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Extracting gait and balance pattern features from skeleton data to diagnose attention deficit/hyperactivity disorder in children

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Abstract

Attention deficit/hyperactivity disorder (ADHD) is a neurodevelopmental disorder affecting various aspects of life. Some features of the mental disorders affect people's movement patterns. In the recent decade, researchers have paid attention to the analysis of gait and balance pattern using new technological tools, as well as artificial intelligence algorithms. Therefore, the present study aims to propose an intelligent method to identify ADHD in children using gait and balance pattern features extracted from the person's movements obtained from the skeleton data. Given that designing and extracting effective motor features for diagnosing the aforementioned disorder is the main objective. In the present applied development experimental study, human movement samples related to the gait and balance were recorded in the standard test of perceptual-motor development, from healthy and ADHD-diagnosed children. After preprocessing the data recorded by the Kinect device, effective features for diagnosis are designed and extracted from the appropriate special movement tests. Comparing the features extracted from gait and balance tests by skeleton data, the results indicated that the data based on other types of methods for differentiation into healthy and ADHD groups are in line with those of the present study. The results of diagnosis and separation of healthy children from those with disorders in the different movement tests, standing on the ground with the superior foot, standing on a balance stick with the superior foot, and walking heel forward on a balance stick, to identify ADHD by SVM classification method are 86.4%, 90.2%, and 88.1%, respectively. The obtained significant results have been achieved relying on machine learning-based methods using the effective features obtained from skeleton gait and balance data of children along with analyzing the descriptive statistics of the features of gait and balance tests.

Keywords Machine learning · Feature engineering · Attention deficit/hyperactivity disorder · Gait and balance · Skeleton data

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1 Introduction

Attention deficit/hyperactivity disorder (ADHD) is a neurobehavioral disorder affecting approximately 3–5% of school-age children [1]. The number of adolescents and children among ADHD patients accounts for more than 80% of the total number of patients. In addition, the number of children and adolescents with ADHD is increasing every year [2]. It is important to diagnosis and treatment of ADHD earlier because if the ADHD remains untreated, it can continue to exist into adulthood for more than 50% of children [3, 4].

Psychiatric disorders are highly complex issues since psychological, biological, and genetic factors cause cognition, emotion, and behavior in specific contexts [5]. Diagnosing ADHD has various methods including clinical method, diagnosis through EEG method, and motor behavior method, each of which has its advantages and disadvantages.

Nowadays, various tools and methods such as psychological questionnaires, EEGs, and diagnostic interviews are used to identify the process of changes, severity, and type of ADHD in medical centers and clinics. However, among the various methods of identifying ADHD, those based on the analysis of motor activities were considered in the present study due to their non-invasiveness, low cost, and applicability in non-clinical and laboratory environments. Therefore, an intelligent system is presented to identify ADHD by analyzing motor activities.

In a clinical method, ADHD in children is usually assessed by the judgment of counselors and the integration of different types of mental information such as parents, teachers, and their reports. This process is highly based on subjective thinking and can hinder correct diagnosis [6]. Diagnosing disorders relies on mental descriptions and external observations utilizing questionnaires and clinical interviews. Therefore, these diagnoses are prone to error even by using the DSM-5[1] diagnostic guide due to the complexity of mental disorders and innateness [7].

Another method to diagnose ADHD is to analyze the EEG and its event-related potential (ERP) information. Accordingly, researchers have made great efforts to obtain biomarkers of mental disorders [8–12]. Most of these markers are genetic, biochemical, and epigenetic in blood and blood plasma [13, 14], while some are called electroencephalography (EEG), evoked potentials of EEG, and functional magnetic resonance imaging (fMRI) [15]. However, unhealthy groups and healthy individuals have complex features, and it is difficult to make a diagnostic operation using individual markers. Thus, diagnostic symptoms can be obtained by different neurobiological approaches [16], a highly accurate method which requires complex and expensive hardware, and a visit to a specialist psychiatrist and clinic for diagnosis.

Regarding the aforementioned problems in the clinical and EEG methods, the researchers presented another method which can partially solve those issues. Hyperactive children have motor coordination problems, also referred to as developmental

[1] Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition.

coordination disorder (DCD) [17–20]. Therefore, the motor mastery method can be used, initially diagnosing ADHD through tests. Children with ADHD have problems with executive functions (EF) which are strongly associated with daily life activities, social and academic performance, and appropriate behaviors [21].

To diagnose ADHD, the present study proposed motor features to distinguish the difference between the motor function of a healthy person and that of a person with ADHD. For this purpose, the Oseretsky test set [22] was utilized for diagnosis, which is a set of tests to assess the motor function of children in the age range of 4.5 and 14.5 years by evaluating motor disorders. Based on the studies, these tests have been used to diagnose and in some cases treat ADHD. Therefore, according to the science of motor behavior and psychology, the present study aims to normalize, i.e., to specialize motor proficiency subtests for ADHD, and digitize motor proficiency test for the initial diagnosis of ADHD using artificial intelligence techniques. This method is used for reducing costs, without relying on complex and specialized hardware, and is easily implemented in the locations where the child is present, especially in deprived areas, where access to a psychiatrist and counseling centers is difficult.

1.1 Related work

As the ADHD progresses, the nerve cells in the brain responsible for performing other activities get harmed and destroyed, causing the disorder to prevent physical activities such as walking, talking, eating, and so on. Various studies conducted in this area in the science of motor behavior have indicated that motor activities, clumsy motor activity of children with ADHD, balance and gait, and daily life activities can be considered as one of the primary indicators to identify these children.

The team of Lee et al. developed an RNN- and LSTM based-deep learning algorithm to obtain an ADHD diagnosis accuracy of 97.82% but they used a robot and screening game in their studies [23]. Chen et al. obtained an ADHD diagnosis accuracy of 88.1% with using a support vector machine algorithm [24]. According to Tseng et al., a strong and significant relationship exists between fine motor skills and ADHD as well as a relatively weak relationship between gross motor skills ADHD [25].

According to Saadat, children with ADHD were significantly different from normal children in fine movements, gross movements, balance, and flexibility. In addition, they are unable to restrain and regulate their own movement, and have difficulty performing fast motor activities. Understanding the relationship between ADHD and motor skills can lead to early diagnosis and better treatment choices, as well as identifying these children's skills [26].

Gait and balance include the function of various parts of the motor system such as positioning, attention, and planning in performing activities and the child's movement. Defects in these parts of a person's motor system can lead to dysfunction and changes in motor function and deviation in their gait pattern and balance from normal, which can indicate the presence of cognitive and clumsy disorders in children with ADHD.

To digitize the diagnosis, each person's activities are automatically recorded using an intelligent system. In general, body movement recording systems with recording sensors can be divided into wearable sensors, (mounted on the body), and non-wearable sensors (mounted in the environment) [27].

In gait and balance analysis methods using wearable sensors, motion sensors are mounted on different parts of the patient's body such as legs, ankles, and hip joints. These sensors may be accelerometers, protractors, pressure sensors, and tilt sensor which can measure various features of gait pattern and balance in each individual. Systems including several types of wearable sensors are usually utilized for accurate and complete measurement of these features [9, 10]. The second category is gait and balance pattern recording systems based on non-wearable sensors. Non-wearable systems for monitoring and analyzing the gait of people operate based on imaging systems and image processing by using cameras installed in the environment. Non-wearable gait analysis systems based on image processing can be divided into color cameras (RGB camera) and in-depth imaging systems (RGB-D camera). In image processing systems with non-wearable cameras, the person can move freely without restrictions on the body by mounting cameras in the environment such as RGB camera systems and installing one or more cameras in a specific location. Then, the recorded images can be analyzed by image processing systems [28]. In-depth cameras are utilized in the systems of recording and analyzing the movements of people based on the image with depth. One of the types of depth cameras used in various studies such as recognizing people, analyzing gait and balance patterns, and physical activities is called Kinect cameras provided by Microsoft. The new proposed motion pattern analysis systems use Kinect in-depth cameras with high resolution and various data such as color images, depth images, and the person's skeleton information.

Parametrizing human movement to understand human activities and behaviors automatically is one of the big challenges of human computer interaction's field of research. Various studies have been done to analyze human movements for different purposes. For instance, human movements are parameterized and modeled, by using a well-known human movement descriptor (Laban) to recognize different human activities [29], for analyzing human–human interaction to understand social behaviors [30], for analyzing body parts motions for human recognition [31], and for analyzing human gait to diagnose Parkinson's disease [32, 33].

The present study proposes an intelligent system to diagnose ADHD based on skeleton data recorded by Kinect in-depth camera for analyzing gait pattern and balance in children. The proposed system can be used in clinical and daily environments due to the use of a Kinect camera, motion protocol, and non-invasive method of recording gait and balance pattern while reducing costs; however, it is not necessary to configure and record complex data such as EEGs and includes a low volume of recorded information and a simple system.

Therefore, the present study sought to extract effective motor features to diagnose ADHD in children using intelligent systems, in which, gait and balance tasks are selected indicating the differences between healthy children and those with ADHD after recording motor data. Then, the data are preprocessed, features are designed and extracted from skeleton data, healthy children and those with ADHD

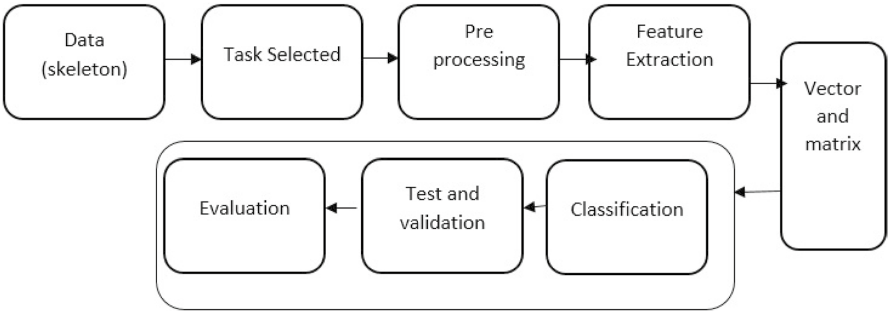

Fig. 1 Block diagram of a step-by-step procedure

are separated by a machine learning model, support vector machine (SVM), and the obtained results are evaluated.

In the following sections, we first explain our data collection methodology in Sect. 2. Next, in Sect. 3, we discuss our preparing dataset and preprocessing and noise cancellation steps. Subsequently, we introduce our feature extraction approaches and present the experiment results for classification in Sect. 4. Finally, we discuss our experimental findings in Sect. 5 and conclude this paper in Sect 6.

2 Methodology

The present method is supposed to use a series of standard motor activities whose quality of performance can show the difference between healthy people and people with ADHD. Figure 1 shows the conceptual model of the research. First, each subject is labeled based on clinical data and EEGs. Then, the necessary scenario for recording the data, selecting motor behavior test, and determining the type of sensory data and data collection process is evaluated based on the science of motor behavior. After collecting the required data by a depth sensor (RGB-D camera), the effective features distinguishing between the healthy and disorder group are proposed and extracted. In the next step, the desired system is trained, and the classification model is tested by using an appropriate validation method. Finally, common approaches are used for evaluation step (Fig. 1).

2.1 Preparing dataset

The second version of the Kinect in-depth camera from Microsoft is used for recording the gait and balance pattern of the children participating in the study. These cameras are able to record complete information in the form of color images, in-depth images, and skeleton information of 25 connection points of joints [34]. Figure 2 shows an example of the utilized camera, the different types of information which can be recorded, and the joints which can be tracked by this camera.

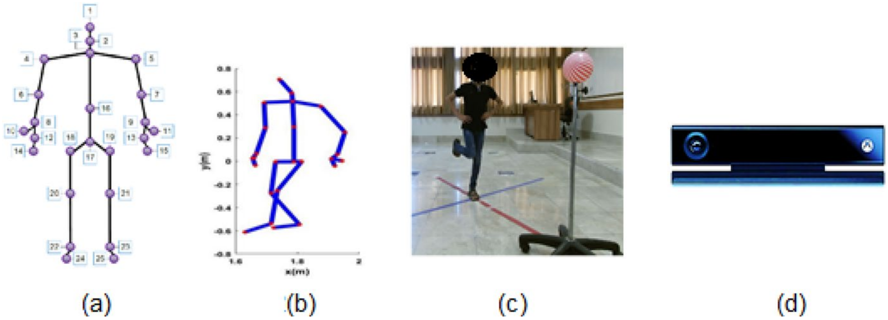

Fig. 2 A sample data collected from the Kinect device. From left to right, **a** the 25 joints Skeleton, **b** a sample of skeleton joint points tracked, **c** RGB image captured by the Kinect, and **d** a Kinect device

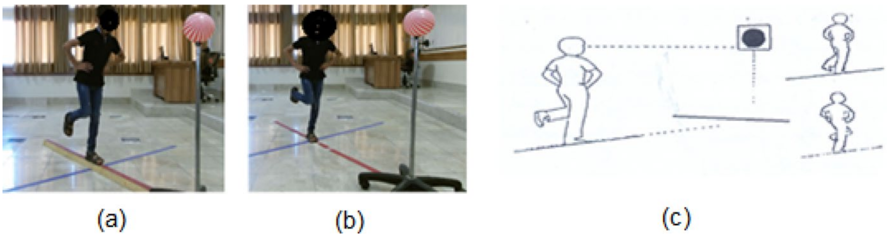

Fig. 3 Presenting collected images for **a** standing on the balance stick and **b** standing on the ground with the superior foot tests, and **c** a schema of those tests

For analyzing gait and balance of children, a set of standard movement test which can present motor performance of the person is needed. In this study, Oseretsky test is used. The Oseretsky test is a set of reference norm tests assessing the motor performance of children in the age range of 4.5–14.5 years. The complete form of this test consists of eight subtests including 46 separate sections examining motor proficiency or gross and fine motor disorders. The gist test consists of eight subtests and 14 separate sections which can be used for teachers, clinicians, and researchers and provides useful information for assessing students' motor abilities in creating and evaluating educational mobility programs. The reliability coefficient of the retest set was 0.87, and its validity was 0.84.

Based on the data in this study and statistical analysis, among the eight tests, standing on the ground with the superior foot, standing on the balance stick with the superior foot, and walking heel forward on the balance stick, are used, and a significant difference is observed between healthy children and those with ADHD. Thus, in this study, the three mentioned tests have been used for the mentioned process. In the following, the selected tests are explained. In this research, the superior foot is the dominant foot.

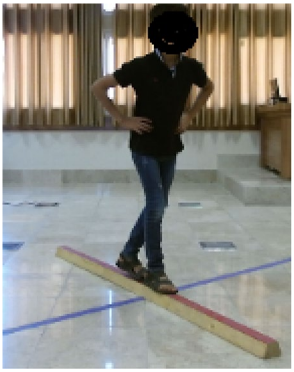

Fig. 4 Walking heel forward on the balance stick

2.1.1 Standing on the ground with the superior foot (first test)

In this experiment, the subject should stand on the walking line with the superior foot while looking at the target, put his/her hands on his/her waist, and bend the knee of the non-superior leg so that the calf is parallel to the ground (Fig. 3). The purpose of this test is to examine the subjects' balance performance. In this task, a healthy child regularly stands on the line and puts his hands on his waist and looks at the target without shaking and maintains his balance without shaking his knees. Instead, a child with ADHD cannot keep his bent knee steady, his body starts to slide and shake and even get off the line.

2.1.2 Standing on the balance stick with the superior foot (second test)

The purpose of this experiment is to evaluate the balance with different conditions and on a balance stick with height. In this experiment, the subject must stand on the balance stick with the superior foot while looking at the target, put his hands on the waist, and bend the knee of the non-superior leg so that the calf is parallel to the ground (Fig. 3). It is the same as the first task, with the difference that the child must maintain his balance on the stick. In this test, the subject of the healthy group had the ability to stand on the balance stick and control the balance and bend the non-dominant leg at an angle of 45 degrees and put the hands on the waist, but the child with ADHD is not able to do these actions.

2.1.3 Walking heel forward on the balance stick (third test)

In this experiment, the subject should step on the balance stick with the hand on the waist so that the heel of the front foot touches the big toe of the back foot (Fig. 4). The purpose of this test is the correct movement of the steps, the number of steps, and balance performance. In this task, the child must keep his balance on the balance stick and walk at the same time. A healthy child is able to walk on a stick while maintaining balance. But, the balance of the child with ADHD will lose in this task, and his body will shake and his hands will separate from his waist, and he will fall down from the balance stick.

The children in the study stood at the position and moved their hands up and down to be detected by the Kinect, before beginning the gait and balance components test. To reduce errors and achieve a higher volume of data on the component of gait and balance, and based on the information of the Oseretsky test for the necessary validity and reliability, the experiments are repeated for each child five attempts and recorded each time. Parallel with the registration by Kinect, the examiner recorded the data in special test forms based on the Oseretsky test scores online in the designed system and on a paper. In addition, the test is explained to the children before the start, and a pre-made film was shown to the children, and the children could do one test performance. After recording the movement data of the participants, to analyze the skeleton data obtained from the Kinect camera recording, steps of preprocessing, feature extraction, analysis based on descriptive statistics, and classification of healthy children and those ADHD are performed by artificial intelligence algorithms. Further, the data recorded by the examiner are analyzed regarding the Oseretsky test norm, and the statistical analysis is performed based on the healthy and ADHD groups labeling. Finally, the results of the proposed method are compared with the results of clinical evaluations of individuals. Python and MATLAB software are used to process the recorded data, extract features, and perform machine learning procedure.

2.2 Preprocessing and noise cancellation

During recording the data with the Kinect device, sometimes the skeleton of the person is not followed correctly in some movements, and as a result, the position of the joints is not recognized correctly. Considering that the data are collected by our team of research and may need to be cleaned. Different methods of cleaning the skeleton data are available, and in this study, the moving average filter is used. Thus, first the points which were not correctly detected were removed from the time-series data by a fixed threshold on the skeleton data along the x, y, and z axes, and then, the deleted data were restored by interpolation using the time-lapse data related to the original signal.

A moving average filter was used to remove the noise of the skeleton data recorded from the subjects during the experiment. In this type of filtering, a moving window with a length of five frames was considered, and then, the average value of x, y, and z coordinates on the data recorded in consecutive frames for each connection point of the joints was obtained [35]. Equation (1) presents the average filter for a window of length N.

$$x^1(t) = \frac{1}{N+1} \sum_{i=-\frac{N-1}{2}}^{i=\frac{N+1}{2}} x(t-i) \tag{1}$$

where $x(t)$ is the filtered data for the t's frame, $x(t)$ shows the original unfiltered data, and N indicates the length of the filtering window that sets the number of frames to average at a given time for skeleton data around a frame. Time is shown by t. By changing the variable i, different frames neighboring the desired frame are selected for averaging.

2.3 Feature extraction

After removing the noise from the recorded data, effective features should be extracted to assess motor function for the purpose of identifying children with ADHD. The present study aims to extract significant features of children's motor function automatically from the data obtained by the Kinect device, which was done with the help of the knowledge of clinical professionals, and the presentation and formulation of features which can act as the experience of a specialist in assessing the motor function of the child. In the following, the needed features are explained, which are summarized in Table 1.

Human body parts poses, can be illustrated by a set of angles in the joints of between all two connected body parts. Thus, calculating the relevant angles in the three-dimensional space is important for our human movements analysis which can be calculated based on the following equations and properties.

It is assumed that based on Fig. 5A, B, and C which are three different points of the body in three-dimensional space, whose coordinates are (A_x, A_y, and A_z), and A_x, A_y, and A_z are the coordinates of point A on the X, Y, and Z axes, respectively.

Equation (2) calculates the angle of a joint which appears by two lines (AC and BC), where $A.B$ can be calculated by Eq. (3), and A and B (norm A and B) can be calculated by Eq. (4). A and B are the three-dimensional positions of the two points relative to point C, thus A_x represents the position of point A on the x-axis relative to point C.

$$\text{Angle} = \text{Arccos}\left(\frac{A \cdot B}{\|A\| \cdot \|B\|}\right) \tag{2}$$

$$A \cdot B = A_x \cdot B_x + A_y \cdot B_y + A_z \cdot B_z \tag{3}$$

$$\|A\| = \sqrt{A \cdot A} = \sqrt{A_x^2 \cdot A_y^2 \cdot A_z^2} \tag{4}$$

Euclidean distance Euclidean distance, which is one of the static properties, is obtained based on the distance between joints and is calculated by the following equation.

$$\mathrm{d}_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2} \tag{5}$$

where d_{ij} is the Euclidean distance of two joints i and j, which are calculated for the three dimensions X, Y, and Z.

Table 1 General depiction of a set of features used in the present study

Features	Formula
Velocity of a body part	$\mathrm{V_i(\,f)} = \sqrt{\dot{x}_i^2(f) + \dot{y}_i^2(f) + \dot{z}_i^2(f)}$
Acceleration of a body part	$\mathrm{Acc_i(f)} = \sqrt{\ddot{X}_\mathrm{i}^2(\mathrm{f}) + \ddot{Y}_\mathrm{i}^2(\mathrm{f}) + \ddot{Z}_\mathrm{i}^2(\mathrm{f})}$
Variance of a body part	$\mathrm{Var} = \frac{\sum_{j=1}^{k} \sqrt{\left(\sum_{i=1}^{n_j} \left(\bar{x}_A - x_{Ai}\right)^2 + \left(\bar{x}_B - x_{Bi}\right)^2\right)/n_j}}{K.R}$
Kinetic energy	$\mathrm{KE}(f) = \frac{1}{2} \sum_{i=1}^{n} m_i v_i^2(f)$
Curvature	$K_i = \frac{\sqrt{\left(\dot{x}_i \cdot \ddot{y}_i - \dot{y}_i \cdot \ddot{x}_i\right)^2 + \left(\dot{z}_i \cdot \ddot{x}_i - \dot{x}_i \cdot \ddot{z}_i\right)^2 + \left(\dot{y}_i \cdot \ddot{z}_i - \dot{z}_i \cdot \ddot{y}_i\right)^2}}{\left(\dot{x}_i^2 + \dot{y}_i^2 + \dot{z}_i^2\right)^{\frac{3}{2}}}$
Density	$\mathrm{DEN} = \frac{1}{n} \sum_{i=1}^{n} \mathrm{d}_{ci}$
Symmetry	$\mathrm{SI_{xi}} = \frac{\left(x_B - x_{Li}\right) - \left(x_B - x_{Ri}\right)}{x_{Ri} - x_{Li}}$
Contraction	$\mathrm{CI} = \frac{\mathrm{DEI}}{\mathrm{BV}}$
Fluidity	$F_i = \frac{\sqrt{\left(\ddot{x}_i . \dddot{y}_i - \ddot{y}_i . \dddot{x}_i\right)^2 + \left(\ddot{z}_i . \dddot{x}_i - \ddot{x}_i . \dddot{z}_i\right)^2 + \left(\ddot{y}_i . \dddot{z}_i - \ddot{z}_i . \dddot{y}_i\right)^2}}{\left(\dddot{x}_i^2 + \dddot{y}_i^2 + \dddot{z}_i^2\right)^{\frac{3}{2}}}$
Anterior and posterior oscillations	$FB_i = \frac{\left(vx_B - vx_{Li}\right) - \left(vx_B - vx_{Ri}\right)}{vx_{Ri} - vx_{Li}}$
Height of a person	$H = \left\lvert y_{\mathrm{head}} - y_{\mathrm{foot}} \right\rvert$
Head to the base joint of the spine distance	$D = \left\lvert y_{\mathrm{head}} - y_{\mathrm{SpineBase}} \right\rvert$
Balance	$\mathrm{Equilibrium} = \mathrm{var}\left(\sqrt{\left(\frac{x_r - x_l}{2} - x_b\right)^2 + \left(\frac{z_r - z_l}{2} - z_b\right)^2}\right)$
Gait symmetry	$\mathrm{CC_{symmetry}} = \sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{x_{r(n)}^{i} . x_{l(n)}^{i}}$
Step length	Distance between two consecutive feet during walking
Step number	Number of steps required to complete a walkway
Stride length	Distance of two consecutive steps to complete a stride
Gait cycle	Time required for a complete gait cycle
Stride velocity	Ratio of spatial displacement in a stride to the time
Mean step length	Average step length
Step length variability	Amount of step length variability
Euclidean distance	$\mathrm{d}_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2}$

Variability The equation used by Sidaway, Heise, and Zohdi was used to measure the variability of an estimated value during a sequence. The mentioned equation is known as the normalized root mean squared difference (NO-RMSD) [36, 37]:

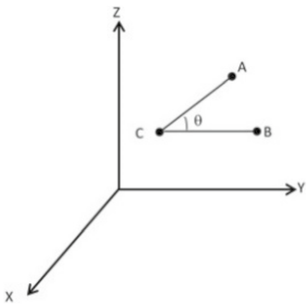

Fig. 5 Angle with the three points in three-dimensional space

$$\mathrm{Var} = \frac{\sum_{j=1}^{k} \sqrt{\left(\sum_{i=1}^{n_j} \left(\overline{x}_A - x_{Ai}\right)^2 + \left(\overline{x}_B - x_{Bi}\right)^2\right)/n_j}}{K.R} \tag{6}$$

where x_A and x_B show the angular displacement of two body parts such as shoulder and elbow. $\overline{x}_B$ and $\overline{x}_A$ are the mean trajectory angles of the two body parts A and B. x_{Ai} and x_{Bi} are the angles of the body parts of A and B at *ith* moment. In addition, K is the number of trials, R indicates the amount of difference remaining, and n is the number of frames for each trial on which the calculation operation is performed. The interpretation of the number obtained from the above equation is that a smaller number indicates that the coordination pattern of the person is more stable.

Velocity The value of velocity in three-dimensional space for all parts of the body in a sequence of frames (f) is obtained from the following equation in which $\dot{x}_i$‘ $\dot{y}_i$ and $\dot{z}_i$ are the velocity of the three dimensions x, y, and z for each part of the body (i).

$$V_i f(x) = \sqrt{\dot{x}_i^2(f) + \dot{y}_i^2(f) + \dot{z}_i^2(f)} \tag{7}$$

Acceleration The amount of acceleration in three-dimensional space for all parts of the body in a sequence of frames (f) is obtained from the following equation in which $\ddot{x}_i$, $\ddot{y}_i$, and $\ddot{z}_i$ are the acceleration of the three dimensions x, y, and z which are for each part of the body (i).

$$\mathrm{Acc}_i(f) = \sqrt{\ddot{x}_i^2(f) + \ddot{y}_i^2(f) + \ddot{z}_i^2(f)} \tag{8}$$

Kinetic energy The kinetic energy index in three-dimensional space for frame f from a sequence of frames is calculated from the total kinetic energy of all parts of the body based on their mass using the following equation, where v_i shows the value of velocity and m_i indicates the approximate mass of each part (i), and n is the number of body parts.

$$\mathrm{KE}(f) = \frac{1}{2} \sum_{i=1}^{n} m_i v_i^2(f) \tag{9}$$

Curvature The curvature index for all parts of the body in three-dimensional space for frame f of a sequence frame is calculated using the following equation for body part of i.

$$K_i = \frac{\sqrt{\left(\dot{x}_i \cdot \ddot{y}_i - \dot{y}_i \cdot \ddot{x}_i\right)^2 + \left(\dot{z}_i \cdot \ddot{x}_i - \dot{x}_i \cdot \ddot{z}_i\right)^2 + \left(\dot{y}_i \cdot \ddot{z}_i - \dot{z}_i \cdot \ddot{y}_i\right)^2}}{\left(\dot{x}_i^2 + \dot{y}_i^2 + \dot{z}_i^2\right)^{\frac{3}{2}}} \tag{10}$$

Density The density index is calculated as mean of the sum of the Euclidean distances of all body parts from the center of the body in each frame f of a sequence frame by using the following equation in which d_{ci} is the Euclidean distance of part of the body i to the center of the body (c).

$$\mathrm{DEN} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{d}_{ci} \tag{11}$$

Symmetry The position of the center of the body and the left and right parts, e.g., left and right shoulders in a series of frames (f) are used to calculate the amount of symmetry in the x dimension using the following equation where x_B is the coordinate of the center of the body, x_{Li} is the coordinate of the i left part, and x_{Ri} is the coordinate of the i right part of the body. The amount of symmetry in the dimensions' y and z is also obtained from the following equation considering the values specific to each dimension. The overall symmetry is estimated using Eq. 13.

$$\mathrm{SI}_{xi} = \frac{\left(x_B - x_{Li}\right) - \left(x_B - x_{Ri}\right)}{x_{Ri} - x_{Li}} \tag{12}$$

$$\mathrm{SI} = \frac{\mathrm{SI}_{xi} + \mathrm{SI}_{yi} + \mathrm{SI}_{zi}}{3} \tag{13}$$

Contraction Contraction index in three-dimensional space in the sequence of frames (f) is defined as the ratio of approximate density to bounding volume (BV) of the participant's body and is obtained from the following equation.

$$\mathrm{CI} = \frac{\mathrm{DEI}}{\mathrm{BV}} \tag{14}$$

To calculate the BV, the difference between the maximum and minimum values of all three dimensions x, y, and z is used, and the approximate density value is obtained from the following equation.

$$\mathrm{DEI} = \frac{3}{4}\pi * \mathrm{DEI}_x * \mathrm{DEI}_y * DEI_z \tag{15}$$

where DEI_x, DEI_y and DEI_z represent approximate densities in three dimensions x, y, z, in a sequence of frames (with n frames), obtained from Eq. (16) in which dx_i, ,dy_i and dz_i are the distance between the i part of the body to the center of the body.

$$\mathrm{DEI}_y = \frac{1}{n}\sum_{i=1}^{n} \mathrm{d}y_i \ \mathrm{DEI}_x = \frac{1}{n}\sum_{i=1}^{n} \mathrm{d}x_i \tag{16}$$

Fluidity The principle of curvature is applied to the velocity of motion and its change in time to calculate fluidity for all parts of the body in three-dimensional space in the sequence of frames (f) using the following equation in which $\ddot{X}_\mathrm{i}$, $\ddot{y}_\mathrm{i}$, and $\ddot{z}_\mathrm{i}$ are acceleration, and $\dddot{x}_\mathrm{i}$, $\dddot{y}_\mathrm{i}$, and $\dddot{z}_i$ are considered as the acceleration's changes in three dimensions x, y, and z for each part.

$$F_i = \frac{\sqrt{\left(\ddot{x}_i.\dddot{y}_i - \ddot{y}_i.\dddot{x}_i\right)^2 + \left(\ddot{z}_i.\dddot{x}_i - \ddot{x}_i.\dddot{z}_i\right)^2 + \left(\ddot{y}_i.\dddot{z}_i - \ddot{z}_i.\dddot{y}_i\right)^2}}{\left(\ddot{x}_i^2 + \ddot{y}_i^2 + \ddot{z}_i^2\right)^{\frac{3}{2}}} \tag{17}$$

Anterior and posterior oscillations The values of anterior and posterior oscillations of each upper body part in three-dimensional space are calculated in a series of frames (f) with the movement velocity of the desired part along the depth component (x) relative to the position and body orientation. The value of FB_i in the following equation indicates the amount of oscillations of the i part of the body in the sequence of frames (f). In addition, vx_{Li} is the velocity of the left part of i,vx_{Ri} shows the velocity of the right part of i, and vx_B is considered as the velocity of the center of the body.

$$\mathrm{FB}_i = \frac{\left(vx_B - vx_{Li}\right) - \left(vx_B - vx_{Ri}\right)}{vx_{Ri} - vx_{Li}} \tag{18}$$

The mentioned equation is used to calculate the amount of anterior oscillations which are symmetrical. These parts are the shoulders, arms, and hands which are located in the left and right areas of the upper body. However, calculating this value for the rest of the upper body parts, i.e., head, neck, and shoulder girdle which are not symmetric is calculated using an equation in the dimensions' y and x.

$$\mathrm{FB}_i = vx_B - vx_i \tag{19}$$

2.3.1 Height of a person

$$H = \left|y_{\mathrm{head}} - y_{\mathrm{foot}}\right| \tag{20}$$

2.3.2 Distance between two joints

For instance, the distance between two shoulders

$$W = \sqrt{X^2 + Z^2} \begin{array}{l} X = \left|x_{\mathrm{heaShoulderLeft}} - x_{\mathrm{heaShoulderRight}}\right| \\ Z = \left|Z_{\mathrm{heaShoulderLeft}} - Z_{\mathrm{heaShoulderRight}}\right| \end{array} \tag{21}$$

2.3.3 Distance from the head to the base joint of the spine

$$D = \left| y_{\text{head}} - y_{\text{SpineBase}} \right| \tag{22}$$

2.3.4 A person's height ratio in two different moments

$$H(t)/H(t - \Delta t) \tag{23}$$

2.3.5 The ratio of the distance of the center of gravity of the person from the head in two different moments

$$D(t)/D(t - \Delta t) \tag{24}$$

2.3.6 Balance

According to the official guidelines, any loss of equilibrium is a severe error that influences the evaluation of the performance. To detect equilibrium loss, we measure the projection of the barycenter of the body on the rectangular area defined by the performer's feet. The algorithm first detects, for each frame, whether both feet are on the ground by checking the values of the vertical component of markers LFAK $=(x_l, y_l, z_l)$ and RBAK $=(x_r, y_r, z_r)$. For each frame, it then defines a rectangle Z with four corners: (x_l, z_l),(x_l, z_r),(x_r, z_r), and (x_r, z_l) and measures the distance between the barycenter $\mathrm{B}=(x_b, y_b, z_b)$ projected on the 2D plane defined by the feet positions and the center of the Z rectangle. The smaller the distance, is the better equilibrium. The computed measure of equilibrium is the variance of such a distance over the analyzed segment:

$$\text{Equilibrium} = \text{var}\left(\sqrt{\left(\frac{x_r - x_l}{2} - x_b\right)^2 + \left(\frac{z_r - z_l}{2} - z_b\right)^2} \right) \tag{25}$$

2.3.7 Gait symmetry

As we have known, the gait symmetry is usually assumed as the identical function of locomotion between the left and right sides of body and its change (i.e., gait asymmetry) can be found by examining the significant difference of activity between two sides such as lower limbs. Where x_r and x_l are the values of the measured gait parameters from the right and left limbs, respectively [38]:

$$\text{CC}_{\text{symmetry}} = \sum_{n=1}^{N} x^i_{r(n)} x^i_{l(n)} \tag{26}$$

2.3.8 Step length

During walking, the distance between the collisions of one side of the foot, i.e., heel with the ground until the same part collides with the ground again is called the step length. In other words, the distance between two consecutive feet during walking is the step length.

2.3.9 Gait cycle

It is the time required for successive contacts of the sole of one foot until it strikes the ground again in the same position.

2.3.10 Stride velocity

It is the ratio of spatial displacement in a stride to the time required for this spatial displacement.

2.4 Relevant features for each test

2.4.1 Features of the balance test—standing on the ground with the superior foot

Since the criterion is placing the hands on the waist, bending the knee of the non-superior leg, i.e., placing the leg parallel to the ground, not opening the knee of the superior leg from a 45-degree angle, not contacting the non-superior knee with the ground, not hooking the non-superior foot to the superior foot, not moving the superior foot, and not swaying the body. Thus, the important body parts and the effective features of this test obtained through feature engineering with the proper performance in diagnosing ADHD shown in Table 2.

2.4.2 Features of balance test—standing on a balance stick with the superior foot

This test is similar to the previous test, the main difference of which is that the subject stands on a balance stick in this test. Thus, in addition to observing the points of the previous test, the subject must bend the non-superior leg at a 45-degree angle and place the hands on the waist, maintain its balance on the wood, and prevent it from falling and swaying too much [39].

2.4.3 Features of the balance test—walking heel forward on the balance stick

Based on the nature of this test, it was found that when walking heel forward on the balance stick, the most important part of this test is the touch of the front heel and the back big toe. To analyze the movement, the distance between the right ankle and the left ankle in each step was measured. This size must be the same as the foot size of the subject; otherwise, the heel of one foot does not hit the toe of

Table 2 List of relevant involved body parts and features in the different tasks

Test	Involved body parts	Features
First test	Elbows, shoulders, arms, hands, above the knees, ankles, toes, forearm, head, neck, shoulder girdle, and spine	Motor coordination, shoulder symmetry, kinetic energy of the whole body, angle between joints, distance between joints, velocity of body members' movement, curvature, acceleration, anterior and posterior oscillation, and density
Second test	Elbows, shoulders, arms, hands, above the knees, ankles, toes, forearms, head, neck, shoulder girdle, and spine	Ratio of height at two different moments, balance measurement [27], motor coordination, total body kinetic energy, symmetry, angle between joints, curvature of the spine, velocity of body parts movement, anterior and posterior oscillation, and density
Third test	Elbows, head, knees, and ankles	Gait symmetry, step length, step number, stride length, gait duration, stride velocity, mean step length, step length variability, step length asymmetry in the left and right legs, joint coordination, body acceleration, height ratio in two different moments, the ratio of the distance from the center of the body to the head at two different moments, and measure of equilibrium

the other foot at each step, which is an error. Therefore, the windowing method was used [40].

The step numbers, as well as the lack of imbalance and not falling off the stick, are of particular importance. The walking process has been studied to obtain these features. The walking process is a hierarchical set made of gait cycle. The gait cycle for one foot involves the successive collision of the heel of one foot with the ground. Each gait cycle was made up of two parts: main phase (standing) and rotation (changing position) [41].

2.5 Classification

Many supervised machine learning methods work by having a set of input feature vectors such as $X=[X_1, X_2, \ldots, X_n]$ and their corresponding output values $T=\{t_1, t_2, \ldots, t_m\}$ used to train the desired model, which is used for predicting the appropriate t output by applying the trained model for a new x input.

Support vector machine (SVM) is a classification method introduced by Vapnik [42] based on the theory of two-class statistical training. The SVM classifier training phase, an attempt was made to select the decision boundary for maximizing the minimum distance between each of the desired classes. In the cases where the data are not linearly separable, the data are mapped to a new space, thus that they can be separated linearly in the new space. The SVM was originally designed to separate two classes, which can be generalized to separate several classes [43]. In the present study, the SVM method was used to separate the healthy and ADHD groups based on the body motion-based features.

2.6 Validation and evaluation

In the supervised learning methods, the available dataset is divided into training and test dataset, which are managed in different ways for validation. The K-fold method is used here for validation.

K-fold cross-validation is considered as one of the most common validation methods for machine learning, in which the entire dataset is divided into K equal parts. The $K-1$ part is used as a training dataset based on which the model is taught, and the trained model is evaluated with the remaining part. The number of repetitions of this process will be K times so that each K part is used only once for evaluation, and each time a value of evaluation is calculated for the constructed model. In this evaluation method, the final accuracy of the classifier is equal to the average K of the calculated evaluation value [44]. The accuracy and F-score criteria were used to evaluate the results of distinguishing groups of ADHD and healthy children quantitatively by the SVM classifier.

The most important factor for determining the efficiency of the classification technique is evaluating the total accuracy of a classification and showing the fact that the designed classification can categorize the percentage of the test records correctly. The classification accuracy can be calculated based on Eq. 27, regarding the concepts of the confusion matrix obtained from the evaluation process.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{27}$$

An F-score is a performance accuracy criterion for the accuracy of test data by considering both the recall (r) and precision (p) of the test data to calculate the score. Precision equals to the number of true and positive prediction results divided by the total number of positive results returned from the classifier, and recall is the number of true and positive prediction results divided by the total number of actual positive test samples. The F-score is the harmonic mean of precision and recall, which equals 1 in the best case and 0 in the worst case. Equations 28, 29, and 30 show the precision, recall, and F-score evaluation criteria, respectively [45].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{28}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{29}$$

$$F - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{30}$$

3 Experimental results

In the present study, children aged 7–9 years in both healthy and ADHD groups were examined experimentally. Examination of healthy children for ADHD and other types of psychological disorders was approved by the experts from questionnaires, EEG testing, and diagnostic interviews. In addition, ADHD children underwent detailed psychiatric examinations by neurologists and psychologists and had a complete record of diagnostic information in the reference psychological clinics, Soroush Clinic in Mashhad. Individuals with disorders other than ADHD, a history of epilepsy or seizures, or IQ below 75 were excluded from the study. Further, all parents of children participating in the research were provided with comprehensive information about the study, whose children participated in this study after they completed the consent form. After examining ADHD and healthy children, 77 ADHD children and 123 healthy children were selected to record movement tests, i.e., gait and balance. Some participants were removed due to irregular cooperation or incomplete data. Finally, the data of both healthy group with 43 subjects and the ADHD group with 43 subjects were analyzed. Table 3 shows the demographic information including the mean and standard deviation of age, height, and weight of the two groups of the participants. The average age is about 8.38. In terms of height and weight, both groups are the same in terms of average weight, but in terms of average height (29 for the healthy group and 32 for the ADHD group). The average IQ scores in the healthy and ADHD group were 89.76 and 109.19, respectively. If P-value was

Table 3 Demographic information of the collected dataset

Variable	Healthy group (1)		ADHD group (2)		P
	43		43		
	Mean	Std.	Mean	Std.	
Age	8.36	1.096	8.38	0.97	0.952
Height (cm)	131	7.85	133	7.47	0.396
Weight (Kg)	29	7.76	32	8.37	0.162

less than 0.05, it means between variables are a meaningful difference. Thus, in the mentioned table, there is no meaningful difference between the two groups.

To examine the differences between the study groups, the Oseretsky clinical movement data recorded by the examiner were investigated whether the distribution of each of the three tests was normal or abnormal using descriptive statistics analysis methods. Parametric analysis of independent t-test and non-parametric Mann–Whitney test [46] was used to compare the score of each test with normal and abnormal distribution of ADHD and healthy groups, respectively. Therefore, the differences between the two groups were examined in each of the tests. The following are the results related to the significance of the tests. Due to the normality of the standing test on a balance stick with the superior foot in both groups (second test), the parametric t-test can be used to compare the mean score of each test in the two groups, the results of which are presented in Table 4.

Considering the rating scale or abnormality of the data of the standing on the ground with the superior foot test (first test) and walking heel forward on a balance stick test (third test), non-parametric Mann–Whitney test is used to compare the mean of the variables in the two groups (Table 5).

Based on the results, a significant difference was observed between the two groups in the two aforementioned *t*-test and Mann–Whitney tests, because of the sig. is lower than 0.05. Regarding the mean parameter, the first group (healthy group) had better performance than the second group (ADHD group).

The results of statistical comparison of the extracted features of gait and balance between the two groups of children with ADHD and healthy children showed significant differences in different features. In addition, the distinguishing feature and difference between the mean values of the features in the two study groups are different. Figure 6 displays the mean values of the extracted features of gait and balance for healthy and ADHD study groups for three tasks that analyzed in the form of a bar chart for comparison.

To identify a child with ADHD and distinguish them from healthy children, a set of independent features was selected from the various features introduced in the previous section for each different tests. Then, those extracted features from skeleton body movements would be the classifier (SVM) inputs for diagnosing if the participant is ADHD or healthy ones. For validation of the process, we have used K-fold cross-validation method with $K = 10$. Table 6 indicates the results of the classifiers for the utilized tests with a number of different defined features depicting the performance results of the proposed method. As can be seen in the results, all tests

Table 4 Results of independent sample *t*-test for the means of the score of clinical movement data for the second test, in the two groups (healthy(1) and ADHD(2)), effect size is the magnitude of the difference between groups, and it would be meaningful the difference between two groups if sig. < 0.05

Features	Group	No.	Mean	Standard deviation	Leven test		*T*-test			Cohen's d (effect size)	Report
					Test statistics	Sig.	Test statistics	Degree of freedom	Sig.		
Second test features	1 (Healthy)	43	5.24	1.707	8.610	0.005	2.322	62.959	0.023	0.563	Meaningful
	2 (ADHD)	43	4.15	2.134							

Table 5 Results of Mann–Whitney test for comparing the means of the variables in the two groups

Feature	Average rank		Z	Significant	Cohen's d (effect size)	Result
	Group 1 (Healthy)	Group 2 (ADHD)			d_{Cohen}	
First test features	38.24	30.76	− 2.052	0.040	0.385	Meaningful
Third test features	41.46	27.54	− 2.985	0.003	0.752	Meaningful

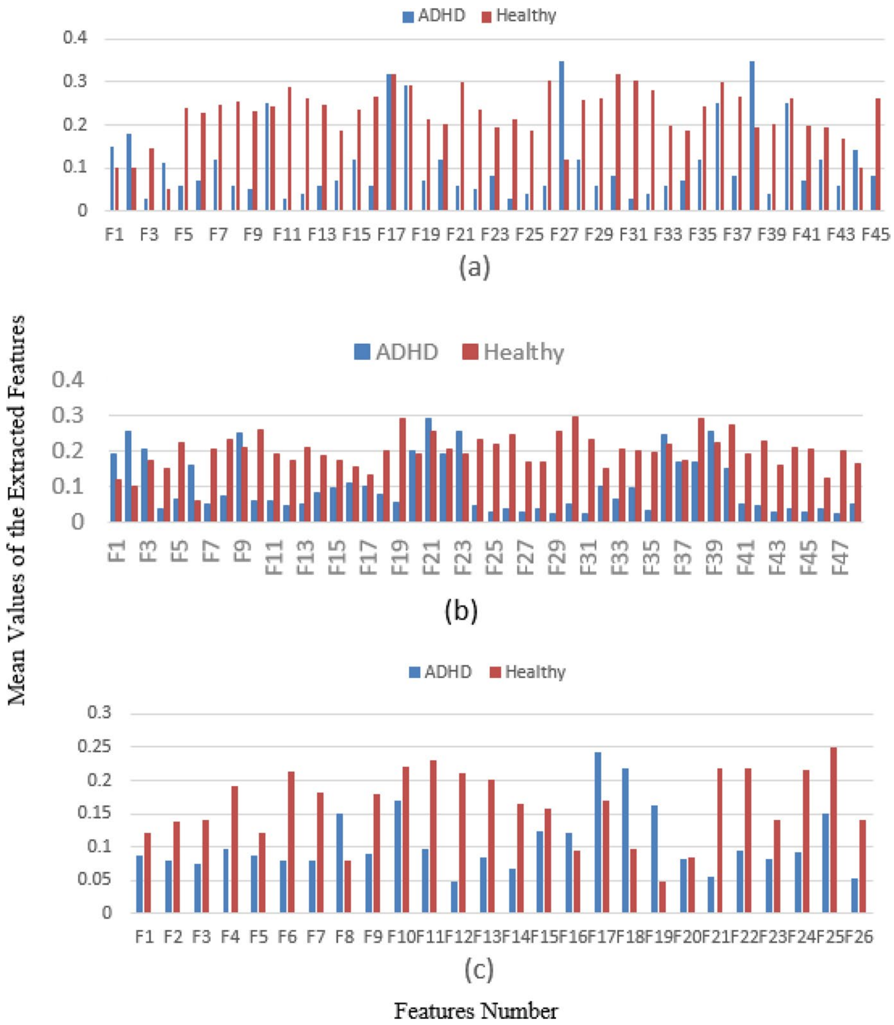

Fig. 6 Comparison of the mean values of the extracted features of gait and balance components between healthy and ADHD

Table 6 Performance results of the proposed method for each test groups in the three tests (from top to down, first, second, and third test), and Std. denotes standard deviation

Test	Accuracy (Std.)	Precision (Std.)	Recall (Std.)	F-score (Std.)
Standing on the ground with the superior foot (first test)	86.4% (± 0.3)	90.1% (± 0.4)	92% (± 0.1)	90% (± 0.2)
Standing on the balance stick with the superior foot (second test)	90.2% (± 0.1)	93.8% (± 0.1)	91.1% (± 0.1)	93.2% (± 0.1)
Walking heel forward on the balance stick (third test)	88.1% (± 0.4)	88.9% (± 0.2)	87.1% (± 0.1)	88.5% (± 0.2)

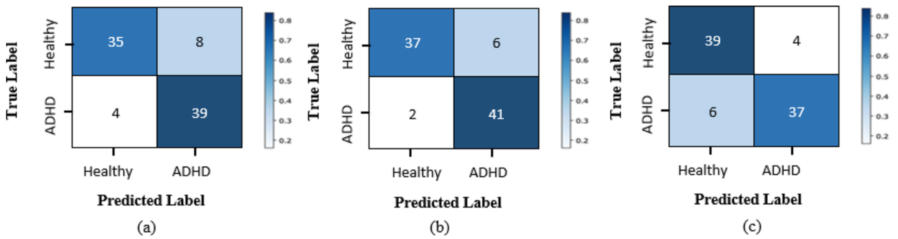

Fig. 7 The figure shows evaluation of the SVM classifier trained on motor behavior features. Confusion matrix shows percentage of correctly classified and mislabeled participants per group averaged on ten-fold cross-validation **a** standing on the ground with the superior foot (first test), **b** standing on the balance stick with the superior foot (second test), and **c** walking heel forward on the balance stick (third test)

are sufficient for the ADHD diagnosing; however, the classifier based on the second test's features shows higher performance.

The confusion matrices of the proposed model for subject-dependent and -independent classification methods according to recall and classification reports are illustrated in Fig. 7.

4 Conclusion

Today, diagnosing ADHD in children through various methods is considered as one of the biggest scientific challenges in the field of psychology which has attracted a lot of attention during the recent years. In most cases, diagnosing this disorder has been made through a questionnaire alone, although it is being developed and studied through EEG by other researchers. However, diagnosing this disorder through motor behavior has been rare along with other diagnostic methods. In the present study, an intelligent model was presented using motor function to assist intelligent diagnostics. For motor function, a database of tests approved by experts in the field of motor behavior was prepared from the subjects in healthy and ADHD groups. Kinect and the examiner recorded and evaluated the test data of different defined tasks; standing on the ground with the superior foot, standing on the balance stick with the superior foot, and walking heel forward on the balance stick. Based on statistical analysis, all three tests showed a significant difference between the two groups of healthy and ADHD. Then, significant features were designed and presented from three tests. Finally, the accuracy of the proposed system was obtained using the SVM classifier in the tests of the three tests 86.4%, 90.2%, and 88.1%, respectively.

Regarding the features extracted from the skeleton of children to diagnose ADHD, one can diagnose this disorder effectively by considering gait and balance. Regarding the features extracted from the standing on the ground with the superior foot test and its accuracy, the result of this test is consistent with statistical analysis and highly efficient in diagnosing the disorder.

In addition, based on the results of feature extraction and classification, the healthy group subjects are able to stand on a balance stick, healthy balance and bend the non-superior leg at a 45-degree angle putting the hands on the waist, while the child with ADHD is not able to do these things in the second test. Therefore, the features extracted from this test demonstrated a significant diagnosis, as well.

To evaluate and extract features to distinguish ADHD from walking heel forward on the balance stick, the data of the healthy group recorded from different features such as step length, step numbers, etc., were used in the third test to compare the two groups. The results were in line with those of feature extraction and statistical analysis by verifying this test for distinguishing between the healthy and ADHD groups.

The idea of this study is providing a new diagnostic method as well as engineering effective features from specified tasks for distinguishing the groups (ADHD and normal). In fact, the present study presented a new method based on the analysis of balance and gait by the recorded skeleton data in order to distinguish the healthy and ADHD groups by the SVM classifier with acceptable quantitative results. However, the study was performed on all ADHD patients, regardless of their subtype. For a more accurate assessment, developing a study is necessary to investigate ADHD subtypes and a larger population of healthy and ADHD people, as well as people with various cognitive disorders or comorbidity such as someone with ADHD in addition to autism. Further, the proposed method in this study can be developed in the future studies by using various other tests due to the importance of early diagnosis of ADHD in its mild stages.

Authors' contributions FR participated in all stages of this study such as data collecting, analysis, implementation, and writing the manuscript. KKR designed the model and the computational framework and analyzed the data, and participate in writing the manuscript. HRT designed motor behavior tasks for the modeling process and data collecting process. AM and AM helped in data collecting process (an interview with subjects and labeling subjects). All authors conceived the study and were in charge of overall direction and planning.

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Availability of data and materials The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval The questionnaire and data and methodology for this study were approved by the Human Research Ethics committee of the Islamic Azad University, Lahijan Branch. (Ethics approval number: REC.IAU.LIAU.IR.1398.013). For each subjects in this study, we have consent to participate.

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