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Depression Prevalence in Postgraduate Students and Its Association With Gait Abnormality

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ABSTRACT In recent years, an increasing number of university students are found to be at high risk of depression. Through a large scale depression screening, this paper finds that around 6.5% of the university postgraduate students in China experience depression. We then investigate whether the gait patterns of these individuals have already changed as depression is suggested to associate with gait abnormality. Significant differences are found in several spatiotemporal, kinematic and postural gait parameters such as walking speed, stride length, head movement, vertical head posture, arm swing, and body sway, between the depressed and non-depressed groups. Applying these features to classifiers with different machine learning algorithms, we examine whether natural gait analysis may serve as a convenient and objective tool to assist in depression recognition. The results show that when using a random forest classifier, the two groups can be classified automatically with a maximum accuracy of 91.58%. Furthermore, a reasonable accuracy can already be achieved by using parameters from the upper body alone, indicating that upper body postures and movements can effectively contribute to depression analysis.

INDEX TERMS Depression prevalence, depression analysis, gait abnormality, machine learning.

I. INTRODUCTION

Rising depression is a worldwide issue that affects a large number of people in society. More than 300 million people are currently affected by depression globally. This mental problem harms cognitive, behavioural and even physical functioning of individuals and might severely impair one's work and daily life. Without timely treatment, it may eventually cause a high rate of suicide. Therefore, finding more objective and effective tools for timely or even real-time depression assessment becomes an urgent task. Given the advancements in computer science and artificial intelligence techniques, interest in automatic depression assessment has grown rapidly in recent years.

As an essential feature of depressive syndromes, psychomotor disturbance has been suggested to be a valid indicator of depression. Analysis of motor behavior such as motor activity, body movements and motor reaction time have been shown to reliably differentiate depressive individuals from healthy ones [1]. Walking as one of the basic and important human mobilities has been examined in depression. [2] reported a linear correlation between walking speed and depression severity. Besides, slouching posture was often reported in depression [3]–[5]. A recent study on elderly

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depression suggests that slower gait speed and shorter step length are tied to depression in later life [6]. All these findings indicate that there is an association between depression and gait abnormality. Human gait provides much more useful information than just mobility. For example, the characteristics it contains can reflect the identity of the walker as well as his or her emotion [7]–[9]. Moreover, clinical gait analysis has already become a developed tool in medical care. It has been applied to early stage diagnosis, treatment planning and tackling of disease progress [10]. Considering the relation between depression and gait abnormality, we expect that natural gait can also serve as an effective indicator of depression. In this study, we aim to investigate depression related gait abnormalities using vision-based gait data and examine whether depressed individuals can be identified by machine learning models based on such features.

Instead of considering clinical cases, our study of gait abnormality in depression is conducted on a more general population, i.e. the potentially depressed individuals in university postgraduate students. Depression has been found as one of the most common health problems for college students [11], [12]. A systematic review reported a mean weighted prevalence rate of 30.6% [13] in university students, which is higher than as seen in the general population [14], [15]. Studies also suggested a steady rise in the number of depressed students in recent years [16], indicating that university students are at high risk of depression. Considering this fact, we choose this specific population as our research subjects.

By carrying out a large scale depression screening, in this article, we first evaluate the prevalence of depression in Chinese postgraduate students. We then explore gait characteristics in the individuals assessed as depression in the screening. Next, we examine whether these individuals and other healthy ones can be accurately classified automatically based on the discriminative gait features we found. Finally, we investigate the contribution of the features from different body regions to the accuracy of the classification.

The rest of this paper is organized as follows. We first introduce the background and related work in Section II. Methods and results of depression prevalence study are presented in Section III. Then we describe the experiment for gait analysis and introduce the features for differentiating the scored-depressed and non-depressed groups in Section IV. Based on such features, we establish classification models that classify individuals into either depressed or non-depressed groups in Section V. General discussion of the results is given in Section VI. Concluding remarks and future work are provided in Section VII.

II. RELATED WORK

The corresponding related works are generally described from three perspectives, namely the prevalence studies of depression in students, gait characteristics associated with depression and the automatic depression assessment.

In clinical studies, the severity of depression is evaluated by standardized diagnostic interviews with psychiatrists or neurologists. While in prevalence studies, it is typically identified through validated, self-report assessment tools. Although such self-administered questionnaires can not be seen as a substitute for clinical diagnosis, for our current purpose (i.e., identifying individuals likely to be suffering from depression) it has been suggested to have high sensitivity and specificity [13]. The reported prevalence rate of depression in university students show wide variability across studies, ranging from relatively low rates around 10% [17], [18] to high rates of above 40% [19]. This variability might be caused by many factors such as the background and size of the studied population, assessment tools and sampling used. In the present study, we limited the investigated subjects to postgraduate students as their lifestyle, ages, studying and financial stress can be distinctive from undergraduate students. The prevalence of depression as well as its comorbidity with anxiety was also examined here.

Clinical gait analysis usually focuses on the lower limb movements. The most frequently investigated parameters include pace, rhythm, variability and asymmetry. By analyzing gait kinematics, [2] found reduced gait velocity, stride length, double limb support and cycle duration in depressive patients. A comparison of the whole body movement during gait between depressed and healthy individuals was made in [3]. By using the motion capture system with video cameras, the authors found reduced walking velocity, arm swing, vertical body movement, increased body sway and more slumped posture in patients. Slumped posture is often observed in depressive individuals during sitting, standing and walking. It was suggested to show a positive cross-sectional relationship with depression severity [5], [20]. Thanks to the development of consumer-grade depth cameras (e.g., Kinect), human body dynamics can be traced accurately in a three dimensional manner without the assistance of the attached markers or the requirement of a specifically designed environment. The recorded depth and skeleton data have been widely and successfully used in human action recognition [21], [22]. In this study, we access students' natural gait characteristics by analyzing the skeleton coordinates recorded by Kinect. The gait parameters we quantified are similar to [3]. Additionally, we also investigated the dependence of such parameters on the genders.

On the side of automatic depression assessment, commonly used valid tools include visual, speech, linguistic and even social media indicators [23]. In [24], deep convolutional neural networks (DCNN) is used on facial appearance for depression recognition. Their MAE reached 7.74 and the RMSE reached 9.91 on the AVEC2013 dataset. Reference [25] used SVM-RBF classifier for visual data of body movement and posture, which reached a classification rate of 76.7%. In [26], the authors investigated the suitability for a classification system formed from the combination of prosodic, voice quality, spectral, and glottal features of acoustic data and reported maximum accuracy above 90% when

TABLE 1. Percent of students scored above critical thresholds.

Category	All ($N = 3669$)	Male ($N = 1555$)	Female ($N = 2114$)
Depression (PHQ-9)	20.5%	24.0%	17.9%
Depression (SDS)	8.4%	10.8%	6.7%
Anxiety (GAD-7)	15.9%	19.9%	13.0%
Anxiety (SAS)	2.4%	3.0%	1.9%

Note: For PHQ-9 and GAD-7, we use a score of 5 as a cutoff. For SDS and SAS, the cutoff is 50.

classifying between absence/presence of depression. In [27], social media linguistic data is used to predict suicide attempts with an accuracy of 65%. The authors in [28] demonstrated an average error of 15.3% (relative) in depression recognition using both speech and visual indicators.

So far little attention has been paid to gait based depression recognition. Gait data show apparent advantages over other prevailing modalities that serve as the potential indicators of mental health, as it is more objective and easily accessible. Our study recorded gait data by Kinect in a non-contact manner so that the potential affect on the mental state from markers and wearable devices can be avoided. Although researchers have identified some statistic gait characteristics in depression, they barely studied how computational models can differentiate depressed and non-depressed groups based on such features. Another novelty of this work is that the study of depression related gait abnormalities is conducted on a more general population rather than only considering clinical cases as in most other studies. Our participants are all young adults with similar backgrounds which may minimize the potential influences from factors such as age, lifestyle or other diseases on their gait patterns.

III. PREVALENCE OF DEPRESSION AND ANXIETY

A. METHODS

Participants were 3669 freshman of master students from multiple faculties of Lanzhou University in 2018 (M: 1555, F: 2114 females). Their ages range from 22 to 28 years old. For the mental condition assessment, the participants were asked to fill in a series of questionnaires. To verify the screening results, the questionnaires we used include two types of self-assessment tools: Patient Health Questionnaire (PHQ-9, Chinese version) [29] and Zung Self-rating Depression Scale (SDS, Chinese version) [30]. At the same time, participants' anxiety levels were also evaluated by Generalized Anxiety Disorder 7 (GAD-7, Chinese version) [31] and Self-rating Anxiety Scale (SAS, Chinese version) [32]. During the assessment, questions from these forms appeared on the monitor one by one in random orders (56 in total). The final score for each questionnaire was calculated in the backstage after all tests have been done.

B. RESULTS

Table 1 shows a general result of the percentage of students scored above the cut points. SDS results show that 8.4% (309) of the participants reach a score above 50 (mild depression, mean = 55.88, SD = 5.92), 2.0% of the participants (73 people) were scored above 60 (moderate depression, mean = 64.47, SD = 5.24). On the other hand, the assessment results by PHQ-9 are slightly different. 20.5% of the participants (752) were scored above 5 (mild depression, mean = 7.26, SD = 2.69). In particular, 90 of them (2.5%) reported suicide ideas or attempts. 2.5% of individuals (93) were scored above 10 (moderate to severe depression, mean = 12.85, SD = 3.26). For the anxiety assessment, 2.4% of individuals (87) show SAS score higher than 50 (mean = 55.56, SD = 7.25). Considering SDS and SAS results together, 24.3% (75) of individuals from the depressed group show above the mild level of anxiety simultaneously. On the other hand, we found 15.9% (583) of individuals show GAD-7 score above 5 (mean = 7.02, SD = 2.61). Together with PHQ-9 results, depression co-occurs with anxiety in 443 individuals (58.9%).

To verify the assessment results, we consider the intersection between the two types of self-reporting forms. The total number of participants scored above the mildly depressed level is 239, in other words, 6.5% of the whole group are assessed to experience depression in both tests. Examining the data closely, we found 137 of them are male and 102 are female. Referring to the total number of participants of the two genders respectively, 8.8% of the males and 4.8% of the females are scored as depressive individuals. Moreover, 70 of these 239 individuals, namely, around 29.3% of depression co-occurs with anxiety in our participants.

IV. DEPRESSION RELATED GAIT ABNORMALITIES

In this section, we describe the process of gait data collection and the corresponding analysis that we have done to quantify the gait characteristics.

A. GAIT DATA

52 individuals (M:28, F:24) whose score was in the healthy range of both PHQ-9 and SDS were recruited as non-depressed group (SDS: mean = 36.85, SD = 7.21; PHQ: mean = 2.04, SD = 2.72). 43 (M:23, F:20) participants were recruited as scored-depressed group (SDS: mean = 62.73, SD = 7.34; PHQ: mean = 13.04, SD = 4.31). The criterion for recruiting the scored-depressed group is that the candidate must be assessed as depression in both questionnaires. Additionally, the score has to reach a moderate level in at least one of them (PHQ-9 score $\geqslant$ 10 or SDS score $\geqslant$ 60).

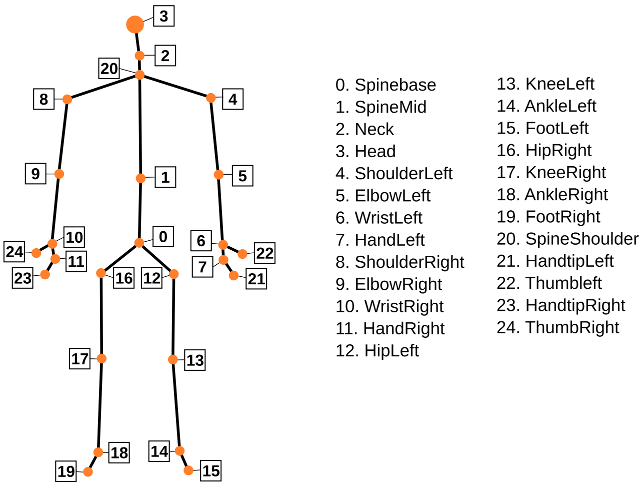

FIGURE 1. The 25 markers on human skeleton generated by Kinect.

In the experiment, all participants were asked to walk a round trip on a 10 meters path with a comfortable speed and posture. The experiment was done immediately after the screening. Our setting for gait data collection is similar to [33]. Two Microsoft Kinect V2 cameras were used to acquire the gait data. The two devices were facing each other (4 meters apart) and attached to the ceiling directly above the path. Their tilt angles were set to its extreme, namely, $-27°$ towards the path. The skeleton joint coordinate streams during walking were generated by Kinect SDK with a frame rate of 30Hz.

B. DATA PREPROCESSING

The obtained skeleton consists of 3-dimensional information of 25 joints from the entire body, the indexes of which are shown in Fig. 1. In each recording, the device estimated skeleton joint coordinates from both front and back views. As a first step, we segmented them into two streams of data. Similar to previous reports, estimated skeletons in the back view are less accurate as those in front view. Since we aimed at quantifying gait characteristics, we only analyze skeletons in front view to obtain precise features. Each segment of our data covers one to two gait cycles depending on the subjects' step size. Considering that our cameras were located in the ceiling and 27° to horizontal, we first have to carry out 2-dimensional (y- and z-axis) coordinate transformation to all recorded data following (1) and (2),

$$y' = ycos\theta + zsin\theta \quad (1)$$
$$z' = zcos\theta - ysin\theta \quad (2)$$

where θ is equal to 27°. The x-axis is not affected in this situation.

As the obtained skeleton streams are noisy and sometimes even with distortions, we use one dimensional Gaussian filter to smooth our data in each dimension before further analysis. We chose $\sigma = 1$ to conduct the sliding window size of this filter. Fig. 2 shows an example of the data before and after filtering.

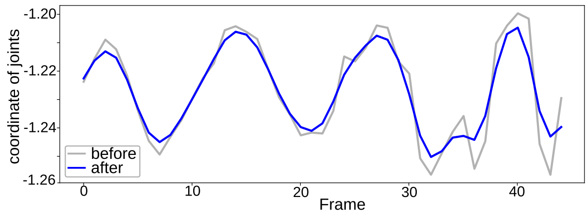

FIGURE 2. *y*-coordinate series of head before and after filtering.

C. GAIT CHARACTERISTICS

To characterize gait patterns, we examined the spatiotemporal parameters, joint kinematics and postural parameters that might potentially differentiate gait patterns between the two groups. We introduce them as follows,

1) WALKING SPEED

We measured the subjects' walking speed (in m/s) according to their head movement (joint 3) along z-axis.

2) ARM SWING

The arm swing in this study refers to the maximum difference of the arm movement between left and right arms in terms of the movement of wrist and hand along z-axis (in mm). To make the measurement more precise, we took the average value of the left wrist (joint 10) and the other three joints (11, 23, 24) from left hand for quantifying the movement of left arm. A similar process was applied to the right arm as well.

3) STRIDE LENGTH

It was measured by the distance along z-axis between successive points of heel contact of the same lower limb (in mm). Similar to the measure of arm swing, we took the average value between z_{18} and z_{19} for the left foot and that between z_{14} and z_{15} for the right foot.

4) VERTICAL HEAD MOVEMENT

During walking, there is a periodic vertical up-and-down movement of the upper body following the periodic movement of lower limbs switching between the standing phase and the swing phase. We measured this parameter in terms of the mean vertical amplitude of y_3 (in mm) across multiple gait circles.

5) BODY SWAY

It was defined as the difference between maximum right and left deflection of the shoulder (in mm). In the experiment, participants were asked to walk straight forward. However, we notice that their actual walking trajectory may deviate slightly from the direction they should have followed. Fig. 3 shows an example where the black line marks the subject's walking direction which should have been horizontal if they

TABLE 2. **Gait characteristics.**

Features	Non-depressed	Scored-depressed	p-value
Walking speed (m/s)	1.39 ± 0.06	1.26 ± 0.12	$< 0.001^*$
Stride length (m)	$1.12 \pm .11$	0.98 ± 0.20	$< 0.001^*$
Step width (mm)	140.01 ± 21.68	145.19 ± 25.95	0.29
Arm swing (mm)	427.74 ± 86.44	336.53 ± 118.06	$< 0.001^*$
Vertical head movement (mm)	55.93 ± 9.53	46.04 ± 12.67	$< 0.001^*$
Body sway (mm)	49.17 ± 9.43	61.20 ± 15.92	$< 0.001^*$
Head posture (°)	-0.26 ± 2.80	1.41 ± 2.77	$< 0.01^*$
Shoulder RoM (°)	34.50 ± 6.00	30.49 ± 9.36	$< 0.05^*$
Elbow RoM (°)	62.18 ± 13.38	54.06 ± 13.32	$< 0.01^*$
Hip RoM (°)	48.09 ± 8.57	46.84 ± 7.32	0.45
Knee RoM (°)	50.79 ± 9.70	48.74 ± 7.39	0.26
Stance duration (%)	60.65 ± 7.52	61.94 ± 6.37	0.37

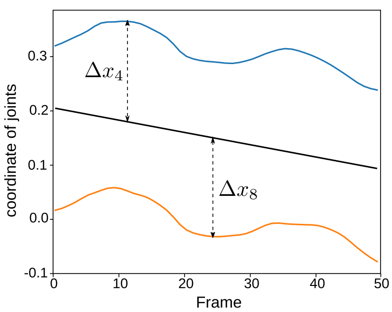

FIGURE 3. **Measure of the body sway. The black line represents the subject's walking trajectory. Blue and orange curves mark the changing of the x-coordinates of left and right shoulders respectively during walking.**

walked straight forward. Blue and orange curves mark the changing of the x-coordinates of left (x_4) and right (x_8) shoulders during walking. To quantify the body sway more precisely, we tracked each subject's walking trajectory and measured the deflection of both shoulder joints from that trajectory as the body sway (Δx_4 and Δx_8). Moreover, the length of the shoulder (L_s) must be removed from this value. More precisely, the body sway S is calculated by,

$$S = |\Delta x_4| + |\Delta x_8| - L_s. \tag{3}$$

6) HEAD POSTURE

We used the mean of the angle (α_h) between the connection of neck (joint 2) and clavicle (joint 20) and the vertical axis to quantify the head posture during gait circle, the value of which can be obtained simply by,

$$\alpha_h = -arctan(\frac{z_{20} - z_2}{y_{20} - y_2}). \tag{4}$$

A negative angle indicates head upward, whereas positive value indicates head down, namely the slumped posture.

7) STEP WIDTH

It was quantified as the average distance along x-axis between the left and the right lower limb during the standing phase (in mm).

8) JOINT RoM

The anatomical angles were computed for shoulder, elbow, hip and knee joint respectively in the sagittal plane. For these variables, the range of motion (RoM) of each joint is derived as the difference between its maximum and minimum value in degree during each gait cycle.

9) STANCE DURATION

It reflects the percentage of the time that the same lower limb is continuously on the ground in the entire stride duration. The swing duration can then be obtained accordingly, which is not shown here.

Note that for those parameters involving both the left and right limbs, we took the average values from both sides.

D. STATISTICAL ANALYSIS

Table 2 presents the mean and the standard deviation of the parameters we obtained by analyzing the skeleton joint coordinates. The significance (p-value) was obtained by the independent samples T-Test, in which we found several features showing significant differences between the scored-depressed and non-depressed groups.

As we expected, a strong difference appears in walking speed between the two groups. The scored-depressed individuals walk more slowly than the non-depressed ones. Besides, they also show significantly smaller stride length, arm swing, vertical head movement, shoulder and elbow RoM. On the other hand, the scored-depressed group show increased body sway compared to non-depressed ones, indicating that body sway is also an effective indicator of depression. The difference in head posture between the two groups is consistent with the idea that a relatively slouching posture is typical in depression. In contrast, no significant difference is observed in hip RoM, knee RoM, step width and stance duration. More details with regards to the differences are visualized in Fig. 4. As 12 statistical hypotheses have been tested simultaneously, we perform Bonferroni correction to counteract the spurious positives caused by multiple comparisons (dividing the significance level by the number of comparisons: $p < 0.0042 = 0.05/12$). Following the adjustment, significance

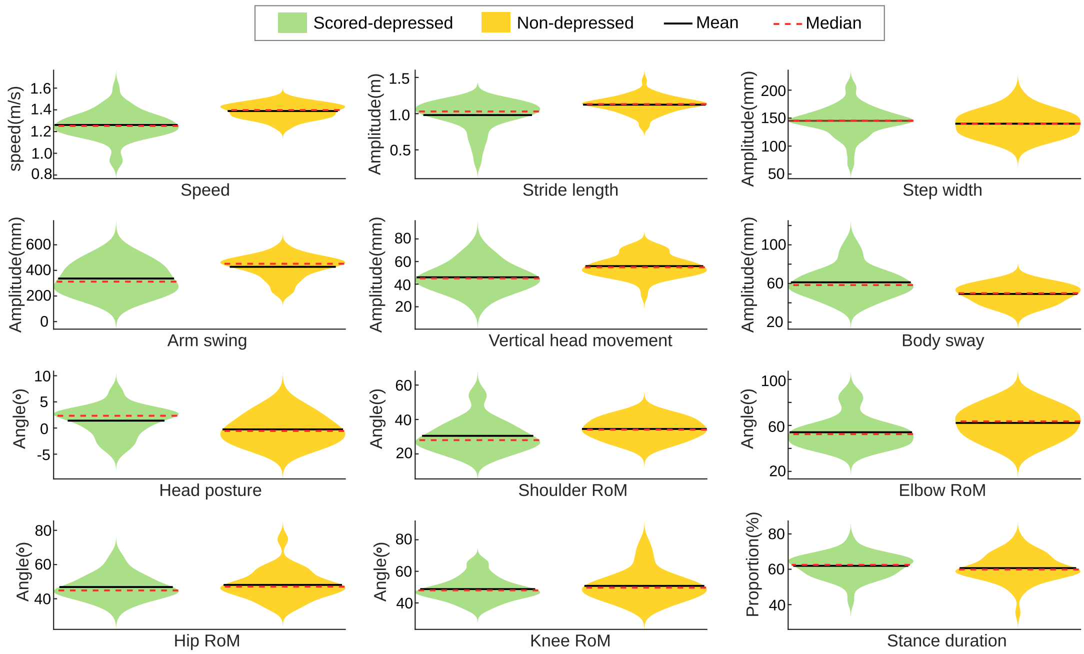

FIGURE 4. **Distribution of gait parameters in scored-depressed and non-depressed group.**

was still maintained for most features except head posture and shoulder RoM.

When analyzing the body sway, we found that most participants deviated slightly from the direction they were supposed to go. We measured this deviation in terms of deviation angle from the goal direction. Interestingly, we found a very subtle but significant difference between the two groups, where the scored-depressed and non-depressed group show $1.40° \pm 0.68$ and $1.08° \pm 0.59$ ($p < 0.05$), respectively. It suggests that scored-depressed individuals are more likely to deviate from their original walking route.

Considering the anatomical and physical differences existing in distinct genders, we compared the above parameters for each respective gender. We found that in both genders most of the parameters show similar trends as the results for the entire group. In general, male participants show larger walking speed, arm movement, stride length, step width, body sway than the females from the same group. However, we noticed that the significant difference in head posture and shoulder RoM only appears in female participants. The shoulder RoM for scored-depressed and non-depressed females are 28.31 ± 8.46, and 33.28 ± 6.68 ($p < 0.05$), respectively, while for males, they are 32.39 ± 9.87 and 35.55 ± 5.24 ($p = 0.18$). The results for head posture are more delicate: 0.88 ± 2.73, and -1.33 ± 2.36 ($p < 0.01$) for scored-depressed, and non-depressed females, respectively, while 1.86 ± 2.79, and 0.66 ± 2.86 ($p = 0.14$), for scored-depressed, and non-depressed males, respectively. These differences between genders raise the possibility that depression affects gait more strongly in females than males. Moreover, it seems to indicate that male participants walk with a more slumped posture than females in general.

TABLE 3. **Features showing above moderate effect size.**

Feature	Hedge's g
walking speed	1.29
stride length	0.89
arm swing	0.89
elbow RoM	0.61
shoulder RoM	0.52
vertical head movement	0.89
head posture	-0.60
body sway	-0.94

To complement statistical hypothesis tests, we estimated the effect size of all these parameters on differentiating the two groups. We use Hedge's g [34], considering the unequal sample size between the two groups in our study. It is a descriptive statistic that represents the magnitude of an effect by evaluating how many standard deviations between the two distribution means. We list the parameters that show the absolute value of Hedge's $g > 0.4$ in Table 3, which are considered to show the existence of moderate effect. Parameters with negligible effects are not shown here.

It is known that walking speed can influence other gait features [35]–[37]. To figure out whether changes of gait patterns in scored-depressed individuals were simply attributed to their lower walking speed, we examined the correlation between walking speed and other gait characteristics including arm swing, body sway, vertical head movement, head posture and stride length. The correlation coefficient and p value are as follows: arm swing, $r = 0.35$ ($p < 0.05$); body sway, $r = -0.24$ ($p = 0.14$); vertical head movement, $r = 0.39$ ($p < 0.05$); head posture, $r = 0.25$ ($p = 0.11$); stride length,

$r = 0.39$ ($p < 0.05$). These results suggest that reduced arm swing, vertical head movement and stride length observed in the scored-depressed group are indeed correlated with their slower walking speed, though the correlation is rather weak. On the contrary, there is no significant correlation between large body sway, changes in head posture, and slow walking speed.

V. CLASSIFICATION

In this section, we explore the discriminative power of the gait characteristics for the score-depressed individuals in classification by using the 12 features obtained above. Here we adopt five frequently used classifiers to classify the two groups automatically. In the following subsections, we describe the methodology for feature selection, the classification models and present our results.

A. FEATURE SELECTION

Although there is only a limited number of features in this study, they show different statistics. Given that some features may be uninformative, irrelevant or redundant for classification, in order to speed up computation and improve classification performance [38], an initial feature selection process is always required. Note that here we perform feature selection not only for dimension reduction, but also for exploring which gait parameters contribute to the classification and the ranking of their contribution. By this process, we also can verify whether the selected features are consistent with those significant ones found in the previous section. In the current study, the F score method was employed for feature ranking [39], which is simple and effective [40].

Here we briefly describe the feature selection process as follow. Given the number of positive instances n_+ and negative instances n_-, the F score of the i^{th} feature is defined in (5). In our case, $1 \leq i \leq 12$,

$$F(i) = \frac{\left(\bar{x_i}^{(+)} - \bar{x_i}\right)^2 + \left(\bar{x_i}^{(-)} - \bar{x_i}\right)^2}{\frac{1}{n_+-1}\sum_{k=1}^{n_+}\left(x_{k,i}^{(+)} - \bar{x_i}^{(+)}\right)^2 + \frac{1}{n_--1}\sum_{k=1}^{n_-}\left(x_{k,i}^{(-)} - \bar{x_i}^{(-)}\right)^2}, \quad (5)$$

where $\bar{x_i}$, $\bar{x_i}^{(+)}$,$\bar{x_i}^{(-)}$ are the average of the i^{th} feature of the whole, positive and negative data sets, respectively; $x_{k,i}$ is the i^{th} feature of the k^{th} instance ($n_+ = 43$, $n_- = 52$ in this study). It is obvious that the larger the F score is, the more discriminative the feature is. Values of the parameters we obtained above varied considerably, i.e., some important features with small values or even negative values might be ignored when training the model. Thus, before the features were fed into the classifiers, we standardized all of them into $\{-1, +1\}$.

To evaluate the performance of the classifiers, we adopt a leave-one-out cross-validation (LOOCV) strategy. For each LOOCV fold, we ranked the features according to their F scores in descending order and retained the highest ranked features for classification.

B. MODELS

Differentiating the scored-depressed individuals from the non-depressed ones is a typical binary classification problem. In order to evaluate the effect of extracted features in the classification performance, this study uses five classical machine learning algorithms, i.e., Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), Logistic Regression (LR), Linear Discriminant Analysis (LDA), some of which have been successfully applied to clinical gait analysis [41]–[43]. In this study, we used the SVM classifier with Gaussian kernel only, which was implemented using LIBSVM toolbox [44] with parameter optimization. RF was implemented by RandomForest-MATLAB [45]. The most important RF parameters, ie., the number of trees n_{tree} and the number of variables to partition at each tree node m_{try} were optimized to improve the performance. The implementations of other classifiers are available in Matlab. We also optimized k value for KNN classifier.

Since feature ranking by F score was based on the subset of the data which could be slightly different from trail to trail, the final features used in classification could differ in each iteration of LOOCV. Nevertheless, we observed that the feature ranked first is always the walking speed which is also selected in each run. Body sway was selected as the second feature in 73.7% of the runs. Furthermore, we found that the same features will always be selected: the speed, arm swing, stride length, body sway, vertical head movement, head posture, shoulder RoM and elbow RoM, when limiting the number of highest ranked features to 8. This is in line with the gait parameters showing significant differences in the previous section.

Accuracy, sensitivity, and specificity were used to evaluate the classification according to the results of LOOCV. Sensitivity refers to the test accuracy of scored-depressed individuals and specificity refers to the test accuracy of non-depressed individuals. AUC value was used as a measure of performance.

C. RESULTS

Table 4 shows the classification results. We first explore the performance of the classifiers by using all 12 features. The best accuracy of 89.47% was achieved by RF, with the corresponding sensitivity of 86.05% and specificity of 92.31%. The other classifiers show weaker but still reasonable classification performances. Introducing the feature selection process improves the performance of all classifiers (see the row ''feature selection''). When 8 features are selected, RF shows the best accuracy of 91.58% in all classifiers, with a sensitivity of 86.05% and specificity of 96.15%. Its AUC value (0.8994) indicates a good classification power.

To illustrate the correlation between the performance and the number of selected features, Fig. 5 shows the predictive accuracy with increasing number of classification features

TABLE 4. Classification results by all classifiers in different scenarios.

	Classifier	Accuracy	Sensitivity	Specificity	AUC
All	SVM	0.8526	0.7907	0.9038	0.9146
	RF	0.8947	0.8605	0.9231	0.9182
	KNN	0.8316	0.7209	0.9231	0.8444
	LR	0.8526	0.8372	0.8654	0.8810
	LDA	0.8632	0.7674	0.9423	0.9208
Feature selection	SVM (8)*	0.9053	0.8372	0.9615	0.8994
	RF (8)*	0.9158	0.8605	0.9615	0.8994
	KNN (7)*	0.8737	0.7907	0.9423	0.8520
	LR (9)*	0.8842	0.8605	0.9038	0.9092
	LDA (5)*	0.8842	0.7907	0.9615	0.9092
Upper body	SVM	0.8316	0.7442	0.9038	0.9003
	RF	0.8632	0.8140	0.9038	0.8640
	KNN	0.8316	0.6977	0.9423	0.7625
	LR	0.8737	0.8140	0.9231	0.9052
	LDA	0.8421	0.7209	0.9423	0.9061
Lower body	SVM	0.7053	0.5349	0.8462	0.7276
	RF	0.6737	0.6047	0.7308	0.6910
	KNN	0.6421	0.7907	0.5192	0.5282
	LR	0.6632	0.5581	0.7500	0.7205
	LDA	0.6421	0.5116	0.7500	0.7039

$*$: the number in the bracket presents the number of selected features; Parameter optimization: RF ($n_{tree} = 40$, $m_{try} = 1$), SVM ($C = 1$, $\gamma = 2.297$), KNN ($k = 8$).

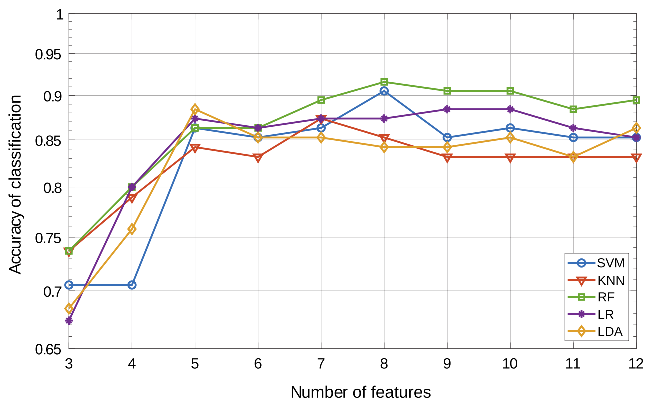

FIGURE 5. Performance of the five classifiers as a function of the number of selected features. The features were ranked according to *F* scores in descending order.

used in each classification process. Initially, recruiting more features improves the performance in all cases. However, the number of features required to achieve the best performance varies with different classifiers. When selecting 5 features, LDA first reaches its best accuracy. For KNN, the number is 7. Both SVM and RF show their highest accuracy when 8 features are selected. LR approaches the best with 9 selected features. Thereafter, the performances are not improved but rather declined by recruiting more features. It indicates that recruiting features with non-significant differences between the two groups disturbs the classification.

Characteristics of the upper body movement are usually neglected in clinical gait analysis. By closely analyzing features for the best performance, we found that more than half of the selected features are from the upper body. Next, we investigated the contribution of features from different body regions to the classification performance. Six features from the upper body (vertical head movement, head posture, elbow RoM, shoulder RoM, arm swing and body sway; walking speed is precluded) were selected for the classification. The results show that LR performs the best in all classifiers with an accuracy of 87.37% (81.40% for sensitivity and 92.31% for specificity), which is slightly worse than its best accuracy. The performances by other classifiers also become worse but are still reasonable. Consequently, we analyzed the case that only the features from lower limbs (Hip RoM, Knee RoM, step length, step width and stance duration) are used. As a result, the performances of all classifiers become much worse, among which SVM achieves the best with an accuracy of 70.53%. These results suggest that in our study, gait characteristics from the upper body can effectively contribute to depression analysis.

The methods of gait based depression detection have not been well established yet. Here we make a comparative analysis of current performance with a similar approach, where they used Fast Fourier Transforms for feature extraction on skeleton data of gait [46]. For the comparison, we transplanted their methods into our dataset. By this approach, SVM achieves the best classification performance of 87.1%, with a sensitivity of 85.71% and specificity of 88.24%, which is worse than the proposed method in terms of accuracy.

VI. DISCUSSION

In this article, we study the prevalence of depression in Chinese postgraduate students. A prevalence rate of 6.5% has been evaluated by the intersection between the results of two types of self-rating assessment instruments. For individuals assessed as depression in the screening, we found abnormalities in several gait characteristics including spatial-temporal parameters, kinematics and postural parameters. Based on these parameters, machine learning classifiers are able to automatically differentiate them from non-depressed individuals with relatively high accuracy.

A. THE PREVALENCE OF DEPRESSION

The ratio of students identified as depressed shows a wide variation according to previous reports, with [13] suggested a weighted rate of 30.6% by a meta-analysis in relevant studies. The prevalence rate we found here is relatively lower than most of the previous studies. One possible reason is that other studies used only one type of the assessment tools such as BDI-I, BDI-II, CES-D, PHQ-9, MINI-RR, etc., while we determined the depressed group by the intersection between PHQ-9 (cut-off: 5) and SDS (cut-off: 50) results, which would lead to a lower prevalence rate. A similar explanation can be applied to the relatively low comorbidity between depression and anxiety found in our study. Another possibility may be due to the fact that we only recruited master students in their first study year into the screening. This population may have relatively lower stress from studying, doing research and job hunting. Moreover, [47] reports that the severity of depression in college students is correlated with youth. Since our subjects are generally older than college students, a relatively lower prevalence rate is reasonable in comparison to the studies whose participants are bachelor students. It is also not surprising for us to find a mismatch between the results of the two assessment tools we used, as different forms have their own biases. For example, [13] suggests that tools such as PHQ tend to pick up psychological distress rather than clinical depression which may inflate the prevalence results. As the validity and reliability of different assessment tools for certain populations (master students in our case) are still under investigation, we used the intersection of the two questionnaires to identify the scored depressed individuals in the current study.

What is surprising in our results is the difference observed in gender related prevalence rate. The percentage of males affected by depression is higher than that of females, which seems controversial to most of the earlier studies (see [13] as a review). However, it is not for the first time that males have been found to show a higher rate than females in depression screening [48]. As the prevalence rate is easily affected by various factors, the difference between the two genders may also be attributed to the specificity of our participants.

One inadequacy of the depression screening carried out in this study is that we have not investigated the past depressive history of the participants, whether they have already been treated or are receiving treatment at present may potentially impact the prevalence rate. One also has to note that the screening score of an individual is not a definitive assessment as usually performed through a clinical diagnosis. Therefore, the individuals assessed as depression through our screening should not be considered as being "real" depressive patients.

B. ABNORMAL GAIT ASSISTING IN DEPRESSION ANALYSIS

Although we obtained the gait parameters by analyzing Kinect recorded skeleton, our results are highly consistent with [3] in which depression is associated with reduced gait velocity, arm swing, vertical head movement and increased body sway. A similar tendency with head posture was also observed in our results. We in addition found significant differences between the scored-depressed and non-depressed groups in terms of shoulder RoM, elbow RoM and stride length which were not included in their study. By closely examining our results, we found that walking speed of our participants, particularly, the scored-depressed group is much higher than those in previous studies (e.g. $1.07 \pm .22$ m/s in [3]); arm swing and vertical head movement in our study are also stronger although a similar method of measurement was adopted. Apart from the difference caused by different data recording devices and set-up, there are two other possible reasons for these differences. Firstly, our depressed individuals have not been clinically diagnosed as such, which could potentially differentiate them from the "real" depressive patients; Secondly, aging is always accompanied by a decline in motor skills. Pronounced increase in movement duration and reduced activity with aging are seen on a variety of tasks [49]. As the average age of the participants in [3] is much older than our participants' ages, it is not surprising that movements with larger velocity and amplitude were observed in our participants. Investigating younger subjects in the present study eliminates the potential influences from aging on gait characteristics. One might also notice that the difference in head posture between the two groups in our results is less obvious than in previous studies. It could because the joints we chose for this measurement were neck and clavicle as opposed to head and clavicle in other studies. Step width and stance duration show no association with depression in our results, which is in line with previous reports [2], [6].

There was a concern that instead of depression, the changes of gait parameters may be simply caused by reduced gait velocity. To verify this, we examined the correlation between some of the gait features and walking speed. The results suggest that reduced arm swing, stride length, vertical head movement in the scored-depressed individuals are indeed correlated with their slower walking speed, but this correlation is weak ($r < 0.5$). Moreover, head posture and body sway show no correlation with the speed, indicating these two features can effectively reflect walkers' depressive state, independently from their gait velocity. Another interesting finding in our results is that depressed individuals tend to deviate more in their walk than non-depressed individuals from the target. However, the difference in the deviation angle between the two groups is subtle. One can hardly claim this tendency as a definitive indication of depression. As this measurement was based on the data stream covering only one to two gait cycles, the situation may be different if we analyze the data covering longer trips. Nevertheless, this finding raises a more general question of whether depressive individuals have difficulties in goal approach. This is interesting for further exploration in the future.

Statistical analysis by gender reveals that male and female participants generally show similar trends in changes of gait patterns, which again suggests that depression is associated with abnormal gaits regardless of the gender. However, for the shoulder RoM and head posture, the significant differences are only observed in females. This non-conclusive result may simply due to the limited amount of data that we have. Alternatively, it may indicate that females' gait patterns are affected more severely by depression than males', which is also worthy for us to explore in the future.

The validation and reliability of Kinect recorded joint dynamics have been a concern in clinical application recently. Although there is a consensus on the high accuracy of spatial temporal features, some studies suggested that the accuracy of kinematic features recorded by Kinect are rather poor during gait analysis [50], [51]. However, the evaluation in most of these studies is based on Kinect V1 and mainly focusing on the measure of lower limbs. In contrast, a study reports that Kinect is reliable and highly validity in shoulder angle estimations from the front view [52]. It is also suggested in [53] that the upper limb joint location recorded by Kinect is more accurate than that of lower limb joints. In our study, we do find the joint coordinates of the lower limb, particularly the y-axis is noisy. Thus, we tried to calculate the gait parameters for lower limbs by avoiding the involvement of y-coordinates. For measuring stance duration, step width and stride length, for example, we determined the timing of heel strike according to z-coordinates, since once the foot touches the floor, its z-coordinate value remains stable until it starts to swing again. However, y-coordinates are inevitable for the measurement of hip and knee RoM. This may explain why we did not find significant differences in these two parameters between the two groups. At present, we only consider the skeleton in the front view. Combining the data from more angles of shooting in the future may improve the validity of the gait features.

Handcrafted features have already been successfully used in biometric identification through gait data [54]–[56]. Our classification results suggest that handcrafted features representing gait characteristics are also efficient in assisting in depression analysis. As shown in Fig. 5, an accuracy of above 80% can be achieved by all classifiers using five or more features. As the features were selected according to their individual discriminative power rather than their combination discriminative power, it is not surprising for us to find the performance fluctuating when recruiting more features. We also notice that walking speed and body sway were ranked the first and second in most LOOCV trails. It indicates that they are the most discriminative features in our gait based depression analysis. In addition to these, arm swing, stride length and vertical head movement are among the top five features, followed by head posture, elbow RoM and shoulder RoM. Consequently, the joints that these parameters rely on can also be seen as discriminative points in the skeleton for depression analysis.

Low strength and weak physical performances in the upper body are tied to depression in women [57], [58]. From a modeling perspective, [25] shows evidence that upper body expression, gestures and head movement can serve as visual cues for depression detection, the efficiency of which is as significant as facial expressions. In the current study, our model using features from the upper body alone achieves a classification accuracy of above 80%, which again confirms that upper body movement in gait is important for depression analysis. Thus, we suggest that movements in the upper body should be paid more attention in clinical gait analysis.

Following the embodiment theory, body posture appears to directly influence the affection and cognition of human. A skipping posture has been suggested to increase energy levels and may potentially change depression conditions [59]. Moreover, upright posture is suggested in [60] to improve affection and fatigue in depressive people. The issue of whether actively correcting abnormal gait could be a potential scheme to improve depression awaits further exploration.

VII. CONCLUSION

In this paper, the Chinese postgraduate students are found to have a depression prevalence rate of around 6.5%. Gait abnormalities are already observed in students assessed as depressed in the prevalence screening. The depressive gaits are represented by reduced walking velocity, arm swing, vertical head movement and stride length, increased body sway and a slumped head posture. On the basis of such discriminative features, the scored-depressed and non-depressed individuals can be well classified by computational models. In particular, the upper body posture and movements effectively contribute to the accuracy of the classification. These findings suggest that gait analysis can serve as an effective tool for assisting in depression analysis.

At present, one limit of our study is that we only consider gait data in front view. To obtain gait information more precisely, we plan to collect and merge the gait data from more angles of shooting in the future. Another issue is that the gait features we extracted are mainly from the spatial domain. As gait is a highly dynamic activity, more features containing information in the temporal domain need to be recruited in the future to better support depression analysis.

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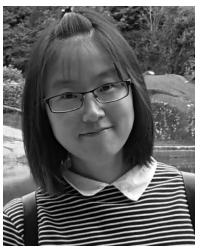

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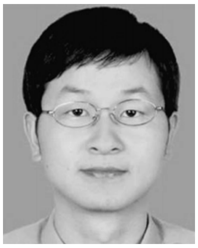

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