Camera-based Early Detection of Cerebral Palsy Movement Patterns In Newborns

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Introduction

- The prevalence of neuromotor conditions in newborns continues to increase, affecting approximately 16% of all children.
- Although characterized by persistent movement and posture disturbances secondary to neurologic injury or malformation , the diagnosis of CP is often delayed to 18-24 months of age due to variations in "typical movement" and rates of development.
- The advent of complex sensor technology and artificial intelligence (AI) methodologies offers the potential for accessible and non-invasive screening tools in pediatric neurodevelopment.
- The objective of this study is to report preliminary findings from experiments involving prospectively collected infant videos towards the prediction of a cerebral palsy diagnosis using time series analysis and computer vision models.

Methods

- Infants between 0 and 6 months corrected age were enrolled in our IRB-approved, prospective video collection study at an academic pediatric hospital and its affiliate locations between October 2020 and September 2023, following written informed parental consent.
- At 2- and 3-years old, a retrospective chart review was completed for each infant. Infants without available medical records at these follow-up points (post video recording) were also excluded from this pilot analysis.
- Using a pose estimation model, we calculated kinematic features such as torso rotation, distances between joints, and angular displacement.
- Deep learning models were trained on the data to classify infants based on a CP diagnosis at a two-year old follow-up. Model performance was evaluated in a cross-validation experimental set-up with an emphasis on ROC-AUC, sensitivity, and specificity metrics.

Data

- A total of 930 infants were enrolled in the study and had complete data at the two year follow-up timepoint.
- 657 infants did not have a neuromotor diagnosis at the 2 or 3 year old timepoint and were categorized as "Typical," or NKD ("No Known Diagnosis").
- The remainder of enrolled infants (273) were categorized as "Atypical," with 42 such patients having a positive cerebral palsy (CP) diagnosis. In the case where a sample had multiple diagnosis labels, if CP was listed at all, the sample was labeled as CP.

Results

- The highest performing median ROC for predicting CP was 0.82.
- "Joint_to_joint" features was the most informative feature when using training data from video snippets that were marked as salient by the clinical team.
- Model performance suggests that distances between multiple joints and their evolution over time is most informative when predicting CP, especially ipsilateral pairs of joints on the same side of the body, namely: wrist to ankle, elbow to knee, wrist to shoulder, and ankle to hip.

Discussion

- This pilot study addresses the feasibility and success of applying pose-derived kinematic features and deep learning for early detection of cerebral palsy in infants.
- Our results indicate that joint-to-joint features are particularly valuable in discriminative power, while individual joint-based tracking contributes minimally. Additionally, we see marked performance gains with clinician-annotated video snippets, highlighting the need for thoughtful data selection in model development.
- The limited number of positive samples in this study will be expanded in future work as we develop machine learning models to detect and describe a more encompassing set of aberrant movement patterns.

Figures

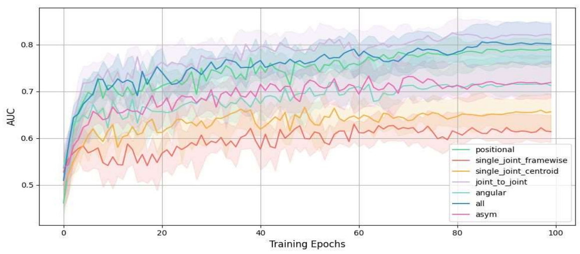

Figure 1: Model training performance broken down by feature set (for salient training scenario).

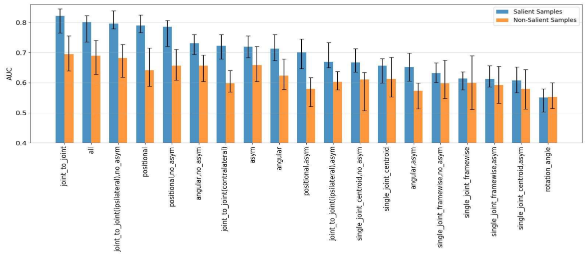

Figure 2: Model testing performance broken down by feature set, for salient and non-salient evaluation scenarios.

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