Machine Learning Analyzations of Infant Limb Motion Using the PANDA Gym

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Takeaway: Preliminary results show that a top-down view results in better predictions than other angles. It is also easier to predict movements when body parts aren't covered or hidden from the camera's view.

Introduction

- A variety of clinical scales to assess infant development exist, but they require training, are time consuming, have low validity, or have age restrictions of older than 1 year old [1].
- The Play and Neuro Development Assessment (PANDA) Gym was created to serve as a universal, portable, quantitative, and affordable screening tool to detect developmental delays earlier in an ecological environment.
- **Objective: Use machine learning to analyze and predict the movement of infants when using the PANDA Gym, ultimately using these results to categorize their interactions with the toy.**

Methods

- **Subject Population:** A random selection of infants who used the toy between 2021-2023.
- **Data Collection:** Seven cameras are placed on the Gym in different angles above the baby: three directly above and four on opposing corners of the Gym. There are six recordings done in each session: three calibrations without the baby, one with the baby and no toy, one with the toy at the baby's arms, and one with the toy at the baby's feet.
- **Video Assessment:** The DeepLabCut GUI created by the Mathis Laboratory takes in the videos and extracts 20 significant frames [2]. The user then labels each of the body parts according to the OpenPose diagram created by the Simms Lab [3]. The labeled frames are run through the DeepLabCut Google Colab program to train the dataset and predict labels for each of the complete videos [4]. Each dataset contains videos from a different camera angle.
- **Label Evaluation:** If the user deems that the machine-generated labels aren't accurate, the user can add more videos to the dataset and retrain.

Fig 1. PANDA Gym with its seven cameras above an infant simulator robot.

Fig 2. DeepLabCut GUI used to label frames.

Results

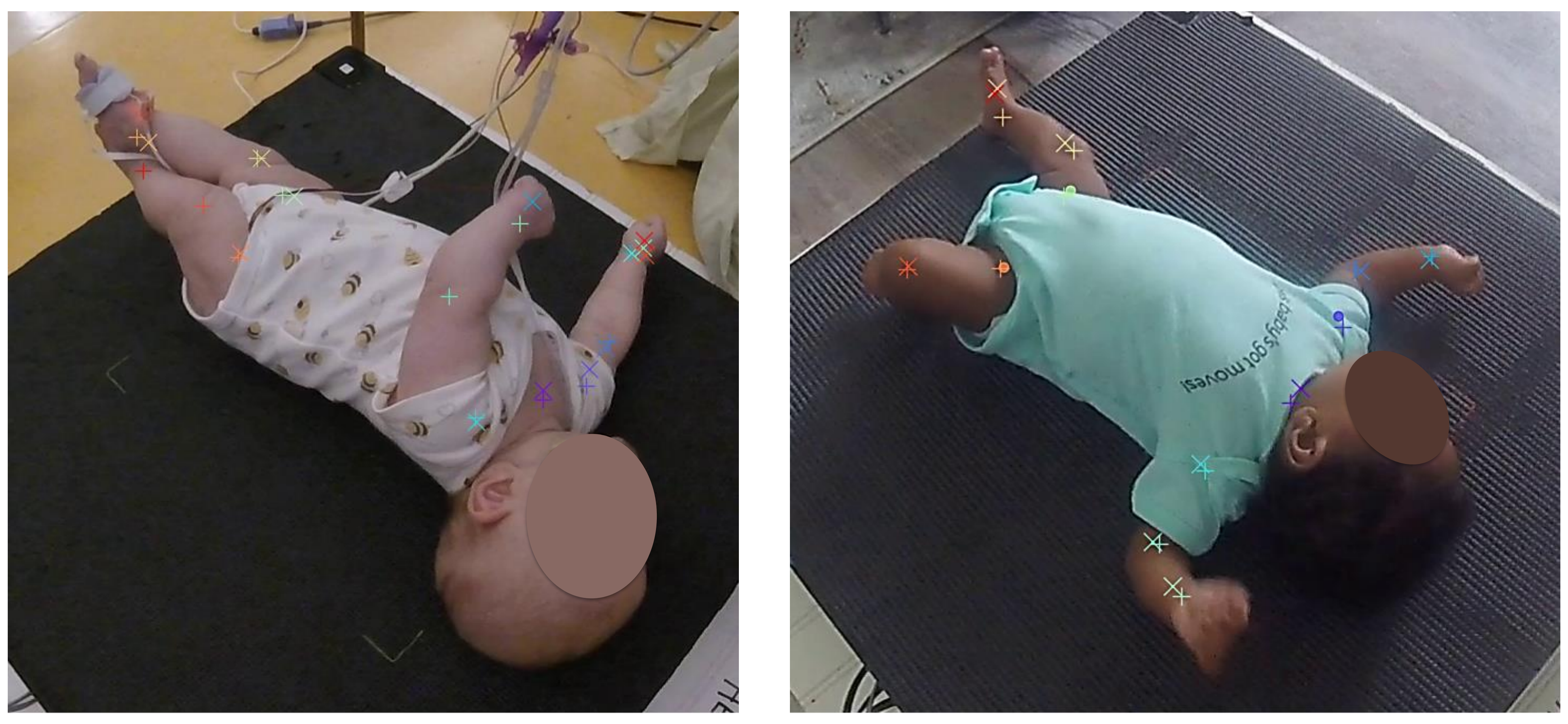

Fig 3. Trained data from camera 5, at the top right corner of the Gym. Plus signs are user labelled points, X's and circles are machine-generated. (Left) Most machine-generated labels are incorrect due to body parts overlapping. (Right) Most machine-generated labels are accurate, with right ankle generating to the left ankle due to right ankle being hidden.

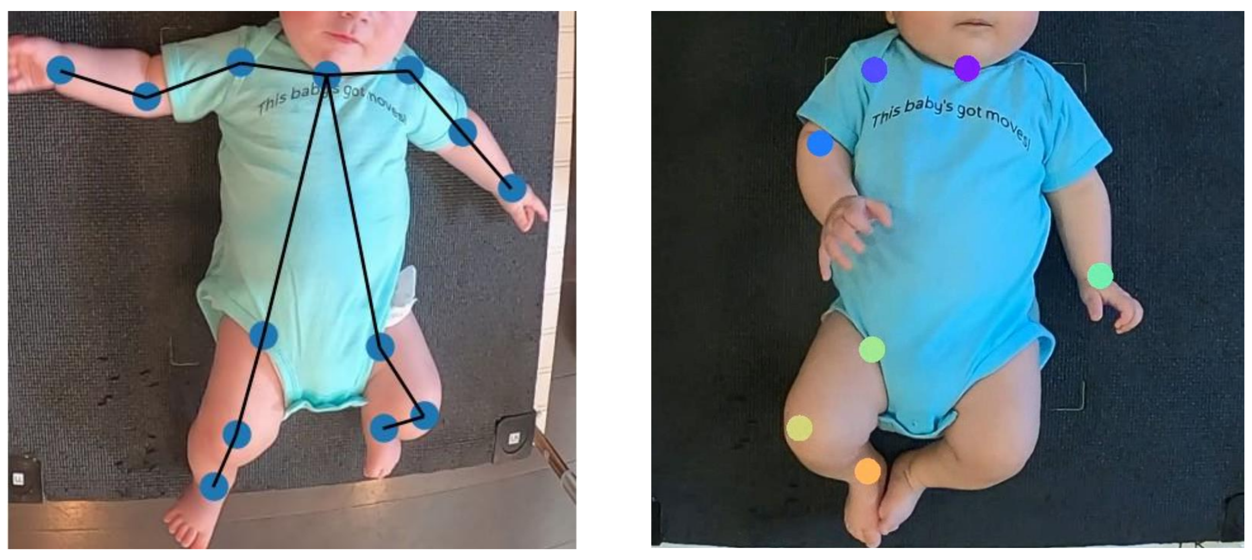

Fig 4. Trained data from camera 3, directly above the baby. (Left) Skeleton generated from the labelled points. (Right) Machine-generated labels placed on video.

Discussion and Conclusions

- These preliminary results show that datasets that used a camera angle that was directly above the baby, as opposed to on the side, had more accurate labels after being trained.
- To have a better trained dataset, the baby's whole body needs to be in view during the video. The program has trouble analyzing when areas such as the lower legs are cut out in the videos. It also has trouble analyzing when body parts are overlapping in the camera's view. To have useful extracted frames, the user needs to crop out the background so external movement isn't being analyzed.
- Going forward, using multiple camera angles in one dataset may be able to help with hidden or cropped body parts. More experimentation will be done to classify the movements of the babies. There will also be testing done to create accurate predicted labels when the toy is obstructing the camera's view.

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References

[1] Goyal, V., Torres, W., Rai, R., Shofer, F., Bogen, D., Bryant, P., Prosser, L., & Johnson, M.J. (2017). Quantifying Infant Physical Interactions using Sensorized Toys in a Natural Play Environment. 2017 International Conference on Rehabilitation Robotics (ICORR), London. doi:10.1109/ICORR.2017.8009360
[2] *DeepLabCut user guide (for Single Animal Projects).* DeepLabCut (2022). https://deeplabcut.github.io/DeepLabCut/docs/standardDeepLabCut_UserGuide.html
[3] *Introduction to OpenPose*. Simms Lab (July 7, 2023). Retrieved from Simms Lab website: https://www.csimmslab.com/blog/introduction-to-openpose
[4] DeepLabCut. (2023). latest_Colab_TrainNetwork_VideoAnalysis.