}_{30^\circ}}{\max(\mathrm{diag}_{-30^\circ}, \mathrm{diag}_{30^\circ})} = \frac{(\mathbf{f}_4 - \mathbf{f}_8) - (\mathbf{f}_2 - \mathbf{f}_6)}{\max((\mathbf{f}_4 - \mathbf{f}_8), (\mathbf{f}_2 - \mathbf{f}_6))}. \tag{2}$$

The proposed multi-height approach is based on the idea of expanding the CI and CVAI points but distributing them in such a way that they cover a larger portion of the head. To compute the feature points on the 3D mesh, the patient's individual coordinate system (see Fig. 2) was constructed. The cephalometric landmarks were used to determine the individual center point $\mathbf{p}_{\mathrm{c}}$ of the patient's head, corresponding to the midpoint between left and right tragion $\mathbf{p}_{\mathrm{tl}}$ and $\mathbf{p}_{\mathrm{tr}}$. We defined the three coordinate axes $\mathbf{u}_{\mathrm{x}}$, $\mathbf{u}_{\mathrm{y}}$ and $\mathbf{u}_{\mathrm{z}}$ according to the coordinate system defined in [4] and visualized in Fig. 2.

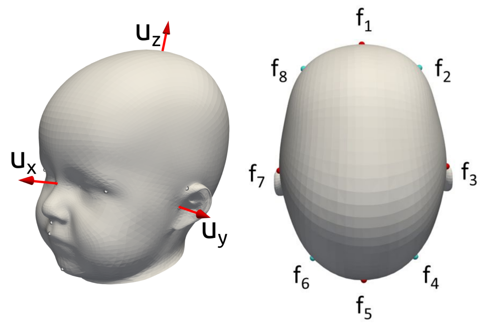

Fig. 2: Visualization of the coordinate axes (left) and enumeration of the feature points (height-independent, right).

For each height, we obtained the regular CI and CVAI feature points (see Fig. 2) using corresponding directional vectors starting from the patient's center point $\mathbf{p}_{\mathrm{c}}$. We determined the distance $\mathbf{d}_{\max}$ between the center point $\mathbf{p}_{\mathrm{c}}$ and the highest point $\mathbf{p}_{\mathrm{tip}}$ of the patient's head using ray tracing and the intersection with the 3D surface mesh.

$$\mathbf{d}_{\max} = \| \mathbf{p}_{\mathrm{tip}} - \mathbf{p}_{\mathrm{c}} \| \tag{3}$$

The CI and CVAI feature points $\mathbf{f}_{\mathrm{init}}$ were then shifted upwards on the axis $\mathbf{u}_{\mathrm{z}}$ to form each individual height. For each height, we used the factor $s = \{0.3, 0.4, 0.5, 0.6\}$ of the distance $\mathbf{d}_{\max}$ for the shift, visualized in Fig. 3.

The CI and CVAI values were then computed for each of the defined heights according to equations 1 and 2. In contrast to the regular CI and CVAI values, the eight features of the multi-height approach were not determined at the largest extension of the head, but were consistent for each subject. The four heights were approximately 12 mm apart.

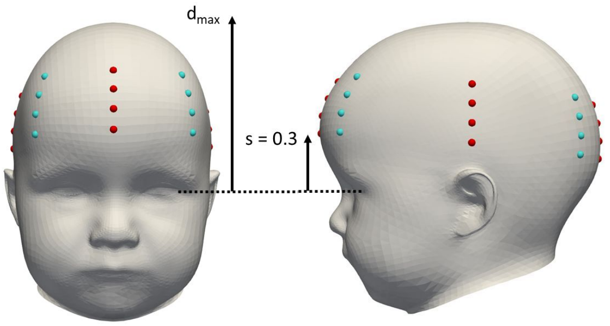

Fig. 3: Final multi-height points for an exemplary control subject. Left: front view, right: side view.

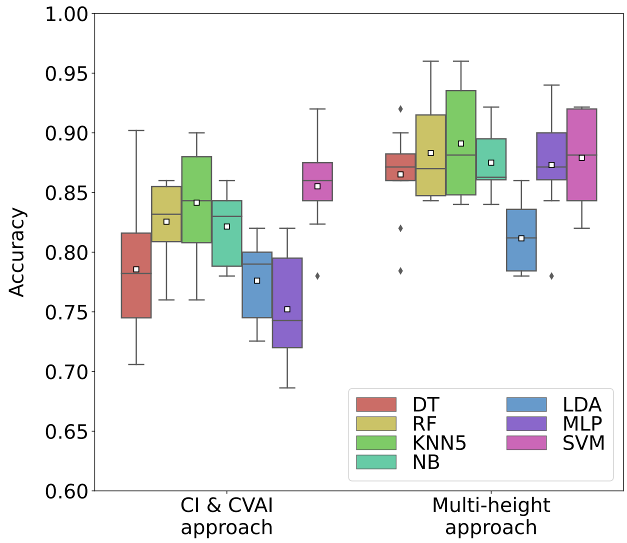

Fig. 4: Accuracy results for different classifiers using the CI and CVAI values vs. our multi-height approach. Mean values are indicated by white squares.

2.3 Experimental Setup and Training Strategies

The classifications were based on a stratified ten-fold cross-validation with reproducible splits to ensure that all classifiers had the same prerequisites. This way, the four classes were evenly distributed across the ten splits so that all classifiers were trained and tested with all available classes. The classification between the four classes was performed using `scikit-learn v1.2.2`.

We used accuracy and F1-score to evaluate classification performance. Mostly, `scikit-learn`'s default settings were used. This includes automatic tree and tree depth generation for decision tree classifier (DT) and random forest classifier (RF). For k-nearest neighbors classifier (KNN), we used $n = 5$ neighbors, and for support vector machine classifier (SVM), we used a kernel based on radial basis functions and a one-versus-one multiclass scheme. The remaining classifiers naive bayes classifier (NB), linear discriminant analysis classifier (LDA), and multi-height perceptron classifier (MLP) were used in their default settings, the MLP using one hidden layer of 100 neurons.

3 Results

For each specific classifier and feature combination, accuracies for each split are displayed in Fig. 4 and F1-scores for each split are displayed in Fig. 5.

Accuracy: Using only CI and CVAI values, the classification results of the individual classifiers varied between 75 % using the MLP and 86 % for the SVM. Compared to the other classifiers, the DT, the KNN and the MLP showed particularly high variances in the results of the individual splits of the cross-validations. For the multi-height approach, the classification accuracy of all classifiers improved. The KNN achieved the overall highest mean accuracy of around 89 % and a slightly reduced variance. The strongest improvements were found for the DT with 8 % and the MLP with 12 %.

F1-score: Similar trends could be observed for the F1-score: All classifiers improved when using the multi-height approach instead of the CI and CVAI approach. A comparatively large variance in the results of the individual splits of the cross-validations was again observed for the KNN and the DT. For both classification approaches, the KNN achieved the highest classification results with an F1-score of about 0.62 and 0.75. The LDA performed poorly compared to the other classifiers even on the multi-height approach with a mean F1-score of 0.59.

4 Discussion

The multi-height approach showed improvements over using the single measurement of the CI and CVAI values. This indicates that taking into account the height dimension improves the classification in this scenario. The information gain likely

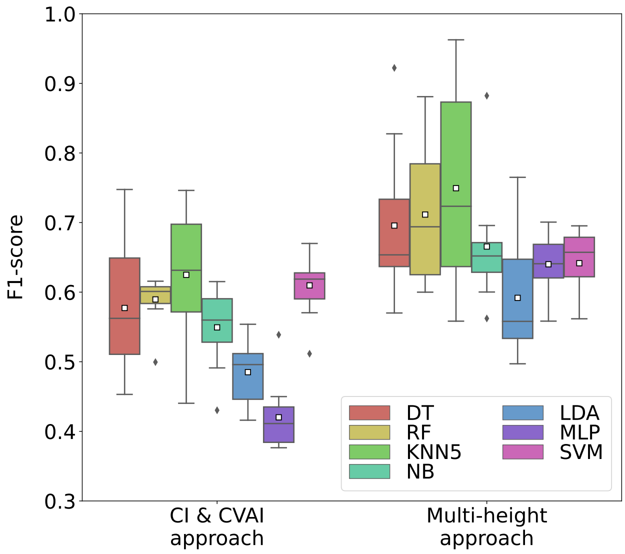

Fig. 5: F1-score results for different classifiers using the CI and CVAI values vs. our multi-height approach. Mean values are indicated by white squares.

occurs because the deformations characteristic for the different types of craniosynostosis also occur at locations of the head that are not used for the determination of the CI and CVAI values. The classifier with the highest performance, KNN, is fully explainable as it classifies the sample according to the closest known sample in the training set. However, the KNN classifier also showed the largest variance indicating that some runs performed well and others poorly. A white-box classifier such as KNN has the additional advantage that the diagnosis can be interpreted by the physicians and patients. However, overall the classification performance falls short compared to more sophisticated approaches taking into account substantially more points [3, 4].

Although the determination of multiple feature points for the multi-height approach is more complex than only using CI and CVAI values, the information gain and the resulting increased classification performance might justify the effort. When determining the feature points automatically from the 3D mesh, the additional effort is negligible. Since the results of this study are dependent on the used dataset, our proposed approach should be validated on another or an extended dataset. To achieve more precise classification results, the classes studied should be represented approximately equally often in the dataset. Data synthesis might be an option to support small and imbalanced datasets.

5 Conclusion

We presented a multi-height approach for the classification of craniosynostosis based on clinical parameters that are already widely used among physicians. While the classification results can still be improved, physicians can draw on existing expertise, ensuring easy application in clinical practice. Due to its simplicity and its foundation in clinical parameters, it might be a suitable path towards an automated and explainable classifier.

Future work could examine the results concerning the age of the children to see if this affects performance. Automatic landmark detection should be employed to remove all manual steps.

Author Statement

Conflict of interest: Authors state no conflict of interest. Ethics approval: Data acquisition and usage was approved by Ethics Committee Medical Faculty of the University of Heidelberg (Ethics number S-237/2009).

References

[1] D. Renier, C. Sainte-Rose, D. Marchac, et al. “Intracranial pressure in craniostenosis”, Journal of Neurosurgery, vol. 57, no. 3, pp. 370–377, Sep. 1982.

[2] J. A. Persing, J. A. Jane, M. Shaffrey, “Virchow and the Pathogenesis of Craniosynostosis: A Translation of His Original Work, Plastic and Reconstructive Surgery”, vol. 83, no. 4, pp. 738–742, Apr. 1989.

[3] de Jong, Guido and Bijlsma, Elmar and Meulstee, et al. “Combining deep learning with 3D stereophotogrammetry for craniosynostosis diagnosis”, Scientific Reports 2020; 10.1038/s41598-020-72143-y

[4] Matthias Schaufelberger, Christian Kaiser, Reinald Kühle, et al. 3D-2D Distance Maps Conversion Enhances Classification of Craniosynostosis. IEEE Transactions on Biomedical Engineering, pages 1–10, 2023.

[5] Schaufelberger M, Kühle R, Wachter A, et al. A Radiation-Free Classification Pipeline for Craniosynostosis Using Statistical Shape Modeling. Diagnostics. 2022; 12(7):1516. 10.3390/diagnostics12071516

[6] Calandrelli, R., Pilato, F., Massimi, L., et al. (2019). The unseen third dimension: a novel approach for assessing head shape severity in infants with isolated sagittal synostosis. Child’s nervous system : ChNS : official journal of the International Society for Pediatric Neurosurgery, 35(8), 1351–1356. 10.1007/s00381-019-04246-5

[7] Kronig, O. D. M., Kronig, S. A. J., Vrooman, H. A., et al. (2020), “Introducing a new method for classifying skull shape abnormalities related to craniosynostosis”, European journal of pediatrics, 179(10), 1569–1577. 10.1007/s00431-020-03643-2