2022 44th Annual International Conference of
the IEEE Engineering in Medicine & Biology Society (EMBC)
Scottish Event Campus, Glasgow, UK, July 11-15, 2022

2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 978-1-7281-2782-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/EMBC48229.2022.9871698

Orthotic Prescription for Pediatric Flexible Flat Feet using Convolutional Neural Networks

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Abstract— **Pediatric flexible flat foot (PFFF) is known to increase the foot structure's load, causing potential disability. Foot orthoses are one of the most common non-surgical methods to improve the medial longitudinal arch of the foot for improving PFFF. However, orthoses are not routinely prescribed due to their high cost, and discomfort caused by a restriction of foot movement. Furthermore, there are no quantitative standards or guidelines for an orthotic prescription, which makes the decision-making process of less experienced podiatrists challenging. In this study, the authors investigated convolutional neural networks to classify the needs of orthotic prescription. Using image augmentation techniques and training a VGG-16 model, we achieved high precision and recall, 1 and 0.969 accordingly, to classify orthotic prescription needs.**

I. INTRODUCTION

Pediatric flexible flat foot (PFFF) involves a cycle of a collapse of the medial longitudinal arch of the foot in a weight-bearing posture and restoration of the arch during non-weight-bearing posture in children. The prevalence of PFFF widely varies from 0.6% to 77.9% due to many factors including body mass index (BMI), age, and gender [1][2].

PFFF can lead to a potential disability, including severe pes plano valgus deformity in adulthood, requiring surgical treatments. For reducing the pain and improving the medial longitudinal arch, the most common non-surgical treatments include intrinsic muscle exercises, and orthotic prescription [3]. Foot orthoses can provide early intervention, promoting musculoskeletal development, stability, and improving lower extremity and foot alignment [4].

While orthoses significantly improve PFFF aggravation for many patients, some clinical outcomes showed non-predictable results in terms of discomfort, intrinsic muscle movement restriction and/or lower self-esteem [5][6][7]. In addition, the cost of custom-made orthotics for PFFF can range between $200 and $800, while it requires newly prescribed orthotics every 6 to 12 months with the growth of foot in children [8]. Given high costs and clinical outcomes, it is crucial to classify patients who need the devices accurately [9]. Unfortunately, there are no reliable quantitative standards for orthotic prescription while primarily relying on the presence of pain and progression of deformities [4][10]. A podiatrist with a depth of experience diagnoses the severity of PFFF and prescribes orthosis based on physical examination, gait analysis, radiography, photography, footprints, and pedobarography, which requires profound training, experience, and expenses [11].

While many studies have classified flexible flat feet, no data-driven study has further classified orthotic prescription needs. Xu et al. developed a gait recognition system using pressure sensors. While this study successfully classifies flat feet using the self-organizing-map (SOM) neural network (NN) and support vector machine (SVM), the study does not address the classification between flexible flatfoot or rigid flatfoot or the needs of orthotic prescription [12]. Li's study collected data from smart-insoles embedding baropodometry, stabilometry, and biomechanical sensors. The authors developed a modified weights-and-structure-determination neural network model to distinguish between flat foot versus non-flat foot. This study also did not extend the analysis further for investigating PFFF and orthotic prescription [13].

In this paper, we trained a convolutional neural network model to predict the need of foot orthotic prescription using pedobarography images. A Pedobargraph is a system that measures plantar pressures using use the critical light reflection technique while walking [14]. Pedobarography measures the contact patterns, pressure distribution, and magnitude between the foot and the floor, widely used in quantitative clinical gait analysis studies [15]. We aim to reduce the time and effort of less experienced podiatrists for determining foot orthotic prescription by using pedobarography images only.

II. DATA

The general hospital Institutional Review Board approved this study (IRB No.: 2021-07-004) and waived the informed consent. This study was performed in accordance with the World Medical Association Declaration of Helsinki and under the approved guidelines.

We retrospectively recruited and collected data from 68 children diagnosed with/without PFFF who are 4 to 12 years old from a rehabilitation outpatient foot clinic between June 2014 and June 2021. Among 68 participants, 64 were diagnosed with PFFF where only 33 individuals were prescribed with orthoses by highly experienced podiatrists. The participants' age, stature, weight, and foot size information is given in Table I.

In this study, the researchers utilized pedobarography to classify PFFF orthotic prescriptions. Pedobarograph data

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TABLE I: Study Participant Information - Among 68 participants, 22 were female.

	Average	Standard Deviation
Age (years)	5.180	1.452
Height (cm)	111.479	10.882
Weight (kg)	20.872	5.368
Foot Size (cm)	18.049	1.959

were collected at 50 Hz using an EMED n-50 pedobarograph (Novel, Munich, Germany) with a sensor area of 475×320 mm^2 with 6,080 sensors (Figure 1). The pedobarograph was located at the midpoint of a 6-m walkway. We collected data from five successful trials of each subject walking at a self-selected speed for each foot. The mean value of 5 trials from each foot was chosen for analysis based on its acceptably low within-subject variability.

III. METHODS

1) Image Preprocessing: In order to achieve high accuracy of image classification through convolutional neural networks, it requires a large amount and diverse set of training data.

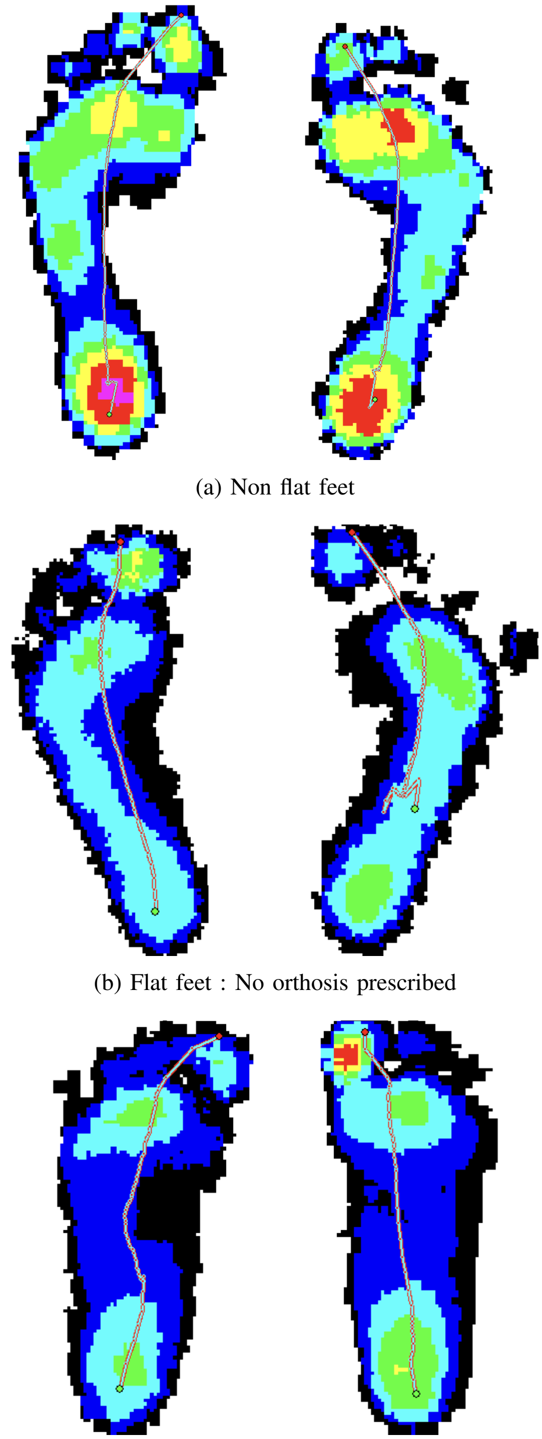
To overcome the limitation of the small data set size, the authors randomly permutated left and right foot images of the data, producing a total of 1,122 images (57.05 GB). Each image was labeled if at least one of the feet was diagnosed as flat foot and required an orthotic prescription.

After image permutation, we applied image augmentation to enhance convolutional neural networks' performance. Image augmentation produces images by slightly changing the original images, including scaling, rotating, shifting, interpolating, and normalization [16][17].

As the original images come in different sizes, we resized their shortest side to 256 pixels and then cropped their middle 256×256 square. Images were also normalized using (1). The mean and standard pixel values were calculated per channel - In our images, we had three channels: red, green, and blue.

$$normalized\_image = \frac{image - mean \times max(pixel\_value)}{std \times max(pixel\_value)} \quad (1)$$

As all foot images might not be aligned in the same direction or skewed on the frames, images were rotated within -15° to 15°, and the corresponding bounding box was updated. We also shifted images to the left, right, up, or down to change the position of the objects in the image to avoid positional bias [18]. For interpolation, we applied bilinear interpolation [19].



(a) Non flat feet

(b) Flat feet : No orthosis prescribed

(c) Flat feet : orthoses prescribed

Fig. 1: Original pedobarography images of non flat feet and flat feet cases

2) Image Classification: In this study, the main objective is classifying whether the subject may require a referral for an orthoses prescription. Experienced podiatrists labeled images in training, validation, and testing sets. Processed images with labels from Section III-.1 were used as input for building an image classification model.

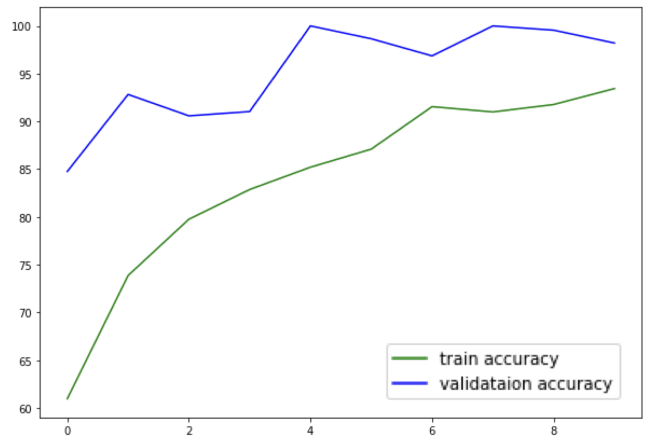


Fig. 2: Accuracy of the model for training and validation data (x-axis : epochs, y-axis : accuracy)

A convolutional neural network (CNN) shows high accuracy in image segmentation, recognition, and classification. CNN consists of a stack of convolutional layers, pooling layers, rectified linear unit (ReLU) layers, fully connected layers, and loss functions [20].

In this study, we utilized the pre-trained VGG-16 model [21]. VGG-16 is an implementation of CNN with 3×3 small receptive filters, 1×1 convolution filters, max-pooling over a 2×2 pixel window, and stride of 2. The depth of VGG-16 is 16 layers, which is significantly deeper and contributes to the model to perform better than many other models, including GoogLeNet [22] for image classification. Utilizing very small filters in all layers allows VGG-16 to have a deeper depth, resulting in superior outcomes.

The model was pre-trained using ImageNet data, which is an image database storing several millions of images with labels [23]. VGG with up to 19 layers won the ImageNet challenge in 2014, showing an outstanding performance in image classification and recognition tasks. Using the pre-trained model, we reshaped the final layer to have the same number of outputs as two, the number of classes in the data set.

IV. RESULTS

After image permutation, we transformed data by image augmentation. We shifted, rotated, and scaled images with the probability of 0.5 and applied bilinear interpolation. For RGB image normalization, we set mean as [0.485, 0.456, 0.406], std as [0.229, 0.224, 0.225], and $max(pixel\_value)$ as 255.0.

TABLE II: Confusion matrix for final validation dataset

	Positive	**Negative**
Positive (Predicted)	125	0
Negative (Predicted)	4	94

Our experiment used 894 images for training, 223 images for validation, and five for testing. For VGG-16, we set our learning rate as 0.001 and momentum as 0.9. The experiment shows that the accuracy increased, while loss decreases as epoch increases (Figure 2 and Figure 3). With the epoch of 10, the validation set accuracy reached 98.21%, with the precision of 1 and the recall of 0.969 (Table II, (2)). Additionally, the accuracy of test data was 100%.

$$precision = \frac{TP}{TP + FP}$$
$$recall = \frac{TP}{TP + FN} \tag{2}$$

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{3}$$

We also compared the model performance with other state-of-the-art convolutional neural network models, including ResNet [24] and GoogLeNet-V3 [25] with the same data set. GoogLeNet-V3 computes multi-level features by using 1×1 and 3×3 convolutions within the same module of the network and sends its concatenated output to the next layer. GoogLeNet-V3 demonstrates high computational efficiency by distributing the depth and width of the network in a balanced way. ResNet overcomes deeper neural networks' performance degradation issues and achieves high accuracy using shortcut connections by skipping one or more layers. While ResNet uses a deeper depth than VGG, the model shows higher computational efficiency than VGG-16 by global average pooling. In our experiment, the depth for ResNet was set as 50.

The experiment result shows that VGG-16 outperforms (Table III). Although the training time takes longer, we found that VGG-16 would be the most accurate model for making a clinical decision to recommend foot orthoses using pedobargraphy images.

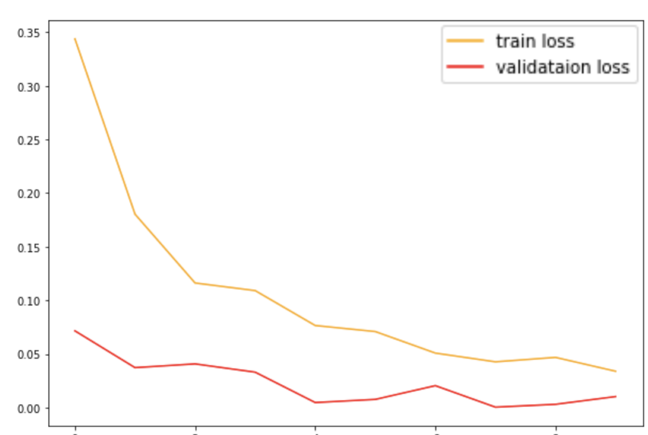


Fig. 3: loss of the model for training and validation data (x-axis : epochs, y-axis : loss)

TABLE III: Validation accuracy (%) of different deep learning models (ResNet [24], GoogLeNet-V3 [25])

	GoogLeNet-V3	Resnet	VGG-16
Validation Accuracy (%)	78.92	86.55	98.21
Training Time (min)	19.33	28.53	52.59

V. DISCUSSION

Foot orthoses can reduce pain, discomfort, and fatigue by keeping the foot in a proper position. As foot orthoses could cause discomfort, causing low acceptability, experts often avoid routinely prescribing foot orthoses in children with PFFF. Without quantitative guidelines, the foot orthoses prescription process heavily depends on experienced pediatric podiatrist opinions and one's discomfort level.

In this study, the authors applied image augmentation and convolutional neural networks to develop a model to assist the orthotic prescription decision-making process for less experienced pediatric podiatrists. The experiment result confirms that VGG-16, a convolutional neural network model could determine the need for a foot orthoses prescription with a high F1 score value (0.984, (3)).

In our future study, we will develop an image classification model using podiatric X-ray data. Furthermore, we will investigate its accuracy, time efficiency, and cost-effectiveness compared to the model introduced in this study. This will further assist inexperienced podiatrists in developing a data-driven decision-making process for PFFF orthotic prescription.

ACKNOWLEDGMENT

This work was supported by grant from the Ewha Alumni Medical Research Grant. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

REFERENCES

[1] F. Halabchi, R. Mazaheri, M. Mirshahi, and L. Abbasian, "Pediatric flexible flatfoot; clinical aspects and algorithmic approach," *Iranian journal of pediatrics*, vol. 23, no. 3, p. 247, 2013.

[2] J.-H. Chang, S.-H. Wang, C.-L. Kuo, H. C. Shen, Y.-W. Hong, and L.-C. Lin, "Prevalence of flexible flatfoot in taiwanese school-aged children in relation to obesity, gender, and age," *European journal of pediatrics*, vol. 169, no. 4, pp. 447–452, 2010.

[3] J. Y. Choi, W. H. Hong, J. S. Suh, J. H. Han, D. J. Lee, and Y. J. Lee, "The long-term structural effect of orthoses for pediatric flexible flat foot: A systematic review," *Foot and ankle surgery*, vol. 26, no. 2, pp. 181–188, 2020.

[4] K. Kane, "Foot orthoses for pediatric flexible flatfoot: evidence and current practices among canadian physical therapists," *Pediatric Physical Therapy*, vol. 27, no. 1, pp. 53–59, 2015.

[5] H. Fox and I. Winson, "Foot orthoses: an audit of expenditure and efficacy," *The Foot*, vol. 4, no. 2, pp. 79–82, 1994.

[6] A. N. Driano, L. Staheli, and L. T. Staheli, "Psychosocial development and corrective shoewear use in childhood," *Journal of Pediatric Orthopaedics*, vol. 18, no. 3, pp. 346–349, 1998.

[7] E. Sobel, S. Levitz, and M. Caselli, "Orthoses in the treatment of rearfoot problems," *Journal of the American Podiatric Medical Association*, vol. 89, no. 5, pp. 220–233, 1999.

[8] L. Atefe, T. Ghomshe, and B. Mahmood, "Comparison of semicustom and custom university of california biomechanics laboratory on lower-limb kinematics in flexible flatfoot," *JPO: Journal of Prosthetics and Orthotics*, 2022.

[9] C. Nicolopoulos, B. Scott, and P. Giannoudis, "Biomechanical basis of foot orthotic prescription," *Current Orthopaedics*, vol. 14, no. 6, pp. 464–469, 2000.

[10] K. Rome, R. L. Ashford, and A. Evans, "Non-surgical interventions for paediatric pes planus," *Cochrane Database of systematic reviews*, no. 7, 2010.

[11] A. M. Evans, "The flat-footed child—to treat or not to treat: what is the clinician to do?" *Journal of the American Podiatric Medical Association*, vol. 98, no. 5, pp. 386–393, 2008.

[12] L. Xu, J. Chen, F. Wang, Y. Chen, W. Yang, and C. Yang, "Machine-learning-based children's pathological gait classification with low-cost gait-recognition system," *BioMedical Engineering OnLine*, vol. 20, no. 1, pp. 1–19, 2021.

[13] H. Li, Z. Huang, J. Fu, Y. Li, N. Zeng, J. Zhang, C. Ye, and L. Jin, "Modified weights-and-structure-determination neural network for pattern classification of flatfoot," *IEEE Access*, vol. 7, pp. 63 146–63 154, 2019.

[14] M. N. Orlin and T. G. McPoil, "Plantar pressure assessment," *Physical therapy*, vol. 80, no. 4, pp. 399–409, 2000.

[15] A. Skopljak, M. Muftic, A. Sukalo, I. Masic, and L. Zunic, "Pedobarography in diagnosis and clinical application," *Acta Informatica Medica*, vol. 22, no. 6, p. 374, 2014.

[16] E. K. V. I. I. A. Buslaev, A. Parinov and A. A. Kalinin, "Albumentations: fast and flexible image augmentations," *ArXiv e-prints*, 2018.

[17] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. 25, pp. 1097–1105, 2012.

[18] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, no. 1, pp. 1–48, 2019.

[19] D. Han, "Comparison of commonly used image interpolation methods," in *Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013)*, vol. 10, 2013.

[20] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: Concepts, cnn architectures, challenges, applications, future directions," *Journal of big Data*, vol. 8, no. 1, pp. 1–74, 2021.

[21] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[22] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[23] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "ImageNet: A Large-Scale Hierarchical Image Database," in *CVPR09*, 2009.

[24] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[25] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 2818–2826.