International Journal of Reliable and Quality E-Healthcare
Volume 11 • Issue 1

Cognitive Human Gait Analysis for Neuro-Physically Challenged Patients by Bat Optimization Algorithm

A. Saranya, Department of Computational Intelligence, SRM Institute of Science and Technology, India*
Anandan R., Vels Institute of Science, Technology, and Advanced Studies, India

ABSTRACT

Autism spectrum disorder and cerebral palsy are called developmental disorders that affect the brain development, communication, and behaviour of a child or an adult. Individuals with Cerebral palsy can also display symptoms of autism. Both conditions have varying degrees of severity, which can make it difficult to form a clear diagnosis. This research paper proposes the model-free green environment for the prediction of the above-mentioned disorders by doing gait analysis only with the camera. The new intelligent algorithm CAGLearner (cognitive analysis for gait) works on the standards of graphical extreme machines. CAGLearner uses the new powerful algorithm called bat optimized ELM for classification, which is then related with the prevailing machine learning algorithms such as artificial neural networks (ANN), support vector machines (SVM), and random forest (RF) algorithms in which the accuracy, sensitivity, and response time were analyzed. In terms of prediction time and precision, the model provided in this paper also yields more benefits.

KEYWORDS

Artificial Neural Networks, ASD, Cerebral Palsy, Extreme Learning Machines, Gait Analysis, Physio-Neuro Disorders, Random Forest (RF), Support Vector Machines (SVM)

INTRODUCTION

ASD is seen primary stage and there are some deficiencies and it is not possible to identify behavioural patterns as symptoms unless it affects infant insignificant life. For the diagnosis of ASD, there are several tools and different methods taken by the therapist with different diagnostic tools. For the ASD predictions, many machine learning and data mining techniques were proposed but the prediction and accuracy fail when the population get increases. In existing projects, many researchers used brain signals for the ASD predictions, but the main drawback is more sensors and high signals will be used to take the signals.so it will be more complex and expansive apart from that it will create additional health issues to the patients. To overcome all this problem our research work concentrating on Model-free green environment to predict the autism spectrum disorder only by implanting the camera to take the various activities of a child or a person.

DOI: 10.4018/IJRQEH.313915 *Corresponding Author

Generally, Gait is represented as the presentation of a person's walking appearance. This walking style or appearance finds important in the biomedical fields to learn about the behavior of the individual. According to the persons walking style many other physical studies can be done and also helpful in surveillance applications. The parameters to be observed for the gait can either be gathered from using sensors or by using image processing tools (Pushpa et al, 2010) and (Pauline Luc, 2016).

Gait, in general, can be defined as how a person walks. An individual's gait is considered to be very important in the biomedical field as it provides valuable information regarding the individual normal and abnormal patterns, which can be used further in physical pathology and human surveillance.

There are two approaches to extract the quantitative parameters-either by the use of sensors, or by the help of Image Processing (Atiqur Rahman Ahad, 2013). The parameters in motion are collectively considered as temporal features. The temporal features such as joint angles can be observed using certain sensor which in turn is cost effective. Thus instead of learning using sensors, if the features are gathered from a recorded video of image sequence finds helpful to extract temporal information. Also real time video processing is also appreciated for gait analysis.

The movement of the person is identified and observed from the video frames and the features are classified using various tracking schemes. The recognition of motion related features are stamped as marker based and no- marker approach.

The no-marker schemes are non-accurate and approximation schemes of feature analysis from acquired data sequence. Few no- marker approaches rely on the real time camera data and their 3D structures. The data captured from only one view angle do not hold all required motion details because of the sagittal view (Deepjoy Das, Alok Chakrabarty,2015), (Roland Zügner,2018), (Ahmed Mahmoud Hamad,2011), (Mandeep Singh,2013) and (Minhua Zhang,2018). Such sagittal view-based information are studied using either model based or model free approach. The model-based schemes use various models to fit and extract the feature information (Chandra Prakash, 2016), (Ana Patrícia Rocha,2014) and (Daehee Kim,2009). This model based schemes always rely on high resolution data which is not always possible. The major advantage of such models are they are less prone to noises and other external artifacts such as clothing and other accessories.

The model free schemes extracts the silhouettes of the individual and study its motion. From this the features are extracted, and this works well in low quality videos (Omer AKGUN,2018). These techniques are available for Gait analysis can be applied for the investigation of different neuro-physio disorders such as the Parkinson diseases, Amyotrophic Lateral Sclerosis (ALS), and Huntington Disease (HD). But the intelligent classification of gait remains in the darker side even though the several AI based algorithms such as the Artificial Neural Networks, Support vector machines and Random forest etc.

The paper proposes the new intelligent, markerless classifier for gaits CAGLearner which is then used to identify the people with cerebral palsy. The paper details about the extraction of the different features used for the classification and presents the novel BAT optimized Extreme learning machines to achieve the high accuracy for abnormal gaits (cerebral palsy) and normal gaits.

The organization of the paper is as follows.

Section-1 deals with the recent surveys on the papers, Section-II details about the working mechanism of the proposed architecture CAGLeaner. Section -III details the experimental methodologies of the proposed architecture. The features of the different subjects, resulting in the analysis were discussed in Section-IV and the conclusion is discussed in Section -V.

BACKGROUND

M. Pushpa Rani proposed a similarity based gait identification approach for the analysis of human movement. They used an adaptive Independent Component Analysis scheme for recognition. The foreground estimation is performed to extract the details of human in the scene to differentiate from the background. The motion based extracted foreground are segmented and the skeleton based silhouettes of the human is extracted. The Independent component analysis-based approach generates eigen vectors for the features extracted and are used to train the model to track the similar silhouettes present in subsequent frames. This is thus termed as a self-similarity approach and the model is deployed for performance comparison.

Pauline et al developed a training based segmentation approach for adversial network. The model checks for non-consistent features in the data and generate segmentation maps on them to train the model. The generated map is compared with the ground truth feature to list it down as detected object. The model is tested for its efficiency using PASCAL VOCR012 dataset and Stanford datasets.

Atigur et al introduced gait based recognition model based on optical flow estimation. They considered the four direction of motion of subject to determine the temporal features. The method is trained and tested with varying environmental conditions. The model can be adapted to real time recognition applications.

Deep et al developed a silhouette based gender model. From the human posture datasets of (CASIA) Centre for Biometrics and security research, the method uses intelligent segmentation and feature classification to differentiate between male and female. The model uses Support Vector Machine (SVM). The model attains an accuracy of around 76% in 100 different subject data.

Roland et al studied the hip motion behavior in patients with arthritis to group them and categorize them based on their movements. A threshold of angle $<7.7^0$ is set for healthy cases, <11.1 for patients with nominal progression and 12.2^0 as most pronounced cases. The experiment is continued for up to 2 years to learn their improvement after medication.

Ahmed et al introduced a background subtraction scheme for silhouettes extraction. The unsupervised k-means clustering algorithm is used to learn the behavior. The model is based on grouping of similar feature to train and classify silhouettes.

Mandeep singh et al developed a model to learn the movement of foot alone for gait analysis. This is mainly targeted to analyze the behavior of neurogenesis patients.

Minhua et al compared the posture of patients for gait analysis to learn the asymmetry in PD patients. The VICON motion video is used as the dataset.

Chandra Prakash et al developed a multi - node technology for gait analysis. The silhouettes are collected from 10 individuals from the CASIA-B data base. They used the Linear Discriminant Analysis (LDA) scheme for kernel prediction.

Ana et al modeled a RGB based kinetic map for movement analysis. Based on the extracted skeleton data, the PD patients and non-PD patients are distinguished with a threshold nominal value of p=0.004. This model helps in medical diagnosis support for PD patients.

Daehee et al introduced an idea of gait recognition using infra-red (IR) images. This model fits only for subject with proper illumination conditions.

Omer et al grouped the ALS patient based on their received gait features. The sensor employed in gait feature extraction is sensible enough to generate the motion parameters with walking style. The average precision of 92% prediction is achieved using artificial neural network model.

Qin et al studied the recognition of gait using smartphone integration. The deep learning method is adapted for feature extraction and classification of gait parameters. Unlike most learning schemes, the model uses recurrent neural network which learns from the past behavior to analyze the gait data. The method is simple with less hardware and achieves an accuracy of about 93.7%.

Ionut et al described a fuzzy based classification model to study the behavioral changes. They adapted the nature-inspired colony scheme to choose the availability of processors used in adaption process.

Alexandra et al developed an ELM based machine learning model to analyze the gait features based on age, height and stride duration. This helps in diagnosis and rehabilitation options for patients.

MAIN FOCUS OF THE CHAPTER

See Figure 1 for the CAGLearner-Proposed Architecture.

Extraction Phase

The first phase of the proposed CAGLEARNER architecture is extraction. The extraction phase is further divided into two sub-stages such as Silhouette extraction and feature extraction.

Silhouette Extraction

Preprocessing is the first step before the silhouette extraction. This step is included to filter out noise levels in the image. The walking postures were recorded as shown in fig. The RGB data format is obtained from the camera is converted into a greyscale image before the background subtraction. Several techniques for background subtraction such as the Fuzzy Model, Gaussian Mixtures and PCA were used commonly in recent times. To obtain better accuracy in silhouette extraction, proposed CAGLEARNER uses PRAT (Pre -reference Adaptive thresholding) mechanism. In the PRAT mechanism, the first frame without the human is considered as the background image. Let J[u] be the Input Image of frame u. Also, the A is considered to be a background image, then the pixel value of the total frame is expressed as:

$$P\left\{F\left[u\right]\right\} = P\left[A\right] - P\left\{J\left[u\right]\right\} \tag{1}$$

The obtained pixels are needed to convert into a binary format which uses the adaptive Thresholding for better accuracy:

$$P = 1, if \ \ PIn \geq T$$

$$0, if \ \ PIn < T \tag{2}$$

After converting into the binaries, CAGLEARNER uses the median filter integrated with the dilation process for the removal of noises from the images.

Feature Extraction

Feature extraction is the next phase of CAGLEARNER which is considered to be important for human gait analysis. In this phase, the novel set of 7 features were extracted from the silhouette images and these images are normalized to reduce the effects caused due to the variable distance from the camera. The subsequent features were extracted for further classification and identification.

Figure 1. Architectural Diagram for the Proposed CAGLearner mechanism

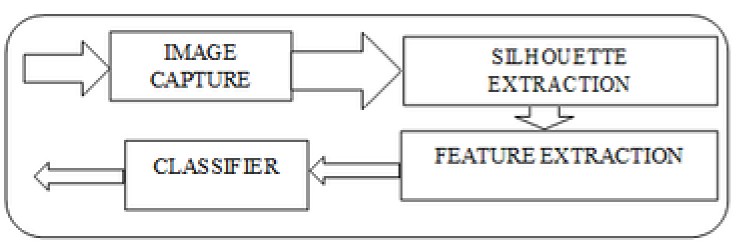
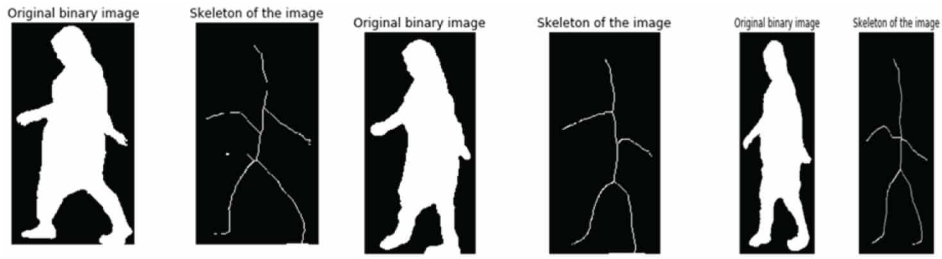


Figure 2. Median filter integrated with the dilation process for the removal of noises from the images



Frames/Gait Cycle

This defines the total number of frames per gait cycles. This measurement gives the normal walking speed of the person. This measurement plays a major role in the classification of different persons in terms of physio- neuro disorders. The frames per gait cycle are measured as the difference between the frame of the heel strike (HF) and the frame of toe-off (TF).

Swing Ratio

It is the measurement of the swing of the hands during the walking. The ratio of the maximum torsal width to the minimum torsal width gives an estimation of the swing ratio. The swing ratio is estimated for all such instances and the final result are obtained by the averaging the values.

Cadence

It is measured in terms of no of steps /minute. This feature is calculated based on the total number of frames necessary for one step and it depends on the frame ratio of the camera.

Velocity

This feature is measured based on the distance enclosed by the body per unit time. Since user-defined velocity changes from time to time, average velocity is taken for the measurement. The average velocity is thus calculated by:

$$A.V = SL \times C \tag{3}$$

where step length is calculated based on the distance between the successive points of heel contact of the opposite feet (SL) C- Cadence which is calculated in the previous case.

Step Length (S.L)

This feature is measured by the step length of the feature from toe to toe. To regularize the value step, step length is fractioned by the height of the subject. The normalized step length is calculated by:

$$SLN = Step\ \ Length\ /\ H \tag{4}$$

where H is the height of the person Foot Length (F.L): This feature is a measurement of the foot length which is then calculated by the distance between the toe and heel. (DF) Again the normalized foot length is calculated by diving by the person's height:

$$F.L = DF\ /\ H \tag{5}$$

where H is the height of the person.

Cycle Time (Tc)

This feature is used to calculate the time to complete one cycle by considering the number of camera frames in the gait cycle.

Mass Location Point (M.L.P)

It is the measurement of the relative position of the body by the center. The normalized Mass location is calculated by dividing the mass location point by the height of the person.

After extraction of the features from the silhouette images, the proposed architecture uses skeletonization mechanism, which is then defined as the thin layer of shape that includes pixels which are equivalent to the margins of the Image. Several morphological techniques were used such that the erosion, dilation and hybrid canny detection mechanism. The proposed algorithm uses the dilation process for skeletonization due to its following features such as higher visual ability and more scalability. The mathematical expression for the adoption of the dilation process is given by:

$$D = B \oplus S = x,\left(x,y\right) \cap B \neq \varnothing \tag{6}$$

where B = Skeleton Image, S= Structured Image Element, x, y- x, y coordinates. Feature extraction and skeletonization has been done for the different subjects which include the normal and disease-affected persons which are then explained in the preceding section.

Classifier and Prediction Model

In this section, the prediction model for the different feature extraction has been discussed. we have used Adaptive kernel-based Extreme learning machines for the classifier and prediction model. The preceding section deals with the general motivation of the Extreme learning machines and implementation of the adaptive kernel-based extreme learning machines.

Extreme Learning Machines - An General Motivation

After extracting the data, the classifier is tested with the input data. The classifier consists of a network constructed by the Extreme learning machines. The eye-catching features of ELM networks that uses a single hidden layer, improved computational time, creating accuracy in approximation. The L neurons present in the hidden layer includes an activation function likely to be sigmoid to generate a linear output. The bias weights of hidden neurons are fixed randomly to tune them. The hidden layer ELM, output is shown as Eqn (7):

$$f_L\left(X\right) = \sum_{i=1}^{L} \beta_i h_i\left(X\right) = h\left(X\right)\beta \tag{7}$$

where x ϵ Rd is an input vector, β = [β1 ... βL]T is the hidden vector weight, L be the neuron count in hidden layer and $h(x)=[h_i(x),\cdots,h_L x)]$ be the output vector.

The L neuron output hi(x) is generated by tuning to relate the approximation capability theorems described (Daehee Kim, 2009), (Omer AKGUN, 2012):

$$h_i\left(X\right) = G\left(a_i, b_i, X\right) \tag{8}$$

where G is the function of neuron, ai ϵ Rd the weights in hidden layer and biϵ Rd the bias parameter. The function G with sigmoid activation function is given:

$$G\left(a_i, b_i, X\right) = \frac{1}{1 + \exp\left(-\left(a_i \cdot X + b_i\right)\right)} \tag{9}$$

The training set includes N objects arranged as{X_i, t_d where X_iϵ R^d are the predictors and t_iϵ $R^m$the targets (i ϵ [1, N]). At the training phase, the weights of the hidden layer neurons are randomly generated based on the approximation functions. The basic training model for ELM network exhibits the criteria for determining the least solution as:

$$H\beta = T \tag{10}$$

where H is output of hidden intermediate layer and T be the target matrix of hidden layer. The training phase is attained such that, the H matrix should have non-square parameters and the neurons in hidden nodes should be less than that of the neurons in training input node. This is expressed as a linear function as:

$$\beta = H^{+}T \tag{11}$$

where H+ is the Moore-Penrose generalized inverse.

Even though the Extreme learning machines verifies to be effective in both training and testing, the main drawback is a non- optimized value of input weights and biases. In order to fine-tune the optimal weights, ELM procedures multiple hidden layers which can affect the precision of detection in human gait recognition. To optimize the input biases, we have used new bio-inspired BAT based Extreme learning machines-hybrid Integration of BAT with ELM (HIB-ELM) to achieve better accuracy and less time computation. The following features of BAT algorithm were used for the optimizing the Extreme learning machines.

Echolocation is the principle of bats for searching the food, prey and differentiating the barriers.

Bats are characterized by the random fly at the location Li with speed Si, hunt the prey using the wavelength μ, loudness L and frequency F. Frequency is set between the F min and F max which depends on the wavelength μmin and μmax.

Using the above features, Bat updates by the following equations:

$$F_i = F_{\min} + \left(F_{\max} - F_{\min}\right)b \tag{12}$$

$$S_i = S_i^{t-1} + \left(L_i - L\right) * F_i \tag{13}$$

$$L_i = L_i^{t-1} + S_i^{t} \tag{14}$$

where b€(0,1) is the random variable Li is the current position of the bats at present t. the hidden neurons are optimized using the bat algorithm to produce the high accuracy of detection.

Methodology of Data Collection

This section details the methodology of the experimental setup, details of the subject's anthropometric data and technical specification of the camera used along with the software specifications.

Methodology for Experimental Setup

The experimental setup has been carried out in two different places for collecting the normal gait patterns and CP affected gait patterns. The normal gaits are obtained at ABE Semiconductor Designs Lab using Intel RealSense Creative Edge Cameras with the resolution of 720X720 with 30 fps. Fig shows the experimental setup for the gait analysis mechanism. The camera is placed at the 2.5 m from the subject to record the normal gaits. The subject has been asked to walk from right to left at average speed in which the 1-2 normal gait cycles were recorded.

For CP affected gaits are recorded at Rehabilitation Centre Located at Theni/Dindigul, Tamil Nadu, India with the same experimental setup which is mentioned above. We recorded for 18 subjects and anthropometric. We have used the TensorFlow libraries for extraction of silhouette and prediction is being computed by MATLAB r2018 version.

RESULTS ANALYSIS

Features Extraction

Different features extracted for 8 subjects like FPG, velocity, foot length, swing ratio, cadence, step length, cycle time and mass length which are then used for better classification and prediction.

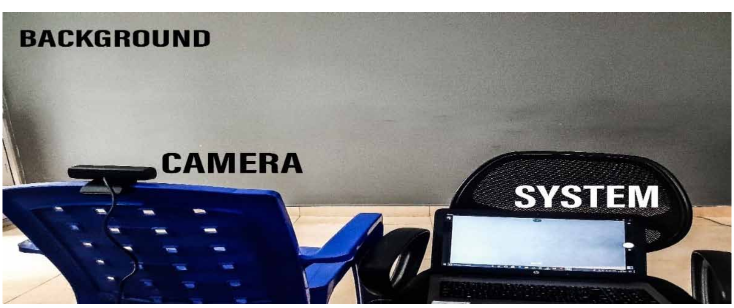
Performance Evaluation

This section demonstrates the performance evaluation of the proposed ELM structure. The performance of the proposed scheme derived from following metrics as follows:

$$Accuracy = \frac{DR}{TNI} \times 100 \tag{15}$$

$$Sensitivity = \frac{TP}{TP + TN} \times 100 \tag{16}$$

Figure 3. Experimental Setup for the CAGLearner Architecture



$$Specificity = \frac{TN}{TP+TN} \times 100 \quad (17)$$

where TP and TN signify True Positive and True Negative values and DR & TNI signifies the number of Detected Results and Total number of Iterations. Also, we have used 10 cross-validated matrices for validating of the different features.

Case (1)

In case 1 evaluation, no of hidden neurons for the BAT -ELM has been selected for which evaluation metrics including accuracy, sensitivity and specificity has been evaluated.

Table 1 clearly shows the BAT optimized Extreme learning machine has the highest accuracy of detection with 96% with 50 neurons, which are considered to be optimized and balanced hidden neurons for the proposed architecture.

Case (2)

In this case, the performance of the proposed architecture with the bat optimized Extreme learning machines have been evaluated with the comparison with the other classifier algorithms including Artificial neural networks, random forests, support vector machines and extreme learning machines.

From the above cases, it clearly shows that the proposed architecture for classification of gaits for the cerebral palsy and normal people has the highest accuracy detection when compared with the other existing algorithms.

Table 1. Illustration for characteristics of extreme learning machines using bat algorithms

Sl. No.	N of Neurons	Accuracy	Sensitivity	Specificity
01	05	89.34%	89%	88%
02	10	88.45%	88.44%	86%
03	15	78.45%	78.5%	79%
04	20	79%	80%	82%
05	30	80%	82%	84%
06	40	81%	83%	86%
07	50	96.45%	95%	95.45%
08	60	90%	94%	93%
09	70	92%	94%	95%

Figure 4. Comparative Analysis of accuracy for the different classifier with that of proposed BAT-Elm in the proposed architecture

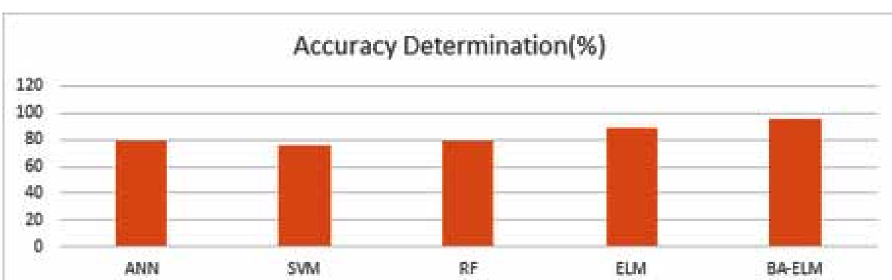


Figure 5. Comparative Analysis of Sensitivity for the different classifier with that of proposed BAT-Elm in the proposed architecture

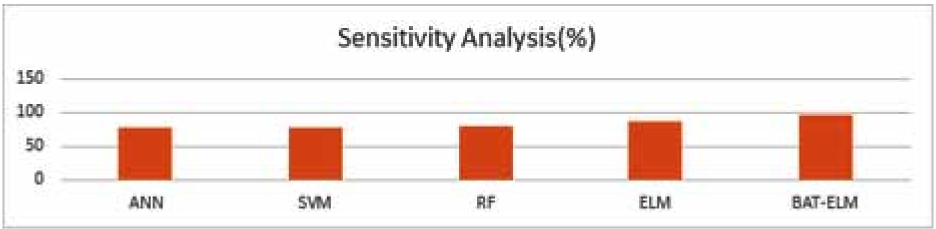
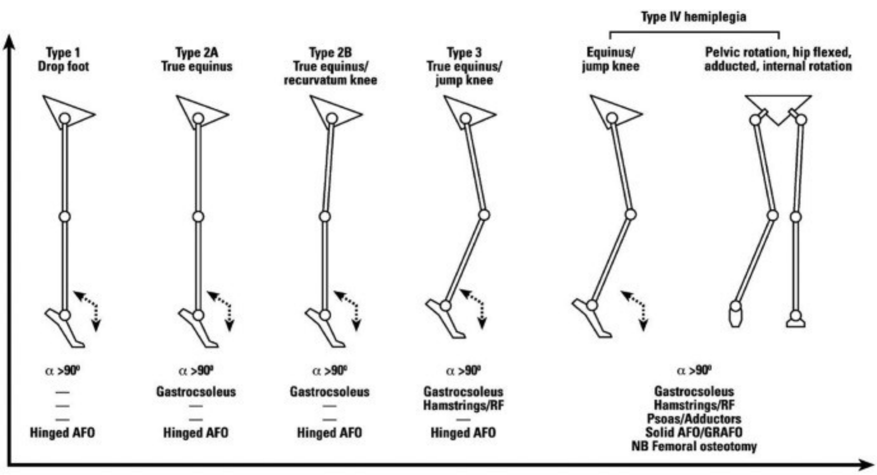


Figure 6. Comparative Analysis of Specificity for the different classifier with that of proposed BAT-Elm in the proposed architecture



CONCLUSION

This paper discussed about the powerful BAT optimizer based Extreme learning machines for the analysis Cerebral palsy using human gait analysis. The extensive experiments were conducted using real time subjects in which parameters like accuracy, sensitivity and specifity were calculated. Out of all machine learning algorithm the proposed algorithm has shown the better performance and proofs its plays in the prediction of Autism and Cerebral palsy. Still the algorithm needs its improvement in terms of scalability, flexibility, and robustness.

ACKNOWLEDGMENT

We like to thank Dr Murali Chief Physiotherapist/PSG Hospitals, Coimbatore for extending its support for the successful completion of the research.

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