# Photographic Cranial Shape Analysis using Deep Learning

**Mohammad Ali Yektaie [a], Zahra Ghasemi[b], S. Hossein Hezaveh[b], Fereshteh Aalamifar[b], Reza Seifabadi [b], and Marius George Linguraru[b]**

[a] Department of Computer Science, Georgetown University, Washington, DC 20007
[b] PediaMetrix Inc, 155 Gibbs St., Suite 537, Rockville, MD, USA, 20850

## ABSTRACT

***Purpose***: To determine the feasibility of using deep learning algorithms that can identify and classify types of cranial malformations, i.e., craniosynostosis and deformational plagiocephaly and brachycephaly (DPB), using top view photographs of the infant head.

***Method***: We used 72 3D head volumes of infants with normal (13), DPB (34), and craniosynostosis (25). These volumes contain only information about the head shape and lack texture. From these 3D volumes, top-view 2D renderings were generated from different viewing angles. We generated 37 2D files were generated from each 3D volume, and we applied additional data augmentation to obtain a total of 5,254 2D images. We then used this dataset to investigate the performance of a well-known deep learning architectures for image classification, i.e., LeNet. The data were divided into training and test sets (85% and 15%, respectively with minimum one data of each class in the test set). We performed model evaluation by cross-validation.

***Results***: The overall accuracy of the cranial shape analysis model was $87.5 \pm 5.59\%$. Cases with craniosynostosis were identified with $0.99 \pm 0.01$ accuracy, while subjects with DPB were identified with $0.78 \pm 0.1$. The accuracy of the model to identify normal cases without cranial deformation was $0.96 \pm 0.04$.

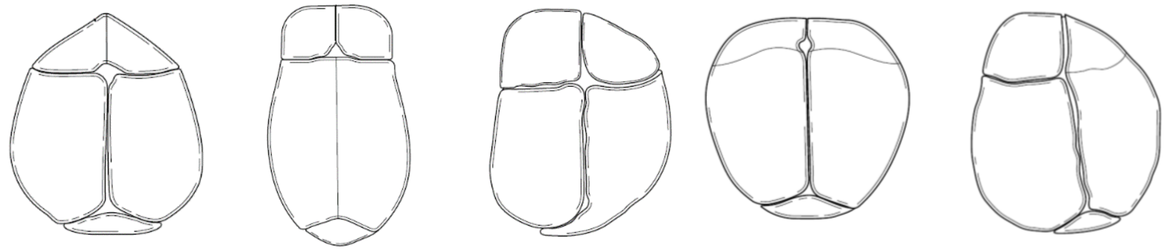
***Conclusions***: Deep learning-based methods can be used for the accurate detection, and classification of different types of conditions with head malformation using 2D photographic data. These algorithms will be packaged as a mobile health solution to make a decision support tool available at the point-of-care.

**Keywords**: Deformational plagiocephaly and brachycephaly, craniosynostosis, point-of-care, smartphone, deep learning, photography

## 1. INTRODUCTION

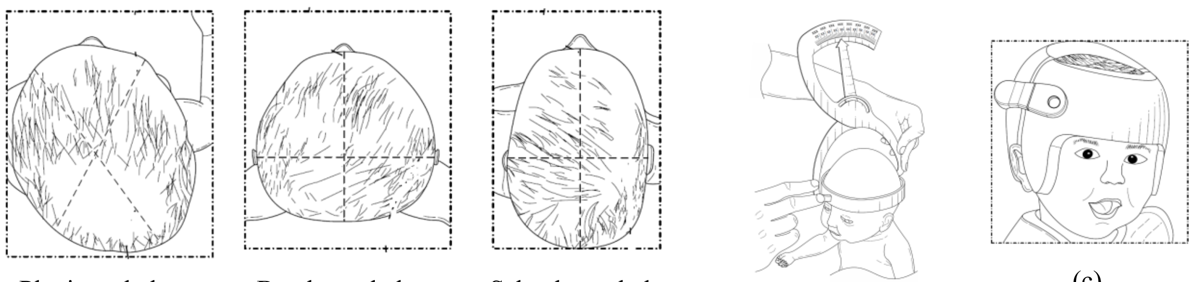
About 20-30% of newborns manifest moderate to severe head deformation in the first months after birth [1], and delayed identification causes significant medical, and societal costs. Infant head deformations can be synostotic (also called craniosynostosis (Figure 1) or nonsynostotic (such as deformational plagiocephaly and brachycephaly or DPB, see Figure 2). These conditions require immediate attention and benefit from early treatment. Abnormal head shape or growth patterns in infants are correlated with other health conditions such as developmental delays, torticollis, microcephaly, and hydrocephalus [1,6-11]. In addition, these children and their families are affected by social stigma, and psychological pressure. Therefore, it is essential to monitor the growth of infant heads to be able to initiate early, and less invasive therapy for children with head deformation, i.e. to prevent the need for helmet therapy for DPB, more complex and multiple surgeries for craniosynostosis, and associated health complications [12-14].

The incidence of DPB is 20-46%. For diagnosis, families are referred by a pediatrician to orthotists or pediatric neurosurgeons who use a mechanical caliper called craniometer (Figure 2.b) or 3D imaging to determine the type, and severity of the cranial deformation. Guidelines for DPB treatment include: 1) conservative/repositioning therapy that can be done by parents at home with potential help of physical therapy, which is effective only if DPB is detected early; and 2) helmet therapy (Figure 2.c), which is necessary for severe cases, and/or older infants (6-12 month).



(a) (b) (c) (d) (e)

**Figure 1**. Types of craniosynostosis: (a) metopic craniosynostosis (trigonocephaly), (b) sagittal synostosis (scaphocephaly), (c) lambdoid synostosis, (d) bicoronal synostosis, and (e) unicoronal synostosis.



Plagiocephaly Brachycephaly Schaphocephaly (b) (c)

(a)

**Fig. 2**. Measurement and management of DPB: a) types of DPB: *plagiocephaly* when the head is asymmetric, *brachycephaly* when the head is wider than normal, and *scaphocephaly* when the head is longer than normal, b) craniometer to measure DPB by a specialist, c) correctional helmet for treatment of DPB.

Craniosynostosis affects one in 2,000 births [3], and is caused by the premature fusion of one or more cranial sutures. Figure 1 illustrates different types of craniosynostosis. Its treatment typically requires surgical intervention. Early detection of craniosynostosis is critical to minimizing the potential brain damage, and facilitating less invasive surgical treatment (e.g., endoscopic interventions) with improved outcome [4,5]. Craniosynostosis is diagnosed by pediatric neurosurgeons who may order a computed tomography (CT) to evaluate the fusion of cranial suture.

A critical challenge in the early detection of cranial deformations is the absence of tools available to pediatricians to perform quantitative head shape assessment during brief well-child visits. Late detection also increases the healthcare expenses, and unsurprisingly, the clinical management of DPB costs over one billion dollars yearly in the U.S. [2].

In this paper, we performed a feasibility study to use deep learning for identifying cranial malformations, and differentiating DPB from craniosynostosis using 2D photographs. Similar studies have been done using 3D scans of the head [16, 17], which requires the use of specialized 3D photogrammetry equipment. Successful implementation of the approach based on simple/2D photography has the potential to help pediatricians with early detection using a smartphone or tablet, and early referral to pediatric neuro/craniofacial surgeons.

## 2. METHODS

We acquired 72 head volumes of infants with normal cranial shape (N=13), DPB (N=34), and craniosynostosis (N=25). Data were acquired with either the 3dMD system (3dMD, Atlanta, GA) or the STAR scanner (Orthomerica, Orlando, FL). Details of the face were removed for deidentification. There were 29 females and 43 males with an average age of 11.85 ± 18.47 months (range 1 to 89 months). The dataset included eight types of conditions: normal (no head deformations); craniosynostosis (sagittal and metopic); and DPB (brachycephaly, left/righ plagiocephaly, and brachycephaly + left/right plagiocephaly). These 3D files contain only information about the head shape and lack texture. Furthermore, details of the face were removed for deidentification.

From these 3D volumes, top-view 2D renderings (in black and white) were generated from different viewing angles. We generated 37 renderings from each 3D volume. We also used data augmentation (i.e., mirroring, rotation, and scaling on the rendered images), a technique commonly used to increase the data sample for machine learning methods.

We rendered the 3D files with 60x80, 90x120, 240x320 and 480x640 pixel resolutions and trained classifiers on all these resolutions. In addition, after the convolutional layers, we flattened the image and fed the flattened vector into fully connected layers. With smaller input images, this flattened vector was considerably smaller, thus requiring a smaller fully connected layer to process. In turn, because these fully connected layers were smaller, the parameter count decreased and required less training data and tuning of the network's weights.

As a result of the steps presented above, we obtained 5,254 renderings. Figure 3 shows the distribution of the data and conditions after performing data augmentation as detailed below.

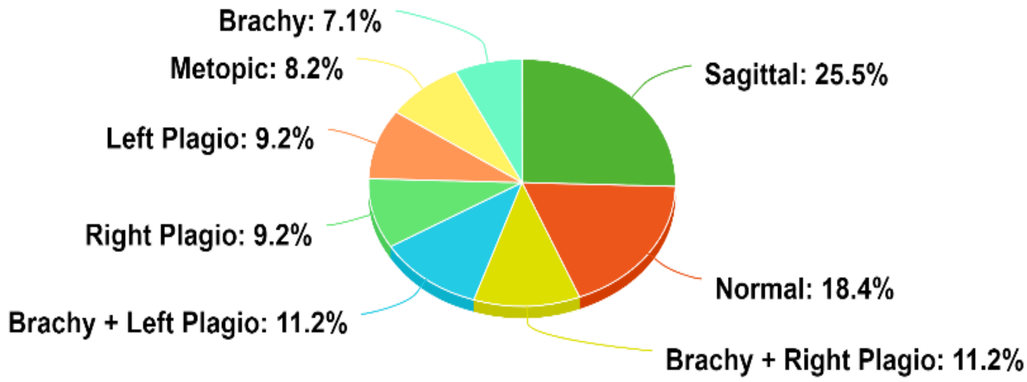



**Fig 3.** The distribution of conditions in training data after preprocessing and augmentation. There were two classes of craniosysnostsis (metopic and sagittal), and three classes of DPB (brachycephaly/brachy, left plagiocephaly/LP and right plagiocephaly/RP). The data included cases with a combination of conditions, e.g., brachycephaly + right/left plagiocephaly.

We extensively experimented with the LeNet architecture. We chose LeNet, which was developed to recognize handwritten digits, a problem also based on the identification of shapes in images. Experimentally, we found that the following configuration yields the best results: a network consisting of 4 convolutional layers with 3x3 filters followed by 2 fully connected layers and a classification layer (Figure 4). Each convolutional layer is followed by a max pooling layer with stride and size of 2. The convolution layers start with 32 channels and increase by a factor of 2 for the first three layers. There is an exception in that last convolutional layer that has the same channel count as the previous one. The fully connected layers have 80 neurons each. Finally, a layer with the size equal to the number of classes (N=8) was added. as the head of the network. The optimization of the classification (loss function) was done using the binary cross entropy with logits to calculate the difference between probability distributions [21].

Given the limited dataset for our feasibility study, we performed model evaluation by cross-validation, i.e., we reshuffled the training and test sets 10 times in a way that each shuffle had the same distribution of classes. The process also ensured that images from the same case were not present in both the test and training sets at one time. We then trained the same classifier with L2 regularization but without drop out on those shuffled sets. Each shuffle was trained through 15 epochs and the maximum accuracy was selected. The data were divided into training and test sets, i.e., 85% and 15%, respectively, ensuring that samples of each class were present in the test set.

## 3. RESULTS

The overall accuracy of the model was 87.5% ± 5.59. Cases with craniosynostosis were identified with 0.99±0.01 accuracy, while subjects with DPB were identified with 0.78±0.1. The accuracy of the model to identify normal cases without cranial deformation was 0.96±0.04. Figure 5 shows additional results for the model to classify craniosynostosis cases into metopic and sagittal, and DPB cases into left plagiocephaly, right plagiocephaly, brachycephaly, and mixed brachycephaly + left plagiocephaly and brachycephaly + left plagiocephaly. Results are shown as the confusion matrix.

Our best performing model used a loss function based on binary cross entropy with logits. We found that the 90x120 image resolution contains sufficient head shape information to obtain the best results, while also guaranteeing efficiency for processing. Our final model had only 600,000 parameters, which makes processing feasible on a single low to medium level GPU. Note that if we increase the input size to 480x640, the number of parameters increase to 80 million.

Our experiments also showed that only the mirroring augmentation had positive effect on the classifier while the other techniques for data augmentation degraded the accuracy. The mirroring augmentation had another desirable impact as it changes the target label for asymmetric conditions such as "left plagiocephaly" to "right plagiocephaly, thus automatically balancing the asymmetric conditions in the dataset. For instance, if 5 left plagiocephaly and 2 right plagiocephaly existed in the dataset, the mirroring augmentation resulted in having 7 examples of each type of condition, thus facilitating the classifier training.

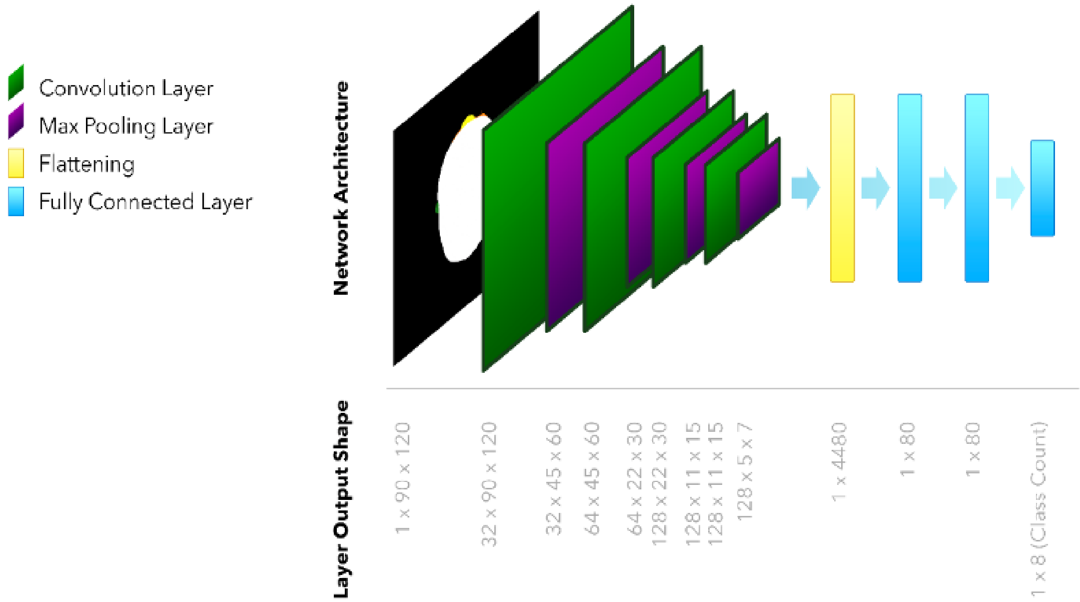



**Fig. 4** Network architecture based on LeNet [15].

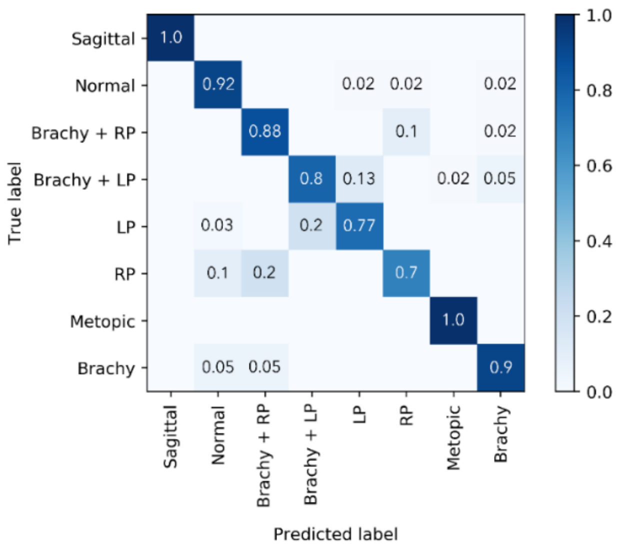



**Fig. 5** Confusion matrix of the classifier to differentiate types of DPB, craniosynostosis and normal cases. There were two classes of craniosysnostsis (metopic and sagittal), and three classes of DPB (brachycephaly/brachy, left plagiocephaly/LP and right plagiocephaly/RP). The data included cases with a combination of conditions, e.g., brachy + RP/LP.

# 1. CONCLUSION

We developed algorithms that can identify, and classify different types of infant cranial deformities from top-view images of the head using deep learning. These results strongly suggest that deep learning with 2D photographic data can provide early and accurate cranial shape analysis at the point-of-care. Successful implementation of the approach has the potential to help pediatricians with detection of craniosynostosis and DPB using a smartphone or tablet, and early referral to pediatric neuro/craniofacial surgeons

**Acknowledgement.** This work was supported by the National Science Foundation SBIR Phase I award No. 1914051.

**References**

1. A. Mawji, et al., “The incidence of positional plagiocephaly: a cohort study,”. Pediatrics. 2013:3438. [doi: https://doi.org/10.1542/peds.2012-3438]
2. SA. Gaetani, “A pediatric epidemic: Deformational plagiocephaly/brachycephaly and congenital muscular torticollis,” Pediatrics, 36(2).
3. Kirmi O, Lo SJ, Johnson D, Anslow P. Craniosynostosis: a radiological and surgical perspective. Seminars in Ultrasound, CT and MRI; Elsevier; 2009.
4. Seruya M, Tan SY, Wray AC, Penington AJ, Greensmith AL, Holmes AD, et al. Total cranial vault remodeling for isolated sagittal synostosis: part I. Postoperative cranial suture patency. Plast Reconstr Surg. 2013;132(4):610e.
5. Proctor MR. Endoscopic craniosynostosis repair. Translational pediatrics. 2014 Jul;3(3):247.
6. IY. Moon, et al., “Analysis of Facial Asymmetry in Deformational Plagiocephaly Using Three-Dimensional Computed Tomographic Review,” Archives of craniofacial surgery," 2014;15(3):109-16. [doi: https://doi.org/10.7181/acfs.2014.15.3.109]
7. BR. Collett, et al., “Development in toddlers with and without deformational plagiocephaly,” Arch Pediatr Adolesc Med. 2011;165(7):653-8. [doi: https://doi.org/10.1001/archpediatrics.2011.92]
8. BR. Collett, et al., “Development at age 36 months in children with deformational plagiocephaly,” Pediatrics. 2013;131(1):e115. [doi: https://doi.org/10.1542/peds.2012-1779]
9. E. Courchesne, et al., “Evidence of brain overgrowth in the first year of life in autism,” JAMA. 2003;290(3):337-44. [doi: https://doi.org/10.1001/jama.290.3.337]
10. E. Fombonne, et al., “Microcephaly and macrocephaly in autism” J autism and developmental disorders. 1999;29(2):113-9. [doi: https://doi.org/10.1023/A:1023036509476]
11. SM. Zahl, et al., “Routine measurement of head circumference as a tool for detecting intracranial expansion in infants: what is the gain? A nationwide survey. Pediatrics. 2008 Mar 1;121(3):e416-20. [doi: https://doi.org/10.1542/peds.2007-1598]
12. M. Seruya et al., “Total cranial vault remodeling for isolated sagittal synostosis: part I. Postoperative cranial suture patency,” J Plastic Reconstructive Surgery, 2013;132(4):610e.
13. DR. Bronfin, ”Misshapen heads in babies: position or pathology?,” The Ochsner Journal. 2001 Oct;3(4):191-9.
14. GH. Noritz, et al., “Motor delays: early identification and evaluation,” Pediatrics. 2013 May 27:peds-2013. [doi: https://doi.org/10.1542/peds.2013-1056]
15. LeCun, Y. 2015. LeNet-5, convolutional neural networks. http://yann.lecun.com/exdb/lenet, Retrieved 31 May, 2020
16. Mendoza CS, Safdar N, Okada K, Myers E, Rogers GF, Linguraru MG. Personalized assessment of craniosynostosis via statistical shape modeling. Med Image Anal. 2014;18(4):635-46.
17. Porras AR, Tu L, Tsering D, Mantilla E, Oh A, Enquobahrie A, Keating R, Rogers GF, Linguraru MG.Quantification of Head Shape from Three-Dimensional Photography for Presurgical and Postsurgical Evaluation of Craniosynostosis. Plast Reconstr Surg. 2019 Dec;144(6):1051e-1060e
18. Aalamifar, F. Hezaveh, S.H. Keating, R. Linguraru, , M.G.: Quantitative Imaging Enables At-Home Assessment of Infants’ Flat Head Syndrome from Head Photographs. In: IEEE Symposium on Biomedical Imaging (ISBI) (2019) 1342

19. Aalamifar, F. Hezaveh, S.H. Linguraru, , M.G., Seifabadi, R.: Evaluation and Correction of Effect of User Input on Accuracy of Smartphone-based Flat Head Syndrome Measurements. In: IEEE Symposium on Biomedical Imaging (ISBI) (2020)
20. Seifabadi, R., Aalamifar, F. Hezaveh, S.H. Linguraru, M.G.: Quantitative Assessment of Deformational Plagiocephaly and Brachycephaly at the Point-of-care, in press, SPIE Medical Imaging Conference, San Diego, Feb 2021.
21. BCE with logits supports multi class classification, https://pytorch.org/docs/master/generated/torch.nn.BCEWithLogitsLoss.html#torch.nn.BCEWithLogitsLoss Accessed on 1/21/2021