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Applying Machine Learning to Identify Autism With Restricted Kinematic Features

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ABSTRACT Existing diagnosis of the autism spectrum disorder (ASD) heavily depends on the informant's evaluation of the patient's behavior, which is both time consuming and labor demanding. In order to develop a rapid diagnostic tool with high accuracy, machine learning (ML) approaches have been proposed to explore the feasibility of identifying ASD with a limited number of features extracted from behavioral evaluation, neuroimaging and kinematic data. Though restricted and repetitive behavior (RRB) is one of the cardinal symptoms of ASD, no study has been conducted to investigate whether restricted kinematic features (RKF) could be used to identify ASD. The present study aimed to address this question. Twenty children with high functioning autism and twenty-three children with typical development (TD) were recruited. They were instructed to perform a motor task that required the execution of the utmost variant movement. Entropy and 95% range of the movement amplitude, velocity and acceleration were computed as indices of RKF. Five ML classifiers were trained and tested including support vector machine (SVM), Linear Discriminant Analysis (LDA), Decision tree (DT), Random forest (RF), and K nearest neighbor (KNN). Results showed that the KNN algorithm ($k = 1$) yielded the highest classification accuracy with four kinematic features (accuracy: 88.37%, specificity: 91.3%, sensitivity: 85%, AUC: 0.8815). Our study demonstrated that RKF could help robustly identify ASD. It is inferred that the application of ML on genetic, neuroimaging, psychological and kinematic features might pose a considerable challenge to the current diagnostic criteria of ASD, and might potentially lead to an automated and objective diagnosis of ASD.

INDEX TERMS Autism, entropy, kinematic feature, machine learning, restricted and repetitive behavior.

I. INTRODUCTION

The current diagnosis of the autism spectrum disorder (ASD) heavily relies on the informant's evaluation of the patient's behavioral presentation, which has been notoriously criticized as labor-demanding [1]. For example, the Autism Diagnostic Observation Schedule (ADOS) is widely considered as a gold-standard diagnostic instrument that requires significant clinical expertise. The length of the ADOS exam and the shortage in trained clinicians significantly contribute to the delayed diagnosis [2]. A study examining data from a large metropolitan area in the US reported that more than a year on average was required between the initial evaluation and the confirmation of the diagnosis [3]. The delayed diagnosis directly postpones the delivery of intervention programs, which negatively impacts the child's developmental outcomes [4]. Therefore, a diagnostic tool that is both human labor-saving and accurate is urgently called upon.

Given the advantage machine learning (ML) exhibits in pattern recognition and in solving classification problems, recent years have witnessed an increasing interest in applying ML for the purpose of ASD diagnosis. Driven by the need for rapid detection of ASD with high accuracy, a variety of studies implemented ML to remove redundant items from the diagnostic instruments such as ADOS and the Autism Diagnostic Interview-Revised (ADI-R) [5]. Some of them

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reported promising results on discriminating cases of ASD from non-ASD cases by using only a few items extracted from the original instruments [5]–[7]. For instance, Wall *et al.* [7] reported that a shortened screening tool with 8 items extracted from ADOS was able to classify ASD with 100% accuracy. The validity of this tool was tested with a larger sample and the classification accuracy remained greater than 95% [6]. All these studies suggest that ML could be an efficient tool to shorten the lengthy observation-based instruments while preserving high diagnostic accuracy.

On the other hand, ML was also applied to classify ASD by extracting features from neuroimaging [8], [9], eye gaze [10], [11], and kinematic data [12]–[14]. Despite the fact that the current diagnosis of ASD primarily depends on the patient's behavior, only a handful of studies have been conducted to explore the feasibility of using kinematic features to predict ASD. For example, a recent study adopted a goal-directed movement to explore the possibility of discriminating patients with ASD from individuals with typical development (TD) by means of kinematic data [12]. Their results showed that the ML model was able to discriminate ASD with the highest accuracy of 96.7%. In another study, it was found that kinematic features extracted from the imitation movement could be used to robustly discriminate ASD from TD [13].

Restricted and repetitive behavior (RRB) was originally noted by Kanner [15] as a hallmark symptom in patients with autism. Previous studies implementing factor analysis showed that RRBs could be loosely classified into lower level of stereotyped movements such as hand flapping and repetitive use of objects [16], [17], and higher level of repetitive behaviors such as ritualistic behavior and restricted interest [16]. It is noticeable that both low and high levels of RRB are characterized by features of restrictedness, rigidity, invariance and inappropriateness [18]. Recent findings reporting a close relation between the frontal lobe and RRB [19], [20], and between cognitive flexibility and RRB [21], [22] suggested that RRB could be the result of executive dysfunction [18], [21], [23]. Specifically, RRB may be derived from the inability to shift from preferred behaviors to new adaptive ones [21], [24]. Patients with ASD might be "locked into" a specific thought or behavior [18]. Thus, when performing a behavioral task that requires variant responses or flexibility, the restricted feature of being unable to shift from one set to another might be manifested at the behavioral level that could be captured by kinematic analysis, and it would be feasible to identify ASD with the restricted kinematic features (RKF).

In order to obtain the RKF, the present study employed a motor task developed by Słowiński *et al.* [25], in which participants were required to perform one dimensional, left-right oscillatory movement as complex (with variant amplitude and frequency) as possible. Since the requirement of the motor task was to perform the utmost variant movement and lack of invariance is the hallmark symptom of ASD, we hypothesized that the restricted feature of being unable to perform variant movement would be manifested in the execution of this specific motor task. As the objective of the present study, we investigated the feasibility of predicting ASD with RKF by implementing the ML approach.

Two contributions have been noted for the present study. First, objective assessment of RRB in ASD patients has always been a challenge for clinical practitioners. In the present study, a novel approach was proposed to objectively assess RRB in patients with ASD by adopting a motor task that requires flexible motor behavior. Second, among all the existing studies which applied the ML approach to predict ASD, only a few utilized kinematic features [12]–[14], which were extracted from the reach-to-drop movement [12], hand imitation [13], and gesture patterns [14]. However, none of these studies examined the kinematic parameters that are related to RRB. Since RRB is recognized as one of the two indispensable symptoms of ASD [26], all patients with ASD should exhibit RRB to some extent. Our research expanded the state-of-the-art findings by illustrating that kinematic features derived from RRB could also be used to robustly identify ASD.

The remainder of this paper is organized as follows: Section II introduces the experimental design, the calculation of kinematic features and the ML procedure. Results on the comparison between ASD and TD with respect to RKF and on the performance of different classifiers are illustrated in Section III. The significance of applying ML in ASD identification is discussed in Section IV, and the limitations as well as the inspiration of the present study are described in Section V.

II. METHODS

Section II introduces the methodology of the present study. Specifically, it presents information on participants, motor task, kinematic data analysis, and the ML procedure.

A. PARTICIPANTS

Twenty children with high functioning autism and twenty-three age-matched TD children participated in the study. Children with ASD were recruited from the Department of Child Psychiatry at Shenzhen Kangning Hospital, China, and only children with high functioning autism were included to ensure the patient's compliance with the experimental protocol. The inclusion criteria were: a) between 6 and 13 years old; b) confirmed diagnosis of high functioning autism by a licensed psychiatrist with the DSM-IV criteria [27]; c) average non-verbal intellectual ability (the Raven's Advanced Progressive Matrices [28] was administered to evaluate the IQ level); d) absence of other clinical conditions such as ADHD, mental retardation, or schizophrenia. The TD participants reported no physical or mental disorders. Written informed consent was signed by the participant's caregivers. The study conformed to the principles of the Declaration of Helsinki, and followed the ethical guidelines of Shenzhen University. Subject's demographic information is presented in Table 1.

TABLE 1. Comparison between ASD and TD on the demographics and the kinematic complexity.

		ASD	TD	Group comparison	*Sig.*
Sex (M:F)		18:2	19:4	$\chi^2(1) = .487$	.485
Age in months	M (SD)	99 ± 24.6	110 ± 25.6	t(41) = 1.48	.146
IQ (Mean ± SD)	M (SD)	118 ± 15.5	102 ± 22.7	t(32.9) = 2.75	.012*
Amp_Entropy_Mdn	M (SD)	5.49 (.35)	5.60 (.40)	t(41) = -.93	n.s.
Vel__Entropy_Mdn	M (SD)	6.24 (.34)	6.44 (.16)	t(26.6) = -2.60	.02*
Accel_Entropy_Mdn	M (SD)	4.69 (.84)	5.09 (.49)	t(29.6) = -.93	.075^
Amp_Entropy_Max	M (SD)	5.74 (.31)	5.78 (.28)	t(41) = -.45	n.s.
Vel__Entropy_Max	M (SD)	6.39 (.21)	6.49 (.15)	t(41) = -1.87	.069^
Accel_Entropy_Max	M (SD)	5.08 (.72)	5.25 (.50)	t(41) = -.90	n.s.
Amp_Entropy_Min	M (SD)	5.15 (.51)	5.39 (.41)	t(41) = -.172	.093^
Vel__Entropy_Min	M (SD)	5.78 (1.1)	6.26 (.28)	t(21.4) = -2.08	.063^
Accel_Entropy_Min	M (SD)	3.97 (1.27)	4.72 (.65)	t(27.4) = -.2.47	.025*
Amp_Range_Mdn	M (SD)	41.32 (10.32)	35.80 (9.64)	t(41) = 1.81	.08^
Vel__Range_Mdn	M (SD)	4.60 (.82)	4.94 (.56)	t(41) = -1.63	n.s
Accel_Range_Mdn	M (SD)	83.95 (38.09)	89.21 (30.57)	t(41) = -.50	n.s
Amp_Range_Max	M (SD)	47.16 (8.37)	39.35 (8.24)	t(41) = 3.08	.004**
Vel__Range_Max	M (SD)	4.96 (.57)	5.13 (.52)	t(41) = -1.01	n.s.
Accel_Range_Max	M (SD)	102.36 (36.12)	100.33 (31.32)	t(41) = .20	n.s.
Amp_Range_Min	M (SD)	33.80 (12.08)	31.74 (10.35)	t(41) = .60	n.s.
Vel__Range_Min	M (SD)	3.81 (1.28)	4.40 (.82)	t(41) = -.1.84	.073^
Accel_Range_Min	M (SD)	60.64 (41.08)	73.40 (32.51)	t(41) = -1.14	n.s.

Amp – Amplitude, Vel – Velocity, Accel – Acceleration, Mdn – Median.
n.s – non significant ($p > .1$). ^ represents $.05 < p < .1$; * represents $.01 < p < .05$; ** represents $p < .01$.
Values related to Amp_Range are presented in centimeters. Values related to Vel_Range are presented in m/s. Values related to Accel_Range are presented in m/s^2.

B. EXPERIMENTAL APPARATUS

We used a computer (Lenovo Legion R720-15IKBN), a LeapMotion device (Leap Motion Inc.), two sticks and a string as the experimental apparatus (Fig. 1). The LeapMotion was utilized to register the participants' hand movement. The string was tied between two sticks for the participants to perform hand movements above it. The distance between the two sticks was 60cm. A solid mat was provided to the needed participants to make sure that the dominant hand could move naturally and comfortably above the string.

C. MOTOR TASK

Participants were encouraged to perform one dimensional movement as complex as possible. In order to ensure that all participants understood the requirement correctly, the experimenter behaviorally demonstrated that simple movement was periodic oscillations with mono amplitude and frequency, and complex movement referred to unpredictable oscillations with variant amplitude and frequency. Participants had practice trials before they fully understood the requirement of the experiment. To avoid falsely registering the movement of the subdominant hand, participants were required to keep their subdominant hand behind the back. All participants performed three trials of movement, each of which lasted 60 seconds. Participants were not allowed to withdraw the dominant hand out of the recording zone or to put the subdominant hand in it. The trial would be reinitiated if any experimental rule was violated (e.g., hand withdraws from the recording zone, stop hand moving voluntarily). The end of a trial was followed by a break of 2 - 5 minutes to avoid fatigue.

D. DATA ANALYSIS

We obtained the time series of the palm position as the raw data, which was interpolated with the piecewise cubic

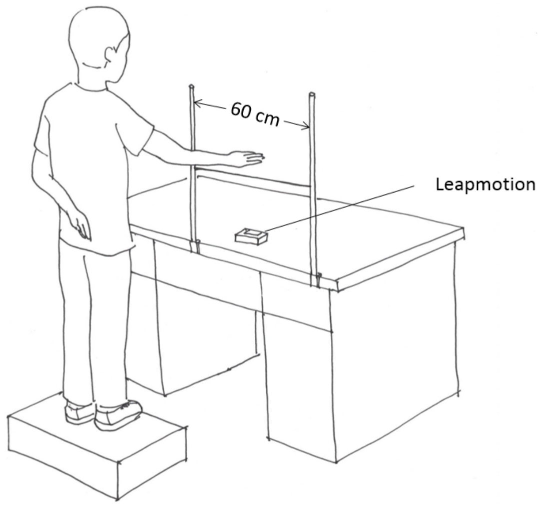

FIGURE 1. **Schematic illustration of the experimental setup.**

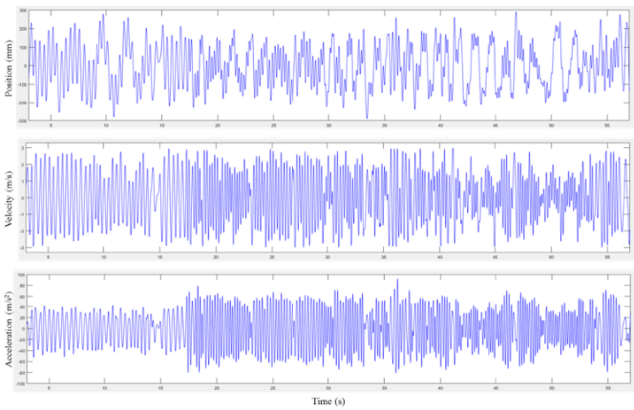

FIGURE 2. **Exemplary time series of position (top panel), velocity (middle panel) and acceleration (bottom panel).**

Hermite interpolating polynomial method and filtered with a second-order low-pass Butterworth filter (5 Hz cut-off). The first and the last 3 seconds of the position time series were cut from data analysis. Since participants performed oscillatory movements in each trial, we calculated the amplitude of each single oscillation from the processed position time series. The amplitude was computed as the distance between two endpoints (where velocity equaled 0). Thus, a set of amplitude values was obtained by including the amplitude values of all oscillations. In terms of the velocity and acceleration time series, they were calculated as the first and second order differentials of the position time series respectively. Exemplary time series of position, velocity and acceleration are plotted in Fig. 2.

We calculated the Shannon entropy (abbreviated as entropy in the following text) and the central 95% range (abbreviated as range in the following text) as indices of the kinematic complexity (the antonym of restricted kinematics). To compute these two variables, we first deleted the noise for amplitude, velocity and acceleration by setting thresholds.

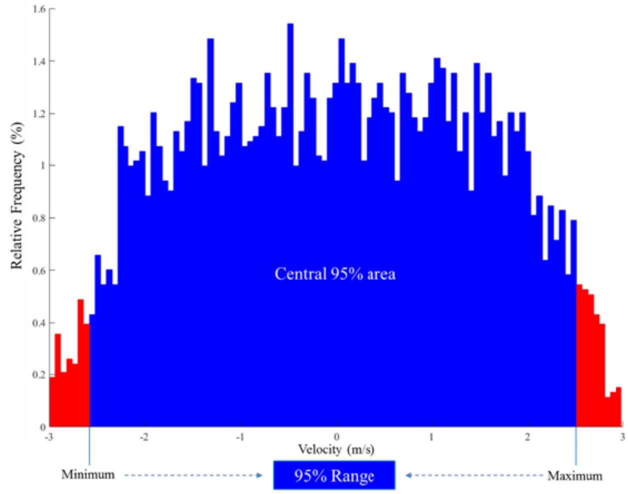

FIGURE 3. **Illustration of the velocity distribution and the 95% range. The blue area represents the central 95% area of the velocity distribution.**

Specifically, the threshold for amplitude was set as 0 – 60 cm, velocity -3 and 3 m/s, and acceleration -130 and 130 m/s^2. These threshold values were selected empirically based on the limits of the movement (e.g., amplitude would not exceed 60cm since the maximum distance of the moving area was 60cm). Values out of these thresholds were deleted from further analysis. As a further step, we used a normalized histogram with 101 equally distant bins [25] to compute the probability of each bin (Fig. 3). The Shannon entropy was calculated as:

$$\text{Entropy} = -\sum\nolimits_{i=1}^{n} p\left(x_i\right) * log2p(x_i) \tag{1}$$

In equation (1), n was assigned to 101, and $p(x_i)$ denoted the probability of the ith bin.

To calculate range, we first obtained the minimal and the maximal value that defined the central 95% area (Fig. 3). The range was computed as the distance between these two values:

$$\text{Range} = Maximum - Minimum \tag{2}$$

Entropy and range captured the restricted kinematics owing to the following reasons. Entropy quantifies the level of variance or complexity of a system. The higher the entropy value, the more variant (less restricted) the system. The range was computed as the width of the distribution of the central 95% area, thus reflecting the variability of the kinematic feature. For example, when performing rhythmic oscillations with mono-amplitude, the 95% range of the amplitude distribution would be much narrower than the execution of complex oscillations with variant amplitude.

To be noted was that each participant's movement was recorded three times. After obtaining the entropy and range for the movement amplitude, velocity and acceleration, we computed the minimal, median and maximal values of these features across the three recorded trials. Finally, 18 kinematic features were obtained altogether (Table 1).

E. MACHINE LEARNING PROCEDURE

1) DESCRIPTION OF DATASET

The participant sample consisted of 20 ASD and 23 TD participants. A total number of 18 kinematic features were computed for all participants. The original dataset used for the ML procedure was a 43 (participants) * 18 (features) matrix. The dataset is not made publicly available.

2) CLASSIFIERS

Five commonly used ML classifiers were applied to perform the prediction task: support vector machine (SVM), Linear Discriminant Analysis (LDA), Decision tree (DT), Random forest (RF), and K nearest neighbor (KNN) to examine which classifier would achieve the best classification result.

SVM is a supervised learning model that outputs an optimal hyperplane in the n-dimensional space with a set of labelled training examples. Testing samples are assigned to one of the labeled categories based on the sign of the distance vector to the hyperplane. A positive correlation exists between its distance to the hyperplane and the probability it belongs to a certain category.

LDA works as a dimensionality reduction technique which builds a linear combination of features as a model to classify two or more classes of objects. In the case of binary classification (ASD and TD), LDA projects all the data points scattered in the high-dimensional space onto one dimension - a straight line, making it straightforward to obtain a threshold to differentiate the two groups.

DT classifier trains a tree-like model to predict which category a testing sample belongs to. The decision tree extends its nodes by maximizing the information gain on every step it takes. Despite its strong interpretability, a single tree is prone to overfitting.

In order to address the overfitting problem of the decision tree algorithm, RF created a series of simple trees trained with a dataset of random features on a random portion of observations. A test sample will be classified by the majority of votes from these trees.

KNN classifier uses the training set as a model and requires no explicit training phase. A testing sample is classified by the plurality vote of its k nearest neighbors. An odd k values needs to be chosen for a binary classification problem, and the present study tested the conditions when $k = 1, 3, 5, 7$.

3) FEATURE SELECTION

The procedure of feature selection involved two steps. In the first step, we selected discriminative features out of the total 18 features and fed these features into the classifiers in order to minimize the number of features for computation efficiency. In consistency with Frazier *et al.*'s work [29], independent t-tests were performed to evaluate the discriminative capacity of each feature. Discriminative features were defined as p-values lower than 0.1 (at least marginally significant [30]). Features with p-values greater than 0.1 were considered as less discriminant features that were lack of the power to discriminate the two groups of participants, and they were discarded from further ML process. Only features with p-values lower than 0.1 were preserved for the ML process.

In the second step, the forward feature selection (FFS) [31] was used to train the ML models. Specifically, it began with the evaluation of each individual discriminative feature to perform the classification task. The one-feature model with the highest prediction accuracy was obtained by incorporating the feature that yielded the optimal classification performance. Afterwards, all possible combinations of the first selected feature and one of the rest features were evaluated. The combination that fulfilled the optimal classification performance was obtained as the two-feature model with the highest prediction accuracy. By following the same procedure, subsequent iterations involved retaining the feature that produced the highest classification accuracy together with the previously selected features. The iteration stopped when the model incorporating all the discriminative features was evaluated.

4) CLASSIFICATION

By implementing FFS, selected features were fed into the five classifiers to evaluate the accuracy, sensitivity, and specificity. Accuracy was calculated as the percentage of the correctly categorized samples in both groups. Specificity represented the model's ability to correctly detect the TD samples, and sensitivity the ASD samples. Leave-one-out cross-validation (LOOCV) was used in all the five classifiers. Specifically, LOOCV involved using one participant sample as a test set and the remaining participant samples as the training set. The same procedure was repeated until each sample was used once as the test set. ML was performed with Matlab (R 2017b), and the whole ML process is illustrated in Fig. 4.

III. RESULTS

Section III exhibits the results on the comparison between ASD and TD with respect to the RKF, and on the classification performance of the ML classifiers.

A. COMPARISON BETWEEN ASD AND TD

Comparisons between ASD and TD with respect to the demographic information and the kinematic features were listed in Table 1. Results showed that ASD children were either significantly ($p < .05$) or marginally ($.05 < p < .1$) different from the TD group on 9 kinematic features: Vel_Entropy_Mdn, Accel_Entropy_Mdn, Vel_Entropy_Max, Amp_Entropy_Min, Vel_Entropy_Min, Accel_Entropy_Min, Amp_Range_Mdn, Amp_Range_Max, and Vel_Range_Min. These 9 features were considered as discriminative features, and were further fed into the classifiers with the FFS procedure. All statistical analysis was conducted with the aid of SPSS (version 17.0).

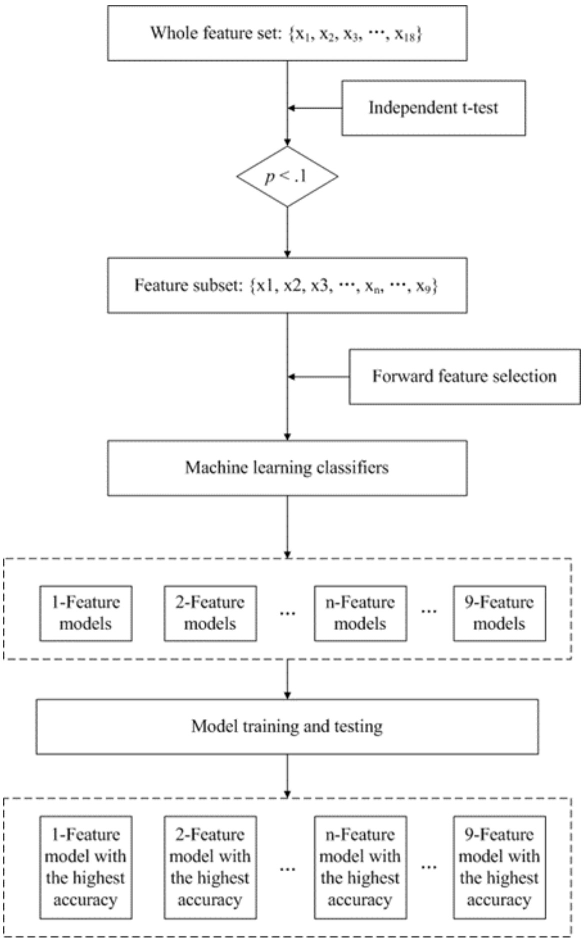

FIGURE 4. Illustration of the ML procedure.

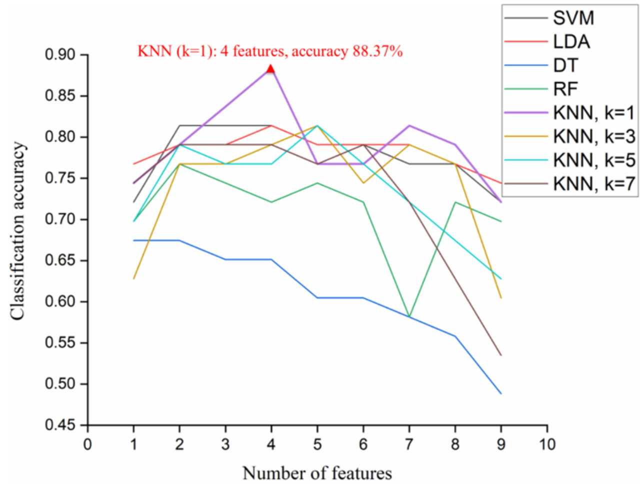

FIGURE 5. Variation of the classification accuracy of the classifiers with the number of features. The Figure shows that KNN classifier outperformed the other four classifiers with 4 features when $k = 1$.

TABLE 2. Confusion matrix of the KNN classifiers ($k = 1$).

Predicted Class / Actual Class	TD	ASD
TD	TN = 21	FP = 2
ASD	FN = 3	TP = 17

True Positives (TP): The model correctly predicted that they were ASD.
True Negatives (TN): The model correctly predicted that they were TD.
False Positives (FP): The model incorrectly predicted that they were ASD.
False Negatives (FN): The model incorrectly predicted that they were TD.

B. ML CLASSIFICATION PERFORMANCE

The classification performance of the five classifiers is plotted in Fig. 5. It shows that the model with the highest classification accuracy (88.37%) was achieved by the KNN classifier ($k = 1$) with four features: maximal amplitude range, minimal velocity range, median velocity entropy, and minimal velocity entropy. The sensitivity and specificity of the model were 91.3% and 85% respectively, and the area under curve (AUC) was 0.8815. Table 2 summarizes the confusion matrix of the KNN classifier.

The highest prediction accuracy, specificity, sensitivity, and the AUC of all ML classifiers, together with the number of features in the best model were listed in Table 3. Our results showed that all ML models except one (the DT classifier) yielded the highest accuracy over 75% with no more than 5 features.

IV. DISCUSSION

Only a handful of studies have so far implemented ML to identify ASD with kinematic features [12]–[14]. As a major innovation, the present study investigated the feasibility of predicting ASD by using kinematic features derived from RRB, which is one of the two indispensable symptoms of ASD. The high classification accuracy of our study demonstrated that ML is an efficient approach to discriminating ASD from TD by utilizing RKF.

By implementing a motor task that required the execution of the utmost variant movement, the present study calculated the entropy and 95% range of the movement amplitude, velocity and acceleration as the indices of kinematic complexity. Our results showed that the KNN algorithm ($k = 1$) outperformed the other four classifiers to yield the most accurate classification performance (88.37%, sensitivity 85% and specificity 91.3%, AUC 0.8815) with four features: the maximal amplitude range, minimal velocity range, median velocity entropy, and minimal velocity entropy. To be noticed was that one of these four features was related to amplitude range, and the other three features pertained to velocity. The group comparison (Table 1) showed that the ASD children had significantly greater maximal amplitude range than the TD participants, indicating that patients with ASD tended to perform oscillations with greater amplitude. This result was consistent with previous studies which found that macrographia was higher prevalent in patients with ASD [32], indicating deficits in fine motor control [33].

TABLE 3. The classification performance of different classifiers.

		Number of features that achieved the highest accuracy	Highest accuracy	Sensitivity	Specificity	AUC
SVM		2	81.40%	75%	86.96%	0.85
LDA		4	81.40%	75%	86.96%	0.8543
DT		1	67.44%	60%	73.91%	0.6935
Random forest		2	76.74%	80%	73.91%	0.7641
KNN	$k = 1$	4	88.37%	85%	91.30%	0.8815
	$k = 3$	5	81.40%	75%	86.96%	0.8228
	$k = 5$	5	81.40%	80%	82.61%	0.7946
	$k = 7$	2	79.70%	65%	91.30%	0.7783

Surprisingly, three features in the KNN algorithm ($k = 1$) were related to the velocity entropy or range. Since entropy and range were derived from the velocity distribution, it was indicated that information residing in the velocity distribution could be used to identify patients with ASD. The finding echoed the study of Słowiński *et al.* [25], which illustrated that the pattern of velocity distribution characterized the subtle difference in motor activities between individuals. In addition, the ML model of Crippa *et al.*'s study [12] also included velocity related features in the classifier that achieved the highest accuracy by showing that children with ASD displayed slower and fragmented movements. All these results evidenced that kinematic features in the velocity profile could be leveraged to identify ASD. Specifically, our study showed that the restrictedness in the velocity profile was a robust feature that could be used to classify ASD from TD.

The application of ML might pose a great challenge to the current diagnostic criteria of ASD. Two indispensable cardinal symptoms are required to confirm the diagnosis of ASD according to the DSM-V criteria: social communication impairment and RRB [26]. Indeed, features extracted from the social gaze behavior (a prominent social deficit in ASD) were found able to discriminate children with ASD from the non-ASD individuals [10], [11]. However, both the neuroimaging studies [8] and Crippa *et al.*'s study [12] showed that features not related to either social deficits or RRB could also be successfully utilized to identify ASD. In the era of "big data", a question was raised as to whether a new diagnostic method could be established by integrating genetic, neurological, psychological and kinematic features. We reckon that integrating features from all these respects might considerably challenge the current diagnostic criteria of ASD. However, another question arises regarding how to create an effective algorithm by selecting relevant features out of a huge number of features at disposal. The high classification accuracy obtained in the present study suggests that our feature selection approach might be widely applied in the autism prediction. Specifically, when dealing with a great deal of attributes, we propose that discriminative features could be screened out as the first step by implementing statistical analysis. Afterwards, FFS could be applied to determine the optimal combination of discriminative features for model training.

V. LIMITATIONS AND FUTURE WORK

The present study only recruited children with high functioning autism to ensure that they could be able to perform the motor task. Whether low functioning patients are also capable of performing the motor task remains an open question. Obviously, this motor task would not work for children less than 2 years old, which suggests that this motor task would not function for the early screening of ASD.

Alternatively, recent studies showed that motion capture techniques could help quantify RRB in ASD. A couple of recent scientific attempts were made to automatically detect repeated behaviors with the aid of motion capture techniques [34], [35]. In general, these studies utilized accelerometers [35], [36] or Microsoft sensor Kinect [37] for motion capture purposes as the first step. Afterwards, motion pattern recognition algorithms were developed to detect repetitive behavior out of a series of other patterns of movement [38], [39]. For instance, Goodwin *et al.* [35] attached accelerometers to the body of 6 ASD patients to record movement data, and then a ML classifier was developed to identify repetitive behaviors such hand flapping or body rocking. These researchers demonstrated that their algorithm could accurately detect repetitive behaviors (accuracy = 88.6%). Indeed, motion capture offers a promising method in quantifying RRB, particularly in early screening since it enables data collection in natural settings without demanding participants to execute a specific movement. However, this technique might only be used in detecting low level of repetitive motor activities, but not higher level of RRB such as circumscribed interest. Therefore, how to quantify the higher level of RRB remains a challenge for motion capture techniques. Based on the idea that both low and high levels of RRB share the same feature of restrictedness, we reckoned that the higher level of RRB could be assessed in a situation demanding variant behavioral response.

VI. CONCLUSION

By using ML, findings from the present study showed that the RKF could be used to efficiently classify ASD from TD. Given the fact that most studies utilized ML to differentiate ASD from TD, future investigation could also be dedicated to the classification of ASD from other groups of individuals, such as between ASD and ADHD [40], [41]. In addition, ML could also be implemented in other aspects such as engagement evaluation [42]. With the increasing accumulation of data from genetic, neurological, psychological and kinematic fields, ML will be a promising tool that will eventually lead to the objective and automated diagnosis of ASD.

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REFERENCES

[1] D. A. M. Pyles, M. M. Riordan, and J. S. Bailey, "The stereotypy analysis: An instrument for examining environmental variables associated with differential rates of stereotypic behavior," *Res. Developmental Disab.*, vol. 18, pp. 11–38, Jan./Feb. 1997.

[2] P. T. Shattuck, M. Durkin, M. Maenner, C. Newschaffer, D. S. Mandell, L. Wiggins, L.-C. Lee, C. Rice, E. Giarelli, R. Kirby, J. Baio, J. Pinto-Martin, and C. Cuniff, "Timing of identification among children with an autism spectrum disorder: Findings from a population-based surveillance study," *J. Amer. Acad. Child Adolescent Psychiatry*, vol. 48, pp. 474–483, May 2009.

[3] L. D. Wiggins, J. Baio, and C. Rice, "Examination of the time between first evaluation and first autism spectrum diagnosis in a population-based sample," *J. Developmental Behav. Pediatrics*, vol. 27, pp. S79–S87, Apr. 2006.

[4] C. M. Corsello, "Early intervention in autism," *Infants Young Children*, vol. 18, pp. 74–85, Apr./Jun. 2005.

[5] D. P. Wall, R. Dally, R. Luyster, J.-Y. Jung, and T. F. Deluca, "Use of artificial intelligence to shorten the behavioral diagnosis of autism," *PLoS ONE*, vol. 7, Aug. 2012, Art. no. e43855.

[6] M. Duda, J. A. Kosmicki, and D. P. Wall, "Testing the accuracy of an observation-based classifier for rapid detection of autism risk," *Transl. Psychiatry*, vol. 4, p. e424, Aug. 2014.

[7] D. P. Wall, J. Kosmicki, T. F. DeLuca, E. Harstad, and V. A. Fusaro, "Use of machine learning to shorten observation-based screening and diagnosis of autism," *Transl. Psychiatry*, vol. 2, p. e100, Apr. 2012.

[8] M. Plitt, K. A. Barnes, and A. Martin, "Functional connectivity classification of autism identifies highly predictive brain features but falls short of biomarker standards," *NeuroImage, Clin.*, vol. 7, pp. 359–366, Jan. 2015.

[9] B. Yamagata *et al.*, "Machine learning approach to identify a resting-state functional connectivity pattern serving as an endophenotype of autism spectrum disorder," *Brain Imag. Behav.*, Oct. 2018.

[10] W. Liu, M. Li, and L. Yi, "Identifying children with autism spectrum disorder based on their face processing abnormality: A machine learning framework," *Autism Res.*, vol. 9, pp. 888–898, Aug. 2016.

[11] G. Wan, X. Kong, B. Sun, S. Yu, Y. Tu, J. Park, C. Lang, M. Koh, Z. Wei, Z. Feng, Y. Lin, and J. Kong, "Applying eye tracking to identify autism spectrum disorder in children," *J. Autism Developmental Disorders*, vol. 49, pp. 209–215, Jan. 2019.

[12] A. Crippa, C. Salvatore, P. Perego, S. Forti, M. Nobile, M. Molteni, and I. Castiglioni, "Use of machine learning to identify children with autism and their motor abnormalities," *J. Autism Developmental Disorders*, vol. 45, pp. 2146–2156, Jul. 2015.

[13] B. Li, A. Sharma, J. Meng, S. Purushwalkam, and E. Gowen, "Applying machine learning to identify autistic adults using imitation: An exploratory study," *PLoS ONE*, vol. 12, Aug. 2017, Art. no. e0182652.

[14] A. Anzulewicz, K. Sobota, and J. T. Delafield-Butt, "Toward the autism motor signature: Gesture patterns during smart tablet gameplay identify children with autism," *Sci. Rep.*, vol. 6, Aug. 2016, Art. no. 31107.

[15] L. Kanner, "Autistic disturbances of affective contact," *Nervous Child*, vol. 2, pp. 217–250, Apr. 1943.

[16] S. H. Kim and C. Lord, "Restricted and repetitive behaviors in toddlers and preschoolers with autism spectrum disorders based on the autism diagnostic observation schedule (ADOS)," *Autism Res.*, vol. 3, pp. 162–173, Aug. 2010.

[17] M. L. Cuccaro, Y. Shao, J. Grubber, M. Slifer, C. M. Wolpert, and S. L. Donnelly, "Factor analysis of restricted and repetitive behaviors in autism using the autism diagnostic interview-R," *Child Psychiatry Hum. Develop.*, vol. 34, no. 1, pp. 3–17, Sep. 2003.

[18] M. Turner, "Annotation: Repetitive behaviour in autism: A review of psychological research," *J. Child Psychol. Psychiatry Allied Disciplines*, vol. 40, pp. 839–849, 1999.

[19] K. Pierce and E. Courchesne, "Evidence for a cerebellar role in reduced exploration and stereotyped behavior in autism," *Biol. Psychiatry*, vol. 49, pp. 655–664, Apr. 2001.

[20] K. M. Shafritz, G. S. Dichter, G. T. Baranek, and A. Belger, "The neural circuitry mediating shifts in behavioral response and cognitive set in autism," *Biol. Psychiatry*, vol. 63, pp. 974–980, May 2008.

[21] B. R. Lopez, A. J. Lincoln, S. Ozonoff, and Z. Lai, "Examining the relationship between executive functions and restricted, repetitive symptoms of autistic disorder," *J. Autism Developmental Disorders*, vol. 35, pp. 445–460, Aug. 2005.

[22] Y. Tanimura, M. C. Yang, and M. H. Lewis, "Procedural learning and cognitive flexibility in a mouse model of restricted, repetitive behaviour," *Behav. Brain Res.*, vol. 189, pp. 250–256, Jun. 2008.

[23] A.-M. D'Cruz, M. E. Ragozzino, M. W. Mosconi, S. Shrestha, E. H. Cook, and J. A. Sweeney, "Reduced behavioral flexibility in autism spectrum disorders," *Neuropsychology*, vol. 27, no. 2, pp. 152–160, 2013.

[24] B. A. Corbett, L. J. Constantine, R. Hendren, D. Rocke, and S. Ozonoff, "Examining executive functioning in children with autism spectrum disorder, attention deficit hyperactivity disorder and typical development," *Psychiatry Res.*, vol. 166, pp. 210–222, Apr. 2009.

[25] P. Słowiński , C. Zhai, F. Alderisio, R. Salesse, M. Gueugnon, L. Marin, B. G. Bardy, M. di Bernardo, and K. Tsaneva-Atanasova, "Dynamic similarity promotes interpersonal coordination in joint action," *J. Roy. Soc. Interface*, vol. 13, no. 116, pp. 1–11, 2016.

[26] American Psychiatric Association, *Diagnostic and Statistical Manual of Mental Disorders*, 5th ed. Arlington, VA, USA, American Psychiatric Association, 2013.

[27] American Psychiatric Association, *Diagnostic and Statistical Manual of Mental Disorders*, 4th ed. Washington, DC, USA, American Psychiatric Association, 1994.

[28] J. Raven, "The Raven's progressive matrices: Change and stability over culture and time," *Cogn. Psychol.*, vol. 41, pp. 1–48, Aug. 2000.

[29] T. W. Frazier, E. W. Klingemier, M. Beukemann, L. Speer, L. Markowitz, S. Parikh, S. Wexberg, K. Giuliano, E. Schulte, C. Delahunty, V. Ahuja, C. Eng, M. J. Manos, A. Y. Hardan, E. A. Youngstrom, and M. S. Strauss, "Development of an objective autism risk index using remote eye tracking," *J. Amer. Acad. Child Adolescent Psychiatry*, vol. 55, pp. 301–309, Apr. 2016.

[30] L. Pritschet, D. Powell, and Z. Horne, "Marginally significant effects as evidence for hypotheses: Changing attitudes over four decades," *Psychol. Sci.*, vol. 27, pp. 1036–1042, Jul. 2016.

[31] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *J. Mach. Learn. Res.*, vol. 3, pp. 1157–1182, Jan. 2003.

[32] D. Q. Beversdorf, J. M. Anderson, S. E. Manning, S. L. Anderson, R. E. Nordgren, G. J. Felopulos, and M. L. Bauman, "Brief report: Macrographia in high-functioning adults with autism spectrum disorder," *J. Autism Developmental Disorders*, vol. 31, pp. 97–101, Feb. 2001.

[33] C. T. Fuentes, S. H. Mostofsky, and A. J. Bastian, "Children with autism show specific handwriting impairments," *Neurology*, vol. 73, pp. 1532–1537, Nov. 2009.

[34] N. M. Rad, S. M. Kia, C. Zarbo, T. van Laarhoven, G. Jurman, P. Venuti, E. Marchiori, and C. Furlanello, "Deep learning for automatic stereotypical motor movement detection using wearable sensors in autism spectrum disorders," *Signal Process.*, vol. 144, pp. 180–191, Mar. 2018.

[35] M. S. Goodwin, S. S. Intille, F. Albinali, and W. F. Velicer, "Automated detection of stereotypical motor movements," *J. Autism Developmental Disorders*, vol. 41, pp. 770–782, Jun. 2011.

[36] T. Westeyn, K. Vadas, X. Bian, T. Starner, and G. D. Abowd, "Recognizing mimicked autistic self-stimulatory behaviors using HMMs," in *Proc. 9th IEEE Int. Symp. Wearable Comput. (ISWC)*, Osaka, Japan, Oct. 2005, pp. 164–167.

[37] N. Gonçalves, J. L. Rodrigues, S. Costa, and F. Soares, "Automatic detection of stereotyped hand flapping movements: Two different approaches," presented at the IEEE RO-MAN, 21st IEEE Int. Symp. Robot Hum. Interact. Commun., Paris, France, Sep. 2012.

[38] L. Sadouk, T. Gadi, and E. H. Essoufi, "A novel deep learning approach for recognizing stereotypical motor movements within and across subjects on the autism spectrum disorder," *Comput. Intell. Neurosci.*, vol. 2018, Jul. 2018, Art. no. 7186762.

[39] U. Großekathöfer, N. V. Manyakov, V. Mihajlović, G. Pandina, A. Skalkin, S. Ness, A. Bangerter, and M. S. Goodwin, "Automated detection of stereotypical motor movements in autism spectrum disorder using recurrence quantification analysis," *Frontiers Neuroinform.*, vol. 11, p. 9, Feb. 2017.

[40] M. Duda, N. Haber, J. Daniels, and D. P. Wall, "Crowdsourced validation of a machine-learning classification system for autism and ADHD," *Transl. Psychiatry*, vol. 7, May 2017, Art. no. e1133.

[41] M. Duda, R. Ma, N. Haber, and D. P. Wall, "Use of machine learning for behavioral distinction of autism and ADHD," *Transl. Psychiatry*, vol. 6, p. e732, Feb. 2016.

[42] Y. Feng, M. Chu, W. Wei, and Q. Jia, "Engagement evaluation for autism intervention by robots based on dynamic Bayesian network and expert elicitation," *IEEE Access*, vol. 5, pp. 19494–19504, 2017.

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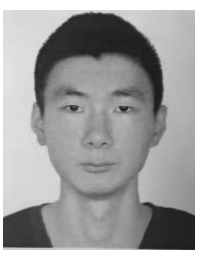

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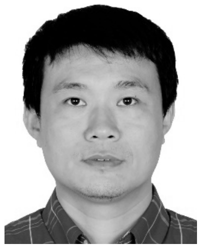

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