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RESEARCH ARTICLE

Using DeepLabCut to Recognize Early Motor Development Patterns Associated With Neurodevelopmental Disorders

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the National Ethics Committee for Clinical Trials of Public Research Bodies (EPR) and other National Public Institutions (CEN).

ABSTRACT Early identification of Neurodevelopmental Disorders (NDD) allows for faster intervention, which in turn improves clinical outcomes and reduces the individual and societal costs associated with the diagnosis. The aims of the study were to 1) investigate the use of the DeepLabCut (DLC) toolbox to automatically analyze the motor patterns of infants at Low Risk (LR) and High Risk (HR) for Autism Spectrum Disorder (ASD); and 2) define the critical time window in which atypical motor patterns discriminate between typically developing infants and those diagnosed with ASD or NDD. The DLC toolbox was used to train a model capable of tracking the movements of both LR and HR infants longitudinally at the ages of 10 days, 6 weeks, 12 weeks, 18 weeks, and 24 weeks. 226 videos of 87 infants (45 females), collected within the Italian Network for Early Detection of Autism Spectrum Disorder (NIDA), were analyzed. Using the Percentage of Correct Key-points (PCKh) accuracy metric, the DLC's tracking performance was verified by comparing the obtained 2D hands and feet coordinates with those extracted by the Movidea software. Furthermore, motor features were computed and fed to three classifiers: Fine Tree, RUSBoosted Trees, and Narrow Neural Network to investigate their usefulness in terms of early NDD prediction. Satisfactory PCKh results were obtained for both hands and feet (left foot: 96.6%, right foot: 96.2 %, left hand: 80.9%, right hand: 82.8%). The best classification results were obtained with the RUSBoosted classifier at the ages of 10 days and 6 weeks. The 5-fold cross-validation accuracy was 81.4%, with a true negative rate of 80.0% and true positive rate 87.5%. Our data confirm the usefulness of DLC as a low-cost approach to track infant movements during the writhing period. Early motor behavior at the ages of 10 days and 6 weeks carries valuable information that has the potential to be suitable in predicting the diagnosis of NDD.

INDEX TERMS Autism, DeepLabCut, high risk infants, early behavior, movement tracking, neurodevelopmental disorders.

I. INTRODUCTION

Neurodevelopmental Disorders (NDD), including Autism Spectrum Disorder (ASD), are early onset conditions,

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characterized by various deficits in one's personal, academic, social, or occupational functioning [1].

Early identification of NDD is critical but challenging due to a long prodromal period through mid- to late infancy [2], [3]. Thanks to the high degree of neuroplasticity in the first years of human life [4], early intervention has the potential not only to maximize individual outcomes and improve prognosis [5], but also to reduce the societal and family costs associated with the diagnosis [6]. Recently, there has been an increased interest in the early detection of NDD, including ASD, which is currently diagnosed, in the best-case scenario, when a child is around 2-3 years of age [7], [8], [9], [10]. According to various studies, differences between children later diagnosed with ASD and those typically developing (TD) ones are already present in the first year of life [11], [12]. Movement atypicality is one of the first signs that might precede social or language abnormalities in ASD [13]. Therefore, even though atypical motor development is not a core symptom of ASD, it is often examined in the context of risk assessment [14]. Indeed, early motor development has been extensively explored in high-risk infants of developing ASD, i.e., siblings of children with a diagnosis of ASD, in whom the prevalence of ASD is higher than that observed in the general population [15].

Although motor problems are among the most important co-occurring conditions in ASD [16], an autism-specific atypical motor profile has not yet been defined. Both qualitative and quantitative motor atypicalities may occur in autistic individuals. Early motor markers of ASD include postural asymmetries [17] and poor postural control [18]. Teitelbaum and colleagues [19] retrospectively analyzed videos of infants aged 4-6 months who were later diagnosed with ASD and found difficulties with lying, righting, sitting, crawling, and walking. Furthermore, some studies have shown that from the age of 12 months, autistic individuals received lower gross and fine motor scores compared to their undiagnosed peers [20], [21], [22], [23]. Additionally, Phagava and co-authors [23] revealed differences between infants with and without ASD in general movements (GMs). GMs are present from early fetal life and are usually assessed until 20 weeks post-term, which is when intentional and antigravity movements appear and begin to dominate [24]. GMs are part of the spontaneous movement repertoire and are easily observable due to their frequent occurrence and extended duration, which facilitates accurate assessment [25]. At term age and during the first two months of life, the GMs are called writhing [26]. They are characterized by an ellipsoid form, and low to moderate speed and amplitude. Normal GMs are perceived as fluid, elegant, and complex, including rotations along the axis of the limbs. They involve the whole body with a variable sequence of trunk, neck, arm, and leg movements. By 6-9 weeks after birth, fidgety movements (FMs) begin to emerge and slowly replace writhing. An awake and alert infant expresses them continuously. They are characterized by small, circular movements of the limbs, neck, and trunk. FMs are small in amplitude and moderate in speed. Even though, according to Einspieler [27], the fidgety GMs might still occur in infants until around 6 months of age, due to the emergence of voluntary, goal-directed movements between 15 and 20 weeks of age, the evaluation of FMs after 15 weeks post-term might be difficult and not fully reliable [24]. According to the study by Phagava and colleagues [23], autistic individuals more often presented a poor repertoire during the writhing period and abnormal or absent FMs. Some authors emphasize that infants later diagnosed with ASD may achieve motor milestones at the same time as their TD peers but might perform them in a qualitatively abnormal manner [28], [29]. Therefore, both qualitative and quantitative assessment of individual behaviors are needed, rather than global measures of motor milestone achievement.

Motor behaviors are often studied by marking people with physical, reflective markers, which are not only intrusive, but whose number and location have to be determined a priori [30], potentially influencing the natural behavior of the subject being studied. Therefore, markerless pose estimation, using computer vision, is becoming increasingly popular in the field of motion analysis. Noticeable improvements have been triggered by advances in convolutional networks [31]. In 2021, Desmarais and colleagues [31] showed that, among the leading human pose estimation methods, the most accurate techniques used various architectures, such as 3D human body models, learnable triangulation, or temporal convolutional networks, and a consensus on the best approach has not yet been reached. According to the authors [31], a well-recognized interdisciplinary pose estimation framework is DeepLabCut (DLC) [30], [32] – which aims to achieve human-like tracking accuracy using Deep Neural Networks. DLC is an open-source toolbox contained within a Python package. It is based on transfer learning with deep neural networks. Thanks to the ability to take a network trained on one task with a large, supervised dataset (in this case ImageNet), and use it for another task with a small, supervised dataset, DLC can use limited training data and accurately track user-defined features [32]. The major advantages of this approach are its powerful generalization ability and flexibility – the labels are personalized, and the user can decide which key points to track.

Recently, a software package called Movidea [33], [34] has been developed for the automatic analysis of movement of infants at risk for NDD. It allows the operator to track the infant's end-effectors in free moving conditions and automatically extract various motor features from a given video. Movidea collects measurable and quantifiable information not based on visual scoring of an infant's motor performance, completed by clinicians or trained operators during the well-child visits.

In this study, we aim to 1) investigate the use of DLC to automatically analyze the motor patterns of infants at low and high risk for ASD; and 2) define the critical time window in which atypical motor patterns discriminate between typically developing infants and those diagnosed with ASD or NDD. The present study represents a significant advancement from traditional methods by employing DLC, which utilize state-of-the-art computer vision and deep learning algorithms for more accurate and less intrusive movement analysis, utilize markerless pose estimation to reduce biases from physical markers, enable automatic and objective extraction of motor features from video recordings compared to manual visual scoring, and focus on defining critical time windows for detecting atypical motor patterns, potentially offering earlier and more precise indicators of ASD.

II. MATERIALS AND METHODS

A. PARTICIPANTS

The Italian Network for Early Detection of Autism Spectrum Disorder (NIDA Network) is the largest development surveillance program for infants at risk of NDD in Italy, coordinated by the National Institute of Health (Istituto Superiore di Sanità, ISS). Infants were recruited between 2012 and 2020 in pediatric hospitals and clinical research centers throughout the entire Italian territory. The study protocol was approved by the Ethics Committee of the ISS (Approval Number: Pre 469/2016). Written informed consent were obtained from parents/guardians before video recording. The inclusion criteria for infants were 1) birth weight $\geq$ 2500 g; 2) absence of known medical, genetic, or neurological conditions associated with ASD; 3) gestational age $\geq$ 36 weeks; 4) absence of major complications in pregnancy and/or delivery likely to affect brain development, and 5) Apgar index $>$ 7 at the 5th minute.

A total of 226 videos of 87 infants (45 females), recorded longitudinally at the age of 10 days, 6 weeks, 12 weeks, 18 weeks, and 24 weeks, were analyzed. Participants were divided into groups with a high (HR, n = 50) or low (LR, n = 37) risk of ASD. Individuals from the HR group had an older autistic sibling, whereas those from the LR had no family history of autism. At the age of 24 or 36 months, participants' clinical outcomes were assessed by blinded expert clinicians from the NIDA Network using standardized tools/tests and structured interviews with parents for checking the presence/absence of an ASD or NDD diagnosis. The NIDA Network's comprehensive clinical protocol allows the characterization of a child's developmental profile in all domains, including motor, communication/language and social domains [35]. 19 participants received an NDD diagnosis, out of which 18 belonged to the HR group. In our sample, NDD diagnosis included ASD, Communication Disorders, Attention Deficit Hyperactivity Disorder, and Motor Disorder.

A total of 126 videos of the HR group, and 100 of the LR group were collected. 180 videos came from infants who did not receive a diagnosis during the assessment stage of the study, whereas 46 came from individuals diagnosed with NDD.

B. VIDEO RECORDING AND PREPARATION

The recordings took place at participants' homes to avoid any infants' and/or parents' discomfort. The child was lying on a green blanket. The camera was placed above the infant, at chest height. The recording lasted at least 5 minutes and aimed to acquire images of spontaneous movement of the child's full body [33]. The researchers (either a psychologist, neurobiologist, or therapist) placed the camera 50 cm away from the child, recorded the infant in a well-lit room, and did not interact with the infant during the process of data collection. Parents were invited to leave the room to avoid attracting the infant's attention which could disturb the expression of movement and to ensure a video recording of an infant spontaneously moving, based on Prechtl's General Movement Assessment [18].

The preliminary evaluation of the recordings showed that high-quality video without any interferences did not last longer than 3 minutes [33]. Therefore, 3-minute video segments where the infant was in supine position, in a condition of well-being, without crying episodes or accidental movements of the camera were selected. If the video lasted for longer than 3 minutes, then the first 3 minutes of the high-quality frames were chosen. If the 3-minute video segments did not reach high quality, they were not included in the analysis.

C. DLC MODEL TRAINING

To train the DLC model, the workflow used in Nath and colleagues [32] was followed. To track the infant's movements, we labeled the central points on the back of the hands and feet (Fig.1).

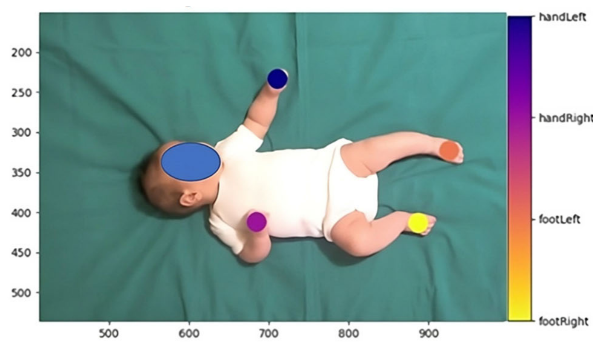

FIGURE 1. **The labeling Graphical User Interface (GUI) in DLC and the tracked body parts.**

To provide good generalization, the final model was trained using 3,597 labeled frames across 129 different videos. Recordings of infants from each age group were used. The algorithm was trained for 850,000 iterations using a laptop with the NVIDIA GPU (RTX 3060). The networ's performance was measured as the mean average Euclidean error between the labels predicted by DLC and the manual ones. To help exclude occluded data, DLC returns not only the x and y coordinates of the body part of interest but also their probability. The user can then determine the likelihood threshold of data points. To choose the best value, the percentage of available data, as well as the train and test errors, were checked for various likelihood thresholds (from 0% to 90%, by every 10 percentage points). Exceeding the likelihood threshold of 10% did not provide a major drop in errors obtained. Therefore, to preserve as much data as possible, the likelihood threshold of 10% was chosen. The obtained train error was then 3.16 pixels, and the test error was equal to 3.47 pixels, less than 1% related to video resolution (640 $\times$ 480).

We performed a stratified 5-fold cross-validation to ensure that each fold is representative of the entire dataset in terms of class distribution. This process was carried out as follows: the dataset was randomly divided into five equal parts, maintaining the proportion of HR and LR videos in each fold. For each fold, four parts were used for training (80%), and one part was used for testing (20%). This procedure was repeated five times, ensuring that each part was used as a test set exactly once. To prevent overfitting, we ensured that the training and testing sets were completely independent for each fold. This means that no video used for training in a given fold was included in the testing set for that fold.

D. TRAJECTORIES' PROCESSING

The trained DLC model was then utilized to perform tracking of the children's hands and feet in all videos within the dataset. To get rid of outliers that could result from any tracking errors, the data were filtered in two ways. First, by using a 1-dimensional median filter with a window size equal to 7 [36]. Second, by calculating a z-score of each data point compared to the entire trajectory of the point in the respective video and eliminating those data points that were further away than 3 SDs from the mean. If the z-score of one of the two coordinates exceeded this threshold, the whole point was eliminated. After these steps, the percentages of missing data were calculated for each tracked body part and for each age group (Fig. 2). Infants tended to point the back of their hands down to the floor during the recording resulting in a high percentage of missing hand data (Fig. 2). Therefore, the computation of motor features was conducted using only the feet trajectories.

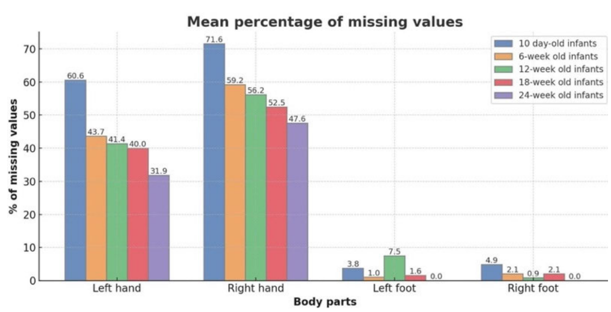

FIGURE 2. Mean percentage of missing data points for left/right hands/feet by age group.

E. TRACKING DLC PERFORMANCE VS MOVIDEA

To further verify the performance of our model, we compared the hands and feet coordinates obtained with DLC with those extracted by Movidea software [33]. Movidea is a semi-automatic software designed for tracking the end-effectors of children in a video. It requires an operator to preselect a set of parameters, including the headline, the central line of the infant's body, and the central point of the end effector. The Percentage of Correct Key-points (PCKh) accuracy metric was calculated using 50% of the head length as a distance threshold. This metric showed how often the predicted key point and the true joint were within the chosen distance limit. The Movidea-extracted trajectories were treated as the ground truth. Unlike the computation of motor features that were based on trajectories and would have been influenced by a high percentage of missing data, here the tracking comparison, not only for feet but also for hands, was done using only those data points that were available after the initial signal filtering and before any data imputation was conducted. When the DLC detected the back of the hand in a video, it was possible to check if the provided coordinates were compatible with those obtained by Movidea.

F. MOTOR FEATURES' COMPUTATION

The motor features of interest were computed in MATLAB R2022b. The missing feet data were first imputed using the default method of the inpaint_nans MATLAB function (Copyright (c) 2009, John D'Errico). Since the home setting did not always allow for the camera to be placed exactly 50 cm away from the baby, using pixels as a measure unit would not allow for comparison of some of the motor features between videos. For instance, mean velocities in pixels/second have different interpretations for various recordings. To overcome this problem, we used head length (measured in pixels, from chin to hairline) to normalize the data and allow comparison between subjects and time.

The list of computed features over a 3-minute period included: mean velocities and mean accelerations of the left and right foot, cross-correlation between feet velocities, cross-correlation between feet accelerations, skewness of speed distribution of each foot, periodicity in feet's trajectories, periodicity in feet's velocities, as well as the area differing from the moving average, and the area out of the SD of the moving average. These features are meaningful for the analysis of atypical motion patterns [37].

The magnitude of velocity, also referred to as speed was computed as the Euclidean distance of the central point on top of the foot between two subsequent frames, multiplied by the number of frames per second (fps) recorded in a specific video. In the dataset employed for this study, some of the videos have a frame rate of 25 fps, while others have 30 fps. By multiplying the Euclidean distance between two consecutive frames by the frame rate, we accounted for the variability in frame rates across the input videos.

Acceleration was then calculated as the difference between two subsequent speed values. Then, the mean speed and mean acceleration were computed.

The cross-correlation (CC) is a measure of synchronicity of the limbs' movement [33]. The CC with zero lag was calculated for velocity magnitude (and analogously for acceleration) between the left and right foot (Eq. (1)).

$$CC_{v1\ v2} = \frac{\sigma_{v12}}{\sqrt{\sigma_{v1}^2 \cdot \sigma_{v2}^2}} \tag{1}$$

where $\boldsymbol{\sigma_{v1v2}}$ is the covariance of $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$, $\boldsymbol{\sigma_{v1}^2}$ is the variance of $\boldsymbol{v_1}$, and $\boldsymbol{\sigma_{v2}^2}$ is a variance of $\boldsymbol{v_2}$.

The skewness (ν) was calculated to evaluate the speed distribution (Eq. (2)):

$$\nu = \frac{\frac{1}{n-1}\sum_{i=1}^{n-1}(v_i - \bar{v})^3}{\sigma_v^3} \tag{2}$$

where n is the number of recorded frames,

$$\bar{v} = \frac{1}{n-1}\sum_{i=1}^{n-1} v_i$$

$$\sigma_v = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n-1}(v_i - \bar{v})^2}$$

To determine the periodicity parameter (Eq. (3)), the trajectory (or velocity magnitude) signal of each video was divided into three equal parts [37]. An arithmetic mean was calculated for each of these parts. Then, the signal values that intersected with the mean were calculated. Further, the mean distance between the intersections and their SD were calculated. Since the videos in the dataset were recorded with various numbers of frames per second, the distance between the intersections was calculated in seconds, rather than in number of frames.

Periodicity:

$$P_{l,n} = \frac{1}{\sigma_{l,n} + d_{l,n}}$$

$$P_{feet} = \sum_n P_{\text{leftfoot},n} + \sum_n P_{\text{rightfoot},n} \tag{3}$$

where $P_{l,n}$ is the periodicity, n = [x,y], and l = [left_foot, right_foot], $\sigma_{l,n}$ is the SD and $\overline{d}_{l,n}$ is the mean distance between all consecutive intersections and P_{feet} is the merged periodicity parameter for the left and right foot.

The area differing from the moving average was calculated using the windowing width k, that corresponded to averaging over 2 s [37]. Therefore, a script was written, which first checked how many frames per second were recorded in each video, then doubles this value and rounds it up. Next, depending on whether the resulting number was even (Eq. (4) and Eq. (5)) or odd (Eq. (6) and Eq. (7)), the appropriate equations were used.

$$\bar{x}_i = \frac{1}{k}\sum_{j=i-\frac{k}{2}}^{i+\frac{k}{2}} x_j \tag{4}$$

$$A_{\text{diff}} = \sum_{i=\frac{k}{2}+1}^{l-\frac{k}{2}} |x_i - \bar{x}_i| \tag{5}$$

$$\bar{x}_i = \frac{1}{k}\sum_{j=i-\frac{k-1}{2}}^{i+\frac{k-1}{2}} x_j \tag{6}$$

$$A_{\text{diff}} = \sum_{i=\frac{k+1}{2}}^{l-\frac{k-1}{2}} |x_i - \bar{x}_i| \tag{7}$$

where $\overline{x_i}$ is the moving average of the i-th frame, k is the window width, x_j is the detected position in the x direction in the j-th frame, A_{diff} is the area differing from the moving average, and l is the number of frames of the video. The same equations were used for the movement in y direction.

Since the value of the area differing from moving average depends on the length of a specific video, the parameter was normalized (Eq. (8)).

$$A_{\text{norm}} = \frac{A_{\text{diff}}}{l-k} \tag{8}$$

where A_{norm} is the normalized value of the area differing from the moving average.

A merged parameter for both feet (A_{feet}), which adds up the calculated areas of both spatial axes to one parameter was also calculated (Eq. (9)).

$$A_{\text{feet}} = \sum_n A_{\text{norm,leftfoot},n} + \sum_n A_{\text{norm,rightfoot},n} \tag{9}$$

where n = [x,y].

As there is always some deviation of the trajectory from the moving average, this parameter tends to be always greater than 0 [37]. The calculation of the area out of SD of the moving average provided information about higher deviations from a smooth movement.

G. NDD RISK CLASSIFICATION AND MOTOR ASSESSMENT BEST AGE

Except for the above-described motor features, gender and the NDD risk status (HR/LR) of each infant were added to the dataset. Then, three models were trained using the MATLAB Classification Learner App: Fine Tree, RUSBoosted Trees, and Narrow Neural Network.

To determine the best age for the assessment of motor behavior, the classifiers were trained separately for each age group but also, given a different movement characteristic in different stage of development, for infant groups divided based on the GM period: writhing (10 days and 6 weeks) and fidgety (12 week, 18 weeks, and 24 weeks).

III. RESULTS

A. TRACKING DLC VS MOVIDEA PERFORMANCE

The comparison of the DLC-derived coordinates with the ones extracted by Movidea (Fig. 3) showed that the average feet tracking accuracy (left foot: 96.6%, right foot: 96.2 %) was higher than the average hand tracking accuracy (left hand: 80.9%, right hand: 82.8%), which might be the result of more feet data available for the model training. The achieved PCKh results are satisfactory and indicate a good performance of the method investigated.

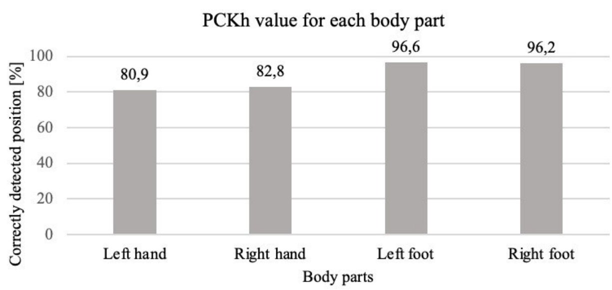

FIGURE 3. The PCKh value for each body part when comparing Movidea and DLC coordinates.

B. CLASSIFICATION RESULTS

The classification results are presented in Table 1 for each age group (10 days, 6 weeks, 12 weeks, 18 weeks, and 24 weeks), and Table 2 for each GM period (writhing: 10 days and 6 weeks, FMs: 12 weeks, 18 weeks, and 24 weeks).

As described in the methods section, the collected data were asymmetric in terms of the diagnostic status of the participants (there were more TD infants than those with NDD). As shown in Tables 1 and 2, the RUSBoosted Trees classifier handled this better than the Fine Tree and the Narrow Neural Network, achieving more balanced results in terms of percentages of correctly identified cases and correctly detected controls. For all three classifiers, the accuracy achieved was higher for 10-day or 6-week-old infant videos than for the older infants. The best results were obtained when data from those two youngest groups were analyzed together. The 5-fold cross-validation accuracy was then 81.4%, with the true negative rate reaching 80.0% and the true positive rate equal to 87.5 % (Table 2).

TABLE 1. NDD vs TD classification.

Model	Age	Accuracy	TNR	TPR
		%	% (c/a)	% (c/a)
Fine Tree	10d	**78.1**	**89.3** (25/28)	0 (0/4)
	6w	64.8	64.3 (27/42)	**66.7** (8/12)
	12w	69.5	78.7 (37/47)	33.3 (4/12)
	18w	73.3	86.6 (33/38)	0 (0/7)
	24w	58.3	72.0 (18/25)	27.3 (3/11)
RUSBoosted Trees	10d	65.6	64.3 (18/28)	**75.0** (3/4)
	6w	**66.7**	**66.7** (28/42)	66.7 (8/12)
	12w	59.3	61.7 (29/47)	50.0 (6/12)
	18w	57.8	60.5 (23/38)	42.9 (3/7)
	24w	58.3	64.0 (16/25)	45.5 (5/11)
Narrow Neural Network	10d	**78.1**	**89.3** (25/28)	0 (0/4)
	6w	70.4	81.0 (34/42)	33.3 (4/12)
	12w	74.6	85.1 (40/47)	33.3 (4/12)
	18w	68.9	78.9 (30/38)	14.3 (1/7)
	24w	66.7	72 (18/25)	**54.5** (6/11)

TNR: True Negative Rate. TPR: True Positive Rate. d: days, w: weeks. (c/a): number of correctly identified individuals/number of all subjects. Bold font indicates the best results for each classifier.

TABLE 2. NDD vs TD classification during the writhing and fidgety period.

Model	GMs	Accuracy	TNR	TPR
		%	% (c/a)	% (c/a)
Fine Tree	W	75.6	82.9 (58/70)	43.8 (7/16)
	FM	63.6	77.3 (85/110)	13.3 (4/30)
RUSBoosted Trees	W	**81.4**	**80.0 (56/70)**	**87.5 (14/16)**
	FM	59.3	60.0 (66/110)	56.7 (17/30)
Narrow Neural Network	W	75.6	84.3 (59/70)	37.5 (6/16)
	FM	75.7	84.5 (93/110)	43.3 (13/30)

W: writhing period at 10 days and 6 weeks. FM: fidgety period at 12 weeks, 18 weeks, and 24 weeks. TNR: True Negative Rate. TPR: True Positive Rate. (c/a): number of correctly identified individuals/number of all subjects. Bold font indicates the results obtained by the best model.

IV. DISCUSSION

The aim of this study was to investigate the usefulness of DLC for the analysis of infant motor patterns in high-risk infants for NDD, taking a step towards the development of an early screening tool for the NDD detection. To evaluate the DLC tracking performance, the mean average Euclidean error between the labels predicted by DLC and the manual ones was verified, and the data obtained by DLC were compared with the coordinates extracted from the same videos using the semi-automatic Movidea software [33]. The investigated approach provided reliable tracking of the infants' hands and feet in the analyzed videos.

Our data are in line with previous studies using similar approaches with the aim of developing automated standardized methods for the quantitative analysis of spontaneous movements in infants at high-risk (i.e., siblings and preterm infants) for NDD. The results showed that complexity indices of infants' hand and foot movements may be potential candidates for detecting developmental outcomes in high-risk infants [38], [39], [40]. A variety of bodily movement features at 4 months of age may be used as predictors in classifying infants with low and high autistic-like behaviors [41].

In the current study, the trajectory-based motor features were computed and fed to Fine Tree, RUSBoosted Trees, and Narrow Neural Network classifiers. Even though only the feet data were complete enough to be used for the analysis, promising results were obtained. The highest 5-fold cross-validation accuracy of 81.4% was obtained when analyzing and combining the data of writhing period (10 days and 6 weeks of age) using the RUSBoosted Trees. The true positive and true negative rates were 87.5% and 80.0%, respectively. The RUSBoost algorithm was specifically designed to improve the performance of models trained on skewed data. It applies the RUS technique, which randomly removes examples from the overrepresented class [42] and, despite its simplicity, has been proven to be very effective [43]. This classifier provided the most balanced results in terms of correct identification of cases and controls. The current work suggests that the RUSBoosted Trees classifier trained on the two early groups of infants (10 days and 6 weeks after birth) could be included in a system for the early detection of NDD.

This study analyzed a large number of videos collected early during the infants' development within the NIDA Network across the entire Italian territory. Moreover, the dataset included five age groups. Thanks to the NIDA video collections, we were able not only to train a classifier that is capable of distinguishing between TD individuals and those diagnosed with NDD at the age of 24/36 months, but also to determine the valuable time point in development to perform an early motor analysis. Our analysis shows that the motor features computed at the age of 10 days and 6 weeks are useful in terms of early identification of NDD and might provide a better distinction between TD and NDD infants than the same motor features analyzed at later stages of development (12, 18, and 24 weeks). The intentional movements observed later in the development may interfere with the assessment of quantitative analysis of motor behaviors.

Even though the older age might be non-optimal for early screening using the presented approach, analysis of FMs may provide valuable information on infant motor development. Nevertheless, it seems that data recorded early in life are more suitable to be used for an automated screening tool, as they do not include intentional movements that occur later in life.

A notable limitation of this study is the focus on extracting parameters related to the magnitude of movement only, without considering its direction. Addressing this aspect represents a significant avenue for future research. In the future, other key points and body parts could be considered for tracking with DLC to find out whether additional information could further improve the classification results. Moreover, in this study the selection of 3-minute segments, described in the methods, was done manually, which is a time-consuming task. For a fully automated tool that could be used in real-world settings, software that would automatically choose only the appropriate video parts should be developed.

This study provides an example of the application of DLC, which holds significant promise for the early assessment of neurodevelopmental delays in research and clinical settings, in combination with gold standard tools. Infant motor development can be objectively quantified and can predict neurodevelopmental outcomes. Future research should aim to promote the development of automated tools that can detect potential neurodevelopmental deficits early enough to provide timely intervention and improve clinical outcomes. Automated tools may be extremely useful in clinical settings where human and economic resources are often scarce. Additionally, future research should include longitudinal tracking of these high-risk infants through grade 1 or 2 to establish a correlation between early screening and later developmental outcomes.

V. CONCLUSION

Although more data should be collected and software for automatic video pre-processing should be developed to apply the presented approach in real-world settings, the results are very promising. The present study confirms the usefulness of DLC as low-cost approach to track infant movements in the writhing period. It has shown that the analysis of early motor patterns can predict the diagnosis of NDD, including ASD, with high accuracy. Furthermore, the very early stage of life (10 days and 6 weeks after birth) seems to be the most suitable time for using the DLC approach.

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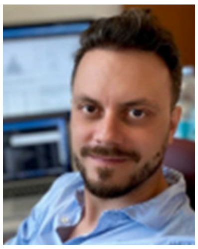

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