Gross Motor Skills Development in Children with and Without Disabilities: A Therapist's Support System Based on Deep Learning and Adaboost Classifiers

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Abstract. Fundamental or Gross Motor Skills (GMS) are a set of essential skills both for basic movement activities and physical activities. Properly developing them is vital for children to develop a healthy lifestyle and prevent serious illnesses at an older stage of life, like obesity and cardiorespiratory problems. This is a problem for therapists because they must attend to many children lacking this skill set, and it's even more time-consuming with children with disabilities. Therefore, this work presents a system that can assist therapists in giving therapy to more children with and without disabilities. To reach this goal, the system is divided into 3 phases: first, the data preprocessing phase, where images from 3 postures are collected: sitting, static crawling, and bound angle. Then all the images are resized. Model construction is the second phase. It consists of implementing the MoveNet algorithm that helps detect human posture through 17 key points of the body. Then, this algorithm is applied to the dataset created to obtain the coordinates from the postures collected. After that, an Adaboost model is created and trained, and tested. Next, the MoveNet algorithm is assembled with the Adaboost model to predict the three postures in live action. Then comes the third phase: model evaluation. This step includes evaluating the model assembled at Instituto de Parálisis Cerebral del Azuay (IPCA). Finally, the results of this evaluation are presented.

Keywords: education · gross motor skills · artificial intelligence · machine learning

1 Introduction

Fundamental or Gross Motor Skills (GMS) are considered a pillar for physical activities because they oversee moving large muscles [18]. For example, crawling, sitting, walking, or running [7]. Therefore, the right development of these skills is crucial as a child as they are linked to a healthy level of body mass index, better cardiorespiratory shape, greater social development, stronger language

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skills, and finer cognitive development [5,19]. Instead, the lack of these skills has four huge impacts on the development of children. First, children who haven't developed GMS early may have trouble developing it throughout their entire life [14]. Second, children are more likely to experience lower self-esteem. Third, children are more prone to higher anxiety levels [18]. Fourth, the lack of GMS is related to academic failure [19].

Research has shown that many children today are not developing adequate gross motor skills, and this is a cause for concern. According to a study conducted by the Centers for Disease Control and Prevention (CDC) in 2018, only 24% of children between the ages of 6 and 17 met the guidelines for physical activity, which include engaging in moderate to vigorous physical activity for at least 60 min per day [2]. This lack of physical activity can have negative consequences on a child's health, including increased risk of obesity, cardiovascular disease, and type 2 diabetes.

There are several related works and fields of study that are relevant to the importance of gross motor skills in childhood development. One such area is physical therapy. Physical therapists work with children to develop customized treatment plans that are tailored to their individual needs and goals. These treatment plans often include a variety of interventions, such as exercises, stretches, and manual therapies, that are designed to improve strength, balance, coordination, and mobility [6]. Physical therapists may also work with children to address any underlying conditions or injuries that may be impacting their gross motor development, such as cerebral palsy, spina bifida, or sports-related injuries. By working with physical therapists, children can improve their gross motor skills and overall physical function, which can have a significant impact on their quality of life and ability to participate in activities that are important to them.

Even though GMS is important for the reasons described above, only 50% of children demonstrate competency through these skills [4]. Therefore, to create an intervention plan, it is necessary to know how GMS are divided into different categories of movements, which are the following 3:

- Locomotion: it is related to any movement that a child performs to move from one location to another. For instance: crawling, rolling, walking, climbing [15]. These actions are vital for assessing the child's ability to move within their environment.
- Stationary: it involves movement in a fixed or stationary place. For example, balance, rising, bending, and turning [21]. These movements are crucial for evaluating the child's posture stability and control while stationary.
- Manipulation: it refers to controlling objects in different manners. For example: catch, throw, move, hang on an object [19]. This category's significance lies in evaluating the child's fine motor skills and their ability to interact with objects in different therapeutic contexts.

  The classification into these categories provides a structured framework for assessing a wide range of movements exhibited by children with disabilities during therapy sessions. By understanding the specific movements within each category and their connection to posture assessment, therapists can better tailor their interventions to address different aspects of a child's physical capabilities.

A therapist must commit and divide his time with a child to practice the categories described above to ensure that the child develops the GMS. Finishing a session with a specific child lacking these skills can take a lot of time. This can be even more complex if a child has a disability. For that reason, new technological tools with the help of artificial intelligence and machine learning should be implemented to assist therapists in addressing more patients effectively.

For these reasons, in this work, we present a machine learning classifier and an artificial intelligence algorithm to predict 17 key points of a body to reach the following goal: to develop a system that can accurately identify and monitor the correct posture of children with and without disabilities in real time. By achieving this, therapists can efficiently redirect their focus to other children, confident in the knowledge that the posture of the child under consideration is being appropriately monitored. This will optimize the therapist's ability to manage multiple children simultaneously and enhance the overall effectiveness of therapy sessions. This work focuses on stationary movements only. The decision to exclusively focus on stationary movements within this study is primarily rooted in the need to establish a solid foundational understanding of posture control and alignment. By concentrating on stationary movements, we are able to meticulously analyze the fundamental aspects of posture without the added complexity of dynamic motion. The system is divided into 3 phases: first, the data preprocessing phase, where images from 3 stationary postures are collected: sitting, static crawling, and bound angle. Then all the images are resized to the camera dimensions. Model construction is the second phase. It consists of implementing the MoveNet algorithm in an Nvidia Jetson Xavier NX. It helps detect human posture through 17 key points of the body. Then, this algorithm is applied to the dataset created to obtain the coordinates from the postures collected to produce numerical data. After that, an Adaboost model is created, trained, and tested with the coordinates extracted. Next, the MoveNet algorithm is blended with the Adaboost model to predict the three stationary postures in live action. Then comes the third phase: model evaluation. This step includes evaluating the model assembled at Instituto de Parálisis Cerebral del Azuay (IPCA). Finally, the results of this evaluation are presented and discussed.

This paper is organized as follows. Section 2 presents the related works. Section 3 describes the methodology, the movement lightning algorithm, and the Adaboost classifier, it also illustrates the experimental setup and the dataset. Section 4 shows the results obtained. Section 5 expresses the limitations of this work. Section 6 narrates the conclusions of this work.

2 Related Work

In [11], the researchers proposed a hybrid model to detect and recognize human postures. They made use of the human body using the galvanic skin response dataset. The model created included a Convolutional Neural Network (CNN) and a Long-Short Term Memory (LSTM). The combination of those formed the final model. They extracted different features including skew, percentile, SR, SD, mean, and kurtosis to feed the model. The hybrid model reached 98.14% accuracy, 98% precision, 98% recall, and 98% f-score.

In [13], the authors made use of 2 transfer learning models: AlexNet, and VGG16 with hyperparameter optimization, a Convolutional Neural Network (CNN), and a Multilayer Perceptron (MLP) to be able to identify different human poses. They worked with the MPII human posture dataset. After all the models were trained and tested, they yielded the following percentage of accuracy: AlexNet 91.2%, CNN 87.5%, VGG16 90.2%, and the MLP 89.9%.

In [14], the researchers conducted a study to research the impact of a structured movement activity program related to the development of GMS in children aged 3 to 5 years. 136 children were part of this study over 24 weeks. They were divided into 2 groups: 28 children for the intervention group and 108 for the comparison group. The last group only performed free-play activities. The McCarthy Children's Psychomotricity and Aptitude Scales (MSCA) battery of psychomotor tests evaluated the GMS development. At the end of the study, the intervention group yielded better results at movement coordination for their right arm (F1,134 = 14,389, p = 0.000, $\eta 2 = 0.097$). Same for leg coordination (F1,134 = 19,281, p = 0.000, $\eta 2 = 0.126$) as the comparison group.

In [3], the authors created a system for posture detection. The system consists of 1 control center and two sensors placed in the leg and another in the spine. The system contains the following devices: two Arduino Nano development boards, two MPU 6050 modules that have both an accelerometer and gyroscope, a Bluetooth module, and an external dual-port battery for powering the device. Also, an application was created to receive the data. This system detected and alert when a posture was mistakenly performed.

In [9], the authors proposed a six-month controlled trial to help develop physical activity and GMS. It counted 150 children aged between 3 and 5 years and six educators. The trial consisted of structured physical activity lessons and unstructured physical activity sessions. Gross motor skills were assessed using the Test of Gross Motor Development (2nd edition) and physical activity was measured objectively using GT3X+ Actigraph accelerometers. As a result of this trial, four out of 5 children improved their GMS, and the same for physical activities.

3 Methodology

Following the models selected are going to be described. These models were selected because is critical to ensure accurate and efficient pose estimation. For our study, we selected the MoveNet algorithm due to its ability to provide real-time and high-quality human pose estimation. MoveNet utilizes a lightweight deep learning architecture, optimized for mobile and edge devices, making it suitable for real-time applications. It has demonstrated robustness and accuracy in estimating human body poses across different scenarios and viewpoints.

Additionally, we incorporated the Adaboost classifier into our pose estimation. Adaboost is an ensemble learning algorithm that combines multiple weak classifiers to create a strong classifier. It has been widely utilized in various machine learning tasks and has shown excellent performance in classification problems. By integrating Adaboost into our system, we aimed to enhance the accuracy and robustness of the pose estimation results obtained from the MoveNet algorithm

The approach presented in this article distinguishes itself from previous methods in terms of the detection methodology employed. While previous approaches have utilized CNNs connected to an ANN or MLP, our method leverages the MoveNet model to extract 17 key points representing the body. Subsequently, these key points are fed into the Adaboost classifier to accurately classify the pose performed by the child. This novel combination of the MoveNet model and Adaboost classifier enhances the accuracy and robustness of pose estimation in our methodology.

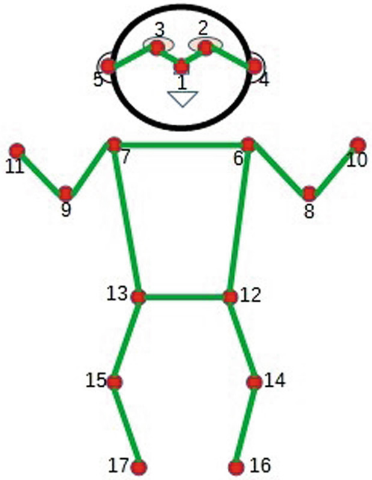
3.1 Models

- Adaboost: it's a boosting technique that generates a series of stumps to create a robust classifier. The difference between a stump and a decision tree is that a stump is not as deep as a decision tree. In the training phase of this technique, the first stump is going to generate an error, and this error is used for the next stump to improve its prediction, and so on with the rest of the stumps generated [16]. Also, this error is employed for the weight value that each stump has for the final decision. Thus, a stump with a lower error has a higher value for the final decision. Next, Table 1 the parameters with which the different models were configured to select the best model.

Table 1. Parameters tested for the Adaboost model.

Classifier	Parameters
Adaboost	tree_depth=2, 3, 4, 5
	learning_rate=0.00001, 0.0001, 0.001, 0.01, 1
	n_estimators=50,100,150,200,250,300,350,400,450,500
	algorithm= samme, samme.r
	cross_validation=5, 7, 10

- MoveNet: It's a model that detects 17 key points from the body [1]. Figure 1 shows an example of the key points that are detected. Hence, it can be used for pose estimation. It was developed by Google and IncludeHealth [8]. It's a bottom-up model that makes use of Tensorflow object detection API. It also implements MobileNet V2 as the feature extractor [12]. There are 2 versions of it: MoveNet Lightning which is mainly used for high performance in latency-critical applications. The other one is MoveNet Thunder, its target is high-performance applications [10].



Number	Body part	Number	Body part
1	Nose	10	Left wrist
2	Left eye	11	Right wrist
3	Right eye	12	Left hip
4	Left ear	13	Right hip
5	Right ear	14	Left knee
6	Left shoulder	15	Right knee
7	Right soulder	16	Left ankle
8	Left elbow	17	Right ankle
9	Right elbow		

Fig. 1. The 17 key points that MoveNet detects for pose estimation.

3.2 Proposed Method

The method created to reach the proposed goal is divided into 3 phases:

Data Preprocessing:

1. Data gathering: in this step, images from 3 poses are gathered: crawling, static crawling, and bound angle.
2. Image resize: after the data was gathered, all the images were resized to 640 × 480.

Model Construction:

3. MoveNet implementation: in this stage, the MoveNet algorithm is implemented in the embedded system: Nvidia Jetson Xavier NX.
4. Keypoints extraction: after MoveNet was implemented, it was applied to the data gathered to extract the coordinates from the 17 key points that MoveNet yields. Thus, a .csv file is created with this numerical data.
5. Model training and testing: once we obtain the numerical data, a machine learning algorithm is trained and tested. The dataset was divided into 70% for training and 30% for testing. In this case, Adaboost was the classifier selected for this step.

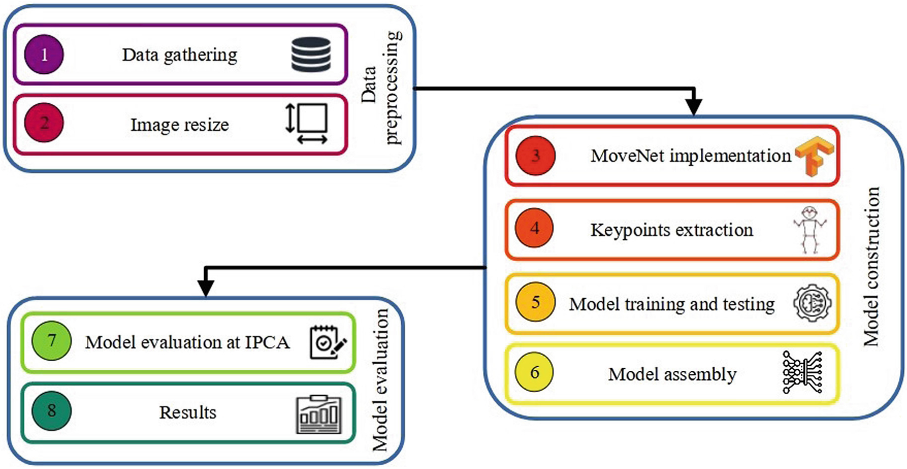


Fig. 2. Method implemented for this work, which is divided into 3 phases: data pre-processing, model construction, and model evaluation.

6. Model assembly: once we have the trained model, it must be assembled with the MoveNet algorithm to be able to predict the pose in live action.

Model Evaluation:

7. Model evaluation at IPCA: in this step, the model assembled in the previous step is tested in live action at IPCA with children with disabilities.
8. Results: Finally, the results obtained at IPCA are presented (Fig. 2).

3.3 Dataset Description

The images recollected come from 2 datasets from Kaggle: Yoga Posture Dataset [17], and Yoga Pose Image classification dataset [20]. These datasets are for yoga pose classification. Yoga contains many poses, where three poses have an exact match to the ones that are needed for this work. For example, the chair pose (Utkatasana) is identical to the sitting posture, the only difference being that in exercises for GMS, a chair is needed. Then, the cat pose (Marjaryasana) is the same as the static crawling posture in GMS. Finally, the easy pose (Sukhasana) matches the bound angle posture for GMS. Therefore, only images with the yoga pose described were selected to create our dataset. Following, Table 2 shows a summary of the final dataset:

3.4 Experimental Setup

The experiments were conducted at Instituto de Parálisis Cerebral del Azuay (IPCA). A screen was placed in the room. A camera was laid down at a height

Table 2. Dataset description according to human posture.

Datasets	Yoga Posture Dataset [17]
	Yoga Pose Image classification dataset [20]
Number of images for sitting posture	73
Number of images for static crawling posture	102
Number of images for bound angle posture	50
Number of total images	225

of 0.75 m. These devices were connected to an Nvidia Jetson Xavier NX. The child was located 2 m away from the camera for better results. In all the experiments carried out, the physical therapist was present. Hence, the system and the therapist could verify the children's postures.

Two experimental scenarios were outlined for the study, and their specifics are elaborated upon below. Both scenarios involved the participation of the same group of 8 children, with ages spanning between 8 and 16 years. The group consisted of one 3-year-old child, one 8-year-old, three 9-year-olds, one 10-year-old, one 13-year-old, and one 16-year-old.

1. **Scenario one: system accuracy without therapist's aid for child's correct posture.** This scenario was developed to explore how accurate the system would be without the therapist's direct intervention. It means the therapist would only give instructions about the posture the child should perform. Therefore, the therapist wouldn't help the child to make the correct posture. Once the child was correctly located, the therapist announced the position to be performed. The order was seating, crawling, and bound angle posture. The child had to stay in each position for 5 s, then he would switch to the next posture announced by the therapist. Every second the system would take the accuracy metric to later obtain a mean to get the results.

2. **Scenario two: system accuracy with therapist's intervention for child's correct posture.** This scenario examined how accurate the system would be with the therapist's intervention. Hence, first, the therapist would announce the posture to be performed and then would help the child to execute the correct posture. After the child was perfectly located, the therapist the postures in the same order as Scenario One. As soon as the therapist stopped helping the child, he had to stay in that posture for 5 s.

4 Experiments and Preliminary Results

First, the best Adaboost model is going to be explained. This model reached 94% accuracy and 93% precision. To reach these results, the dataset was divided into

70% for training and 30% for testing. The model had the following configurations: tree_depth was set to 5, the learning_rate was 1, the n_estimators were 300, the best algorithm was same and the number of folds for cross_validation was 5.

4.1 Results Scenario One

In this segment, after 8 children were tested without the therapist's help to do the right posture, the mean of each child for each posture is calculated. Following the results obtained:

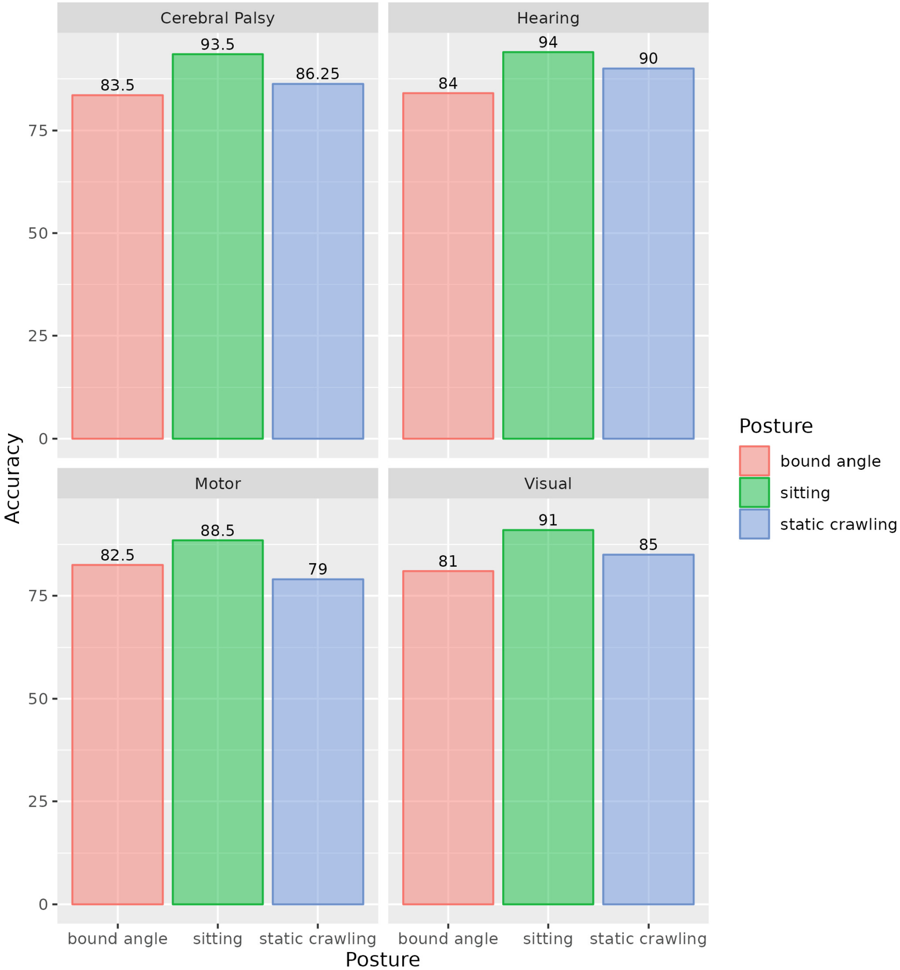


Fig. 3. Results obtained from scenario one.

As can be seen in Fig. 3, the system had a little bit of difficulty with children with motor disabilities, especially for static crawling. This is due to their difficulty moving certain parts of their body. Another important outcome that can be seen is that the system has a lower accuracy prediction for the bound angle posture, but still, it's a good accuracy because it stays higher than 80% in each case. The same with the other postures.

4.2 Results Scenario Two

In this segment, after the same 8 children were tested in scenario one, they were tested with the therapist's help for the children to do the right posture. Then the mean of each child for each posture is calculated. Following the results obtained:

As can be seen in Fig. 4, the same problem presented in scenario one appears in this scenario. The system got a lower accuracy for children with motor dis-

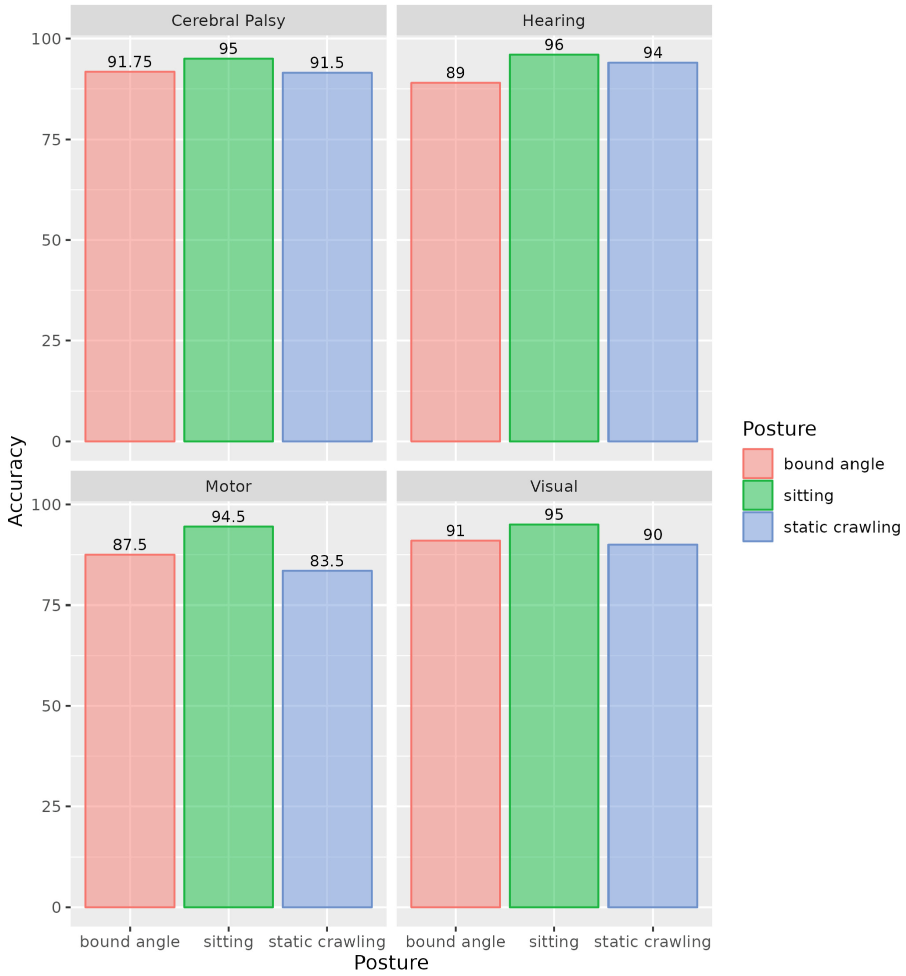


Fig. 4. Results obtained from scenario two.

abilities, but in this scenario, with the help of a therapist, the results were better than scenario one.

5 Limitations

The main limitation of this study is the amount of data recollected. The dataset created contains 225 images that aren't equally distributed. With more data, the Adaboost model could achieve higher results and therefore better results when testing the system in live action. To restrain this problem, more datasets containing the same poses as described in this paper should be discovered on public platforms.

Another limitation is the number of postures the system can predict. This problem is due to the lack of data to solve GMS problems. There aren't GMS datasets to predict the posture of a person or a child. To solve this problem, data should be gathered in schools with the consent of parents and the schools. This would take some time, but it would help create systems to aid therapists with patients with GMS problems.

6 Conclusions

In conclusion, this study successfully achieves its intended objective of accurately detecting the posture of children with disabilities, both with and without the assistance of a therapist, in order to ensure correct posture alignment. Thus, a therapist doesn't necessarily need to be present at the moment of the session. Therefore, therapists could attend to more patients. First, during the image preprocessing phase, the dataset created ended up with 225 images of 3 postures: sitting, static crawling, and bound angle. Then, all the images were resized to 640×480. Second, in the model construction phase, the MoveNet algorithm was implemented and applied to the dataset to be able to gather the coordinates of 17 key points of a human body. After that, an Adaboost model was trained and tested. The best model reached 94% of accuracy and 93% precision. The best parameters of this model were: tree_depth was set to 5, the learning_rate was 1, the n_estimators were 300, the best algorithm was samme, and the number of folds for cross_validation was 5. At last, for this phase, the Adaboost model and the MoveNet algorithm were assembled to be able to be used in live action. Third, in the model evaluation phase, the system was tested at IPCA with 8 children for 2 scenarios that were explained in the experimental setup. Finally, the results for each child were shown and the system proved that it's capable of having great accuracy at prediction for each scenario. For that reason, the system created can be used to help children perform therapy sessions without the help of a therapist. In this manner, therapists could attend to more patients. It is worth mentioning that this study has made significant strides in the development of a posture recognition system for children with disabilities, the limitations arising from the lack of comprehensive data for predicting a broader spectrum of postures, integral to Gross Motor Skills (GMS) development, warrant careful consideration. Consequently, as we contemplate the practical implications of the proposed system, we must recognize the importance of contextualizing its outcomes within the parameters of this data limitation. Looking ahead, efforts to expand the dataset and enhance the system's capacity to predict a wider array of postures could undoubtedly contribute to further advancements in assisting children with disabilities in achieving their motor skill development goals.

For future work, we propose the following lines:

– To implement a different pose detection algorithm like PoseNet.
– To train and test other machine learning algorithms like XGboost, Random Forest, and Catboost, among others.
– To gather more data from different postures that are commonly performed during therapy sessions to develop GMS.

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