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Accessible autism screening in children: a pilot study of markerless gait analysis from ordinary walking videos

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ABSTRACT

Objectives: Formal autism diagnosis typically follows initial concern by more than two years, and current screening tools rely on subjective caregiver reports. Motor differences in walking gait are well documented but not used in standard screening. This pilot study examined whether gait features from 2D walking videos could distinguish autistic from non-autistic children.

Methods: Using OpenPose, a 2D pose estimation system, we analyzed front- and side-view walking videos of 72 children aged 3–12 years (30 autistic, 42 non-autistic). From joint coordinates, 163 biomechanical gait features were computed and reduced to eight *via* random-forest-based selection. Three classifiers were compared: logistic regression, random forest, and support vector machine (SVM).

Results: On a stratified held-out test set, the SVM achieved the strongest performance (AUC = 0.935; accuracy = 0.810; sensitivity = 0.889; specificity = 0.750), a profile consistent with screening use. Random forest reached moderate performance but paired high specificity with low sensitivity, while logistic regression performed least effectively, suggesting linear models capture this signal poorly.

Conclusions: These pilot findings support the feasibility of 2D video-based gait analysis as an accessible, objective complement to existing autism screening, though validation in larger, more diverse samples is needed before any clinical application.

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Introduction

Autism prevalence and the screening gap

Autism is one of the most prevalent neurodevelopmental conditions in the United States, identified in approximately 1 in 31 children aged 8 years (CDC 2025), and approximately 1 in 100 children globally (Zeidan et al. 2022). Lifetime support costs exceed three million US dollars per individual (Ganz 2007), and aggregate national costs are projected to surpass 460 billion dollars annually in the U.S. (Leigh and Du 2015). A major driver of the long-term cost is delayed identification: children typically wait more than two years after initial screening to receive a formal diagnosis (Chen et al. 2023; Gordon-Lipkin, Foster, and Peacock 2016; van 't Hof et al. 2021).

These delays are not evenly distributed. Girls are diagnosed later and less often than boys, in part

because current screeners encode signs more readily noticed in boys (Belcher et al. 2023; Lockwood Estrin et al. 2021). Children in rural areas (CDC 2025) and from racial, ethnic, and lower-socioeconomic-status backgrounds are less likely to be identified through standard surveillance and screening pathways (Durkin et al. 2017; Mandell et al. 2009), with disparities documented across decades of U.S. surveillance data. Similar diagnostic-access disparities have been documented internationally: in a total-population study of more than 55,000 children in South Korea, more than two-thirds of those meeting diagnostic criteria for autism were in mainstream schools and previously unrecognized by clinical-referral pipelines (Kim et al. 2011); and a national-cohort study in Japan reported 5-year cumulative incidence of autism diagnosis varying from 0.9% to 7.9% across prefectures within a single national health-insurance dataset, with much of

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this variation attributed to differences in service accessibility (Sasayama et al. 2021).

Reducing the time from concern to identification is a direct route to improving outcomes and lowering costs, because early interventions, particularly those initiated before age three, improve developmental trajectories and reduce long-term service needs (Guthrie et al. 2023; Kaiser and Roberts 2011; Roberts and Kaiser 2011). Around the globe, formal diagnostic assessment relies principally on the Autism Diagnostic Observation Schedule (ADOS-2) and the Autism Diagnostic Interview-Revised (ADI-R), which retain moderate-to-high validity in non-U.S. populations (Chojnicka and Pisula 2019) but require extensive clinician training and typically cost between 2,000 and 4,000 dollars per kit (Western Psychological Services 2012). Before formal diagnosis, children are typically screened using caregiver questionnaires such as the Modified Checklist for Autism in Toddlers, Revised (M-CHAT-R/F), which improves accessibility but remains inherently subjective and varies in performance across demographic groups, and depends on caregiver recall and literacy (Guthrie et al. 2019; Robins et al. 2014). While parents often report concerns spanning motor, sensory, and behavioral domains (Guinchat et al. 2012), existing screeners focus almost exclusively on social communication and repetitive behaviors. Motor characteristics, although robustly documented in autism research (Downey and Rapport 2012; Miller et al. 2024) and considered by autistic individuals themselves to be a core aspect of their experience (Autistic Self Advocacy Network 2020), remain absent from standardized screening.

Motor differences in autism

Most autistic individuals present with motor differences relative to non-autistic peers (Green et al. 2009; Odeh et al. 2022; Stachura et al. 2025). In a SPARK cohort of more than 11,000 autistic children, approximately 87% of children aged 5–15 were at risk for motor impairment (Bhat 2020). Autistic children are approximately 22.2 times more likely than children in the general population to screen positive for motor impairment on the Developmental Coordination Disorder Questionnaire, with risk increasing alongside social-communication, cognitive, repetitive-behavior, and functional severity (Bhat 2021). These differences span gross motor coordination, postural control, walking, and visuo-motor and fine motor coordination (Bojanek et al. 2020; Miller et al. 2024; Rinehart et al. 2006).

Motor differences emerge early and show predictive value. Infant motor skill predicts later expressive language and autism diagnosis (Iverson et al. 2019; LeBarton and Landa 2019). Additionally, parents who first notice motor or general developmental concerns tend to seek professional assistance earlier than parents whose first concerns are language- or social-communication-based (Guinchat et al. 2012; Yimgang, Albury, and Leppert 2017), giving motor-based screening a practical advantage in shortening the diagnostic timeline. Clinical gait analysis in older autistic children confirms that these differences persist beyond early childhood (Shetreat-Klein, Shinnar, and Rapin 2014; Wu et al. 2024).

Among motor signals, walking gait is uniquely well-suited as a screening modality because it integrates lower-extremity strength, trunk stability, balance, and motor planning into a single observable behavior. A meta-analysis of 18 studies (Lum et al. 2020) showed that autistic children walk with wider step width, greater stride-length variability, longer gait cycles, longer stance and step times, and slower walking speed than non-autistic peers, and that these differences persist across the lifespan. Reduced mean stride length has also been reported in older autistic children using treadmill-based clinical gait analysis (Wu et al. 2024). The neurobiological basis is thought to involve cerebellar and basal-ganglia development (Rinehart et al. 2006).

Two equity properties make gait especially attractive as a screening signal. First, motor delay is at least as common in autistic girls as in autistic boys (Gabis et al. 2020), therefore, gait-based screening offers a path to reducing the gender gap that arises when screeners ask only about social-communication signs more readily noticed in boys. Second, movement does not require verbal communication, sidestepping language and literacy confounds that limit social-communication-based screeners. Gait is not culture-free, however, and screening pipelines should be designed to accommodate this variability (Buac et al. 2023). Despite this convergent evidence, motor signals, and walking gait specifically, have never been incorporated into standardized autism screening, because quantitative gait analysis traditionally required specialized three-dimensional motion-capture laboratories not deployable in homes, schools, or pediatric clinics.

Markerless 2D video gait analysis

Although three-dimensional motion capture systems using reflective markers and high-speed cameras remain the gold standard for quantitative gait analysis, their cost (typically 50,000 to 500,000 dollars per

installation), space requirements, and need for trained technicians make them impractical for population screening. Recent advances in computer vision have produced markerless pose estimation systems that extract joint positions from ordinary two-dimensional videos, such as OpenPose (Cao et al. 2021) and MediaPipe (Lugaresi et al. 2019). Validation studies report strong agreement between 2D pose estimation and 3D motion capture for sagittal-plane kinematics (Stenum, Rossi, and Roemmich 2021; Widhalm et al. 2024), and this agreement extends to pediatric and toddler populations (Verhoeven, Zandvoort, and Dominici 2025). Compared with other technology-based autism screening approaches, including eye-tracking systems that require dedicated hardware (Jones et al. 2023), digital phenotyping platforms operating in narrow age ranges (Perochon et al. 2023), and mobile apps for toddler screening (Krishnappa Babu et al. 2024), markerless 2D gait analysis requires only a consumer-grade recording device and can be conducted in any environment. These properties make it distinctively accessible relative to other technology-based screening approaches.

The present pilot study

In the present pilot study, we examine whether gait characteristics extracted from ordinary walking videos can distinguish autistic from non-autistic children, using two-dimensional pose estimation and data-driven feature selection. The work makes two contributions. First, it tests whether ordinary 2D walking videos, which a caregiver could plausibly record, carry a gait signal that separates autistic from non-autistic children, and so whether motor behavior is worth incorporating alongside questionnaire-based screening. Second, it shows how an analysis pipeline anchored in established clinical gait findings can be implemented on 2D video rather than 3D motion-capture, removing a major accessibility barrier.

Machine learning has been applied to autism detection across questionnaire, facial-image, behavioral-video, and motor modalities (Crippa et al. 2015; Tariq et al. 2018). Within the gait domain specifically, two studies are the closest published comparators to the present work. Kojovic et al. (2021) used 2D video-based pose estimation in ADOS recordings to predict autism in young children, demonstrating that pose features can support automated prediction. Ganai et al. (2025) used MediaPipe to extract gait features from front-view videos and established a logistic regression model for autism detection. However, the

field lacks studies with comprehensive feature engineering, rigorous feature selection, and comparison of multiple classifiers.

This study extends prior work in three respects. First, where earlier 2D-video gait studies in autism have used compact, hand-picked feature sets, we engineered a broader pool of candidate gait descriptors and used systematic selection to retain a small, interpretable subset. Second, instead of reporting a single classifier, we compared several interpretable models on the same features so that the choice of model is grounded in head-to-head performance. Third, our recording protocol uses both front- and side-view video, which lets us examine sagittal- and frontal-plane motion together, and the features that survive selection map onto gait patterns previously described in the clinical literature (e.g. Rinehart et al. 2006).

Materials and methods

Participants

The cohort of participants in this study comprised 72 children aged 3–12 years (Mean = 7.6, SD = 2.3), recruited from the Northern Illinois region of the United States. Participants were recruited through a variety of community-based outreach efforts, including the distribution of study flyers to local school districts, public libraries, daycare centers, therapy centers, and the university campus and surrounding community locations. In addition, members of the research team attended community events organized through local park districts and participated in family engagement events hosted by a local school district, where information about the study was shared directly with families. Children with a confirmed autism diagnosis from a medical professional or documented in an Individualized Education Program (IEP) were eligible for the autistic group. In the United States, the autism diagnostic process is based on comprehensive clinical assessment (Hirota and King 2023) and requires children to meet the criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders fifth edition text revision (DSM-5-TR; American Psychiatric Association 2022). All participants were required to be independently ambulatory and able to walk unassisted along the recording path. Children in the non-autistic group were required to have no prior autism diagnosis and no autism designation in an Individualized Education Program. Co-occurring neurodevelopmental, psychiatric, and learning conditions were not exclusionary in either group. Children prescribed antipsychotic medications known to affect

motor control were excluded. Non-autistic children were not formally matched to autistic participants on age, sex, or sociocultural background; the sample was a convenience cohort recruited as they enrolled, with group differences on demographic variables examined descriptively below. As a pilot study, sample size was determined by feasibility and resource availability rather than an a-priori power analysis. The achieved sample ($n=72$) is comparable in scale to other published pilot gait-classification studies in autism (e.g. Ganai et al. 2025) and provides preliminary evidence to motivate a larger validation cohort planned for follow-on work.

Thirty children met criteria for the autistic group (Mean age = 8.0, SD = 2.2, Range 4–12) and 42 did not (non-autistic group; Mean age = 7.3, SD = 2.4, Range 3–12); an unpaired t test shows no statistically significant difference in age between groups ($p=0.21$). Self-reported gender across the full sample was male for 49 children (68%), female for 22 (31%), and non-binary for 1 (1%); the autistic group skewed somewhat more strongly male (73%) than the non-autistic group (64%), consistent with documented sex differences in autism prevalence (CDC 2025). Racial-ethnic composition was comparable across groups, with most participants identifying as White ($n=58$; 81%) and/or Hispanic ($n=14$; 19%), 4 identifying as Black (6%), and 2 as Asian or Pacific Islander (3%). English was the primary home language for the majority of participants reporting language information, with several multilingual households (English with Spanish, German, or Polish). Height and weight were available for 23 autistic and 40 non-autistic participants; these measures were not collected at all recruitment sites. The groups did not differ significantly in height ($p=0.126$), but the autistic group was significantly heavier than the non-autistic group (77.5 ± 31.7 lb vs. 60.1 ± 19.6 lb, $p=0.009$). The implications of this difference for interpretation of the selected gait features are addressed in the Discussion. The demographic and clinical characteristics by group of the cohort can be found in Table 1.

Co-occurring conditions were reported in both groups. Among non-autistic participants, 8 of 42 (19%) reported at least one neurodevelopmental, psychiatric, or learning co-occurring condition; Attention Deficit Hyperactivity Disorder (ADHD) was the most common ($n=6$, alone or with co-occurring conditions such as anxiety, oppositional defiant disorder, dyslexia, depression, or disruptive mood dysregulation disorder), with isolated reports of sensory processing disorder, ocular motor apraxia, auditory processing

Table 1. Demographic and clinical characteristics by group.

Characteristic	Autistic	Non-autistic
n	30	42
Age (years), mean (SD)	8.0 (2.2)	7.3 (2.4)
Age (years), range	4–12	3–12
Sex, n (%)		
Male	22 (73)	27 (64)
Female	7 (23)	15 (36)
Non-binary	1 (3)	0 (0)
Race and ethnicity, n (%) ^a		
White	26 (87)	32 (76)
Hispanic or Latino	6 (20)	8 (19)
Black or African American	1 (3)	3 (7)
Asian or Pacific Islander	1 (3)	1 (2)
Height (in), mean (SD) ^b	52.3 (6.9)	49.8 (5.6)
Weight (lb), mean (SD) ^b	77.5 (31.7)	60.1 (19.6)
SRS-2 Total T-score, mean (SD) ^c	73.2 (10.3)	55.1 (12.1)
≥ 1 co-occurring condition, n (%) ^d	8/20 (40)	8/42 (19)

^aCategories are not mutually exclusive; participants could report more than one racial or ethnic identity, so percentages sum to more than 100. One participant did not report their race and ethnicity.

^bHeight and weight were available for 23 autistic and 40 non-autistic participants; these measures were not collected at all recruitment sites.

^cSRS-2 Total T-scores were available for all 42 non-autistic participants and for 21 of 30 autistic participants; the measure was not part of the protocol at one community camp partner site.

^dCo-occurring condition information was unavailable for 10 autistic participants.

disorder, and a non-verbal learning disability. Among autistic participants for whom diagnostic information was collected ($n=20$ of 30), 8 (40%) reported a co-occurring condition, including ADHD ($n=2$), anxiety ($n=2$), obsessive compulsive disorder ($n=1$), sensory processing disorder ($n=1$), and various medical conditions (precocious puberty, vesicoureteral reflux, asthma/allergies, prematurity, fine motor delay). Co-occurring psychological conditions are highly prevalent in autistic children, with estimates reaching 91% (Mosner et al. 2019) and consistently exceeding rates in the general population (Micai et al. 2023). To ensure that our screening approach generalizes to real-world populations rather than an idealized subset, we retained participants with co-occurring conditions in both the autistic and non-autistic groups; reported accuracy therefore reflects performance under realistic clinical heterogeneity rather than under artificially clean inclusion criteria.

Procedure

Study sessions were conducted by trained graduate students in speech-language pathology, physical therapy, and industrial engineering in a university research laboratory or at community partner sites. Each session lasted approximately 30 to 45 min, with the majority of that time devoted to caregiver completion of questionnaires and consent procedures; the gait recording task itself required only a few minutes. Data were collected between February 2023 and

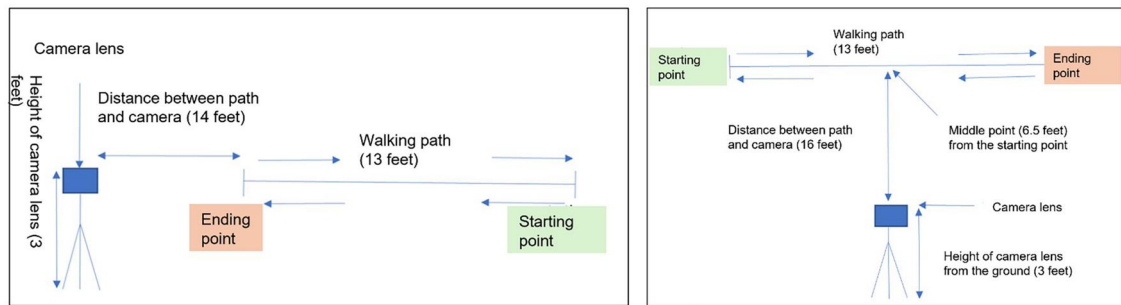


Figure 1. Gait video task setup (front- and side-views).

October 2025. The graduate student researchers conducted the sessions, recorded the gait videos, and collected study data using standardized protocols. Study data were subsequently stored and maintained by the research team in secure, password-protected systems in accordance with Institutional Review Board requirements and university data-management policies. Sensory needs were inquired about prior to each session so the recording environment could be adjusted (lighting, ambient sound, presence or absence of family members). After explicit caregiver consent and child assent, caregivers completed a brief background questionnaire and the Social Responsiveness Scale, Second Edition (see Measures), and the child completed the gait video task. The recording environment had bright, global lighting, neutral-colored non-reflective flooring, and clutter-free backgrounds. Participants wore solid-colored clothing to maximize pose-estimation visibility. Institutional Review Board approval was obtained prior to data collection, and written informed caregiver consent and verbal child assent were obtained from all participants.

Measures

Background questionnaire

Caregivers completed an electronic background questionnaire on the child's demographics, birth history, language environment, cultural background, educational placement, social context, and health and medication history.

Social Responsiveness Scale, Second Edition (SRS-2; Constantino 2012). The SRS-2 is a 65-item caregiver-report questionnaire measuring autism-related social, communication, and restricted/repetitive behavioral traits, normed for ages 2.5 to 18 years and available with separate male and female forms (Bruni 2014; Constantino 2012). The SRS-2 has excellent overall diagnostic accuracy in U.S. populations,

with a reported area under the receiver operating characteristic (ROC) curve of 96.8% (Constantino 2012). Using a cutoff score of ≥ 60 , the SRS-2 showed high sensitivity (93%) and high specificity (91%) and excellent internal consistency (Cronbach's $\alpha = 0.94\text{--}0.97$; Constantino 2012). SRS-2 Total T-scores were available for all 42 non-autistic participants (Mean = 55.1, SD = 12.1) and for 21 of the 30 autistic participants (Mean = 73.2, SD = 10.3); SRS-2 was not collected for 9 autistic participants who took part through a community camp partner where this measure was not part of the camp protocol.

Gait video task

Children were recorded while walking in straight lines using two iPads positioned on tripods, with the camera lens placed approximately three feet above the ground. Two recordings were obtained per child: a side view (walking path of 13 feet) and a front view (walking path of 11 feet). For each view, the child walked back and forth along the path two times, producing multiple gait cycles. The walking task was deliberately simple to ensure comprehension and consistent execution across the 3- to 12-year age range. Figure 1 illustrates the setup.

Pose estimation and preprocessing

OpenPose (Cao et al. 2021), an open-source markerless pose estimation system, was used to extract two-dimensional joint ('keypoint') coordinates and per-frame confidence scores from each video (Figure 2). Pose estimation was performed on the original full-resolution recordings without blurring, smoothing, or other image degradation. Keypoints for the lower-extremity joints (ankles, knees, hips), pelvis landmarks, and trunk regions were retained for analysis. Keypoints with confidence scores below 0.5 (in a range from 0 to 1) were treated as missing, on the rationale that frames in which a joint

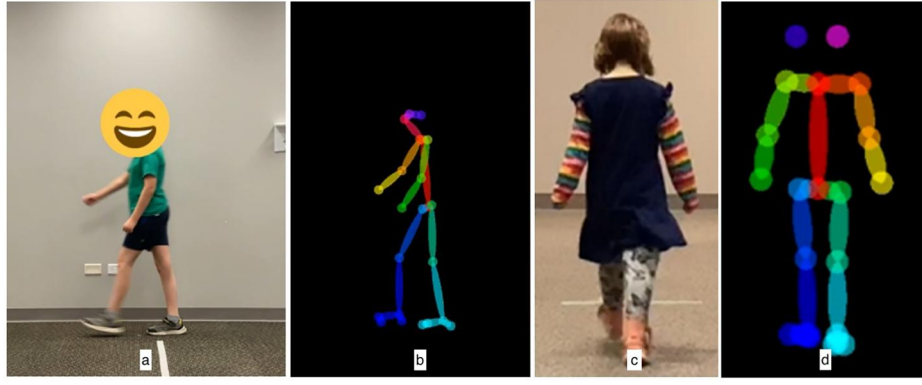


Figure 2. Representative video frames and OpenPose pose estimation output. (a) Side-view frame; (b) rendered pose output for the frame in (a); (c) front-view frame; (d) rendered pose output for the frame in (c). The participant's face in (a) is covered by a graphic overlay applied to this figure only to protect participant privacy; all pose estimation was performed on the original unmodified full-resolution recordings.

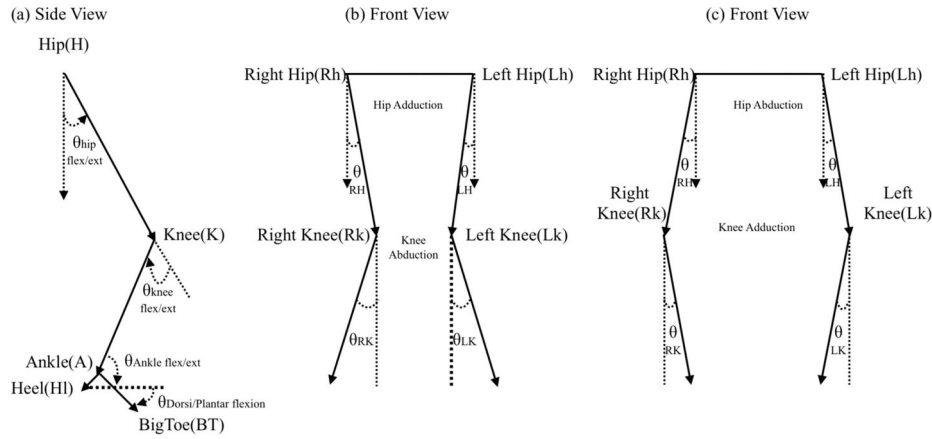


Figure 3. Joint kinematic features (angles). (a) Sagittal plane: Hip, knee, and ankle flexion/extension and dorsiflexion/plantarflexion. (b) & (c) Frontal plane: hip and knee abduction/adduction.

could not be reliably localized should not contribute to downstream kinematic estimates; this threshold was selected empirically as a balance between retaining sufficient data and excluding unreliable detections.

Missing keypoints were addressed in two stages. Short temporal gaps were first filled by linear interpolation along the time axis, which bridges brief tracking gaps without inventing motion not actually observed. Any remaining missing values were then imputed using a multivariate iterative procedure that estimates each missing value from the other available keypoint trajectories. Video segments corresponding to straight-line walking were retained; segments corresponding to turning were excluded because turning phases produce irregular kinematics and frequent occlusions that distort gait-cycle metrics. Joint-coordinate trajectories were smoothed with a Savitzky–Golay filter to reduce pose-estimator jitter while preserving the shape of the underlying gait patterns.

Feature engineering

We denote the segment between two consecutive right heel strikes as a gait cycle. Four gait cycles per participant were selected from the videos and resampled to 30 frames per cycle. The 30-frame target was chosen empirically based on the median observed cycle length across participants. Joint angles were computed from the smoothed two-dimensional keypoint coordinates using the standard three-point dot-product formulation. From the side-view recordings, bilateral knee and hip flexion-extension angles, ankle angles, and dorsiflexion-plantarflexion angles were derived. From the front-view recordings, bilateral hip and knee abduction-adduction angles were derived. **Figure 3** illustrates how each joint angle is computed.

From each smoothed joint-angle and pose-keypoint signal, eleven summary statistics were computed across the 120-frame standardized sequence: five magnitude descriptors (mean, standard deviation, minimum, maximum, range of motion) capturing the size and

excursion of the signal in its own units, and six variability and shape descriptors (coefficient of variation, skewness, kurtosis, peak count, trough count, mean-crossing rate) capturing within-signal irregularity. These eleven statistics were applied to fourteen channels, including ten joint-angle channels (bilateral hip, knee, ankle, and dorsiflexion-plantarflexion from the side view; bilateral hip abduction-adduction from the front view) and four spatiotemporal channels (vertical trunk position, vertical mid-hip position from the front view, step width, and inter-ankle Euclidean distance). Furthermore, we added five between-limb symmetry indices (one per bilateral pair) and four scalar gait summaries (cadence, total step count, mean inter-ankle distance, and a stride-length proxy), yielding 163 candidate features per child.

The 163 features map onto three clinical groups: spatiotemporal features describe how the body progresses through space and time (5 magnitude statistics on each of the 4 spatiotemporal channels + 4 scalar summaries = 24); joint-kinematic features describe joint-angle excursion and posture (5 magnitude statistics on each of the 10 joint-angle channels = 50); and variability and symmetry features describe within-signal variability and between-limb asymmetry (6 variability and shape statistics on each of the 14 channels + 5 between-limb symmetry indices = 89). The variability and shape statistics were computed within participant across the full 120-frame standardized sequence, and therefore index intra-individual variability in each child's own movement signal. Applied to the inter-ankle distance channel, these statistics (for example, the coefficient of variation of inter-ankle distance) capture variability in the continuous step-length waveform across the gait cycle; the corresponding statistics on the step-width channel capture frontal-plane variability. This is a construct related to, but distinct from, variability computed across discrete strides (Lum et al. 2020).

Near-zero-variance features were then removed and pairs of features with absolute Pearson correlation greater than 0.95 were pruned, retaining 142 features for the selection stage. Full feature definitions and operational details are provided in the [Supplementary Materials](#).

Feature selection

From the 142 candidate features, the most informative subset was identified using the Boruta wrapper algorithm, a random-forest-based feature-selection method (Kursa and Rudnicki 2010). Eight features were confirmed by the Boruta algorithm as carrying

predictive information beyond random-permutation baselines: minimum left hip angle, right knee angle skewness, right ankle angle skewness, left ankle angle kurtosis, left dorsiflexion-plantarflexion coefficient of variation, maximum trunk vertical displacement, minimum center-of-mass vertical displacement, and step length. These eight features were carried forward as the input set for all classification models. To assess the stability of the selection, Boruta was re-run under four additional random seeds (1, 16, 90, 66) with all other pipeline components held fixed, so that only Boruta's internal shadow-feature permutation varied. Four features—right knee angle skewness, right ankle angle skewness, maximum trunk vertical displacement, and minimum center-of-mass vertical displacement—were confirmed in all five runs. Left dorsiflexion-plantarflexion coefficient of variation was confirmed in four runs and step length in three. Left ankle angle kurtosis and minimum left hip angle were confirmed in two and one run respectively and are therefore treated as borderline. The primary analysis used seed 42, set as a default before any results were examined.

Classification models

Three machine learning classifiers were trained on the eight Boruta-selected features. Logistic regression with elastic-net regularization served as a linear baseline; the elastic-net penalty combines two forms of regularization to prevent overfitting and stabilize coefficient estimates in small samples. Random forest, an ensemble of 1,000 decision trees, was selected because it can capture non-linear feature interactions while remaining interpretable through feature-importance scores. Support vector machine (SVM) with a radial basis function kernel was selected for its capacity to model complex, non-linear decision boundaries. Hyperparameters for each model were selected by grid search nested within cross-validation.

Training and evaluation

The 72 participants were divided into a training set (51 participants, 70%) and a held-out test set (21 participants, 30%) using stratified random sampling to preserve the proportion of autistic and non-autistic children in each set. Because the training set contained unequal group sizes, the Synthetic Minority Over-sampling Technique (SMOTE; Chawla et al. 2002) was applied to generate synthetic examples of the smaller group until the two groups were balanced

in the training set, but not the test set. All features were standardized (mean-centered, scaled to unit variance) using statistics computed from the training set only; the same transformation was then applied to the test set.

Hyperparameter tuning used five-fold cross-validation with three repeats on the SMOTE-balanced training set, scored by the area under the ROC curve (AUC). AUC was chosen as the primary tuning metric because it evaluates discrimination across all possible classification thresholds, is relatively robust to mild class imbalance, and reflects the screening-relevant ability to rank children by likelihood of autism. Final models were evaluated once on the held-out test set and reported using AUC, accuracy, sensitivity, specificity, and F1 score, with 95% confidence intervals when applicable.

Results

Selected gait features

Boruta selection identified eight gait features as carrying genuine predictive information beyond random permutation. Three of the eight were spatiotemporal: maximum trunk vertical displacement, which captures how high the trunk rises during walking and indexes lift-off and propulsion mechanics; minimum center-of-mass vertical displacement, which captures the lowest point of the body's rise-and-fall cycle and indexes weight-bearing posture during stance; and step length. Five of the eight were joint-kinematic: one magnitude descriptor (minimum left hip angle) and four distribution-shape descriptors. Minimum left hip angle reflects the extreme of hip extension reached during the gait cycle, which is sensitive to compensatory hip strategies that have been reported in autistic gait. Right knee skewness and right ankle skewness describe the asymmetry of those joints' angle distributions across the gait cycle; non-zero skewness indicates that the joint spends

disproportionate time near one end of its range, consistent with restricted or atypical excursion patterns. Left ankle kurtosis indicates how peaked or flat the ankle-angle distribution is, with lower kurtosis corresponding to more uniform distribution of angle values across the cycle. Left dorsiflexion-plantarflexion coefficient of variation captures the variability of foot orientation across the analyzed sequence, indexing consistency of ankle positioning at push-off and clearance, which has been linked to motor-coordination differences. Notably, no spatial-symmetry index between left and right limbs survived Boruta selection, suggesting that for this limited sample the discriminative signal was carried by the shape and variability of single-limb signals rather than by between-limb asymmetry.

Group means and standard errors for the eight selected features are presented in Table 2. Four of the eight features showed statistically significant univariate group differences: right ankle angle skewness ($p = 0.0002$), left ankle angle kurtosis ($p = 0.0392$), maximum trunk vertical displacement ($p = 0.0163$), and minimum center-of-mass vertical displacement ($p = 0.0037$). The remaining four did not reach univariate significance but were confirmed as informative by Boruta, reflecting complementary contribution within the multivariate model rather than independent discriminative ability. Because the three spatial features are in pixel units rather than physical units, their absolute values are not directly comparable with the centimeter- and second-based values reported in the instrumented-gait literature; scale calibration against a physical reference object is planned for future work.

Classification performance

Table 3 presents test-set performance for the three classifiers on the eight Boruta-selected features, with ROC curves shown in Figure 4. The SVM achieved the strongest overall performance, with an AUC of

Table 2. Descriptive statistics and univariate group comparisons for the eight selected gait features.

Feature	Autistic, mean $\pm$ SEM	Non-autistic, mean $\pm$ SEM	p	Test
Minimum left hip angle ($^{\circ}$)	142.67 $\pm$ 1.73	143.67 $\pm$ 1.02	0.941	Mann-Whitney
Right knee angle skewness	-0.90 $\pm$ 0.04	-0.88 $\pm$ 0.02	0.687	t-test
Right ankle angle skewness	0.15 $\pm$ 0.06	0.52 $\pm$ 0.07	< 0.001	t-test
Left ankle angle kurtosis	0.24 $\pm$ 0.23	0.67 $\pm$ 0.18	0.039	Mann-Whitney
Left dorsiflexion-plantarflexion CV	1.03 $\pm$ 0.02	1.00 $\pm$ 0.01	0.213	t-test
Maximum trunk vertical displacement (px)	663.98 $\pm$ 16.59	709.36 $\pm$ 10.13	0.016	t-test
Minimum center-of-mass vertical displacement (px)	568.19 $\pm$ 28.62	669.75 $\pm$ 7.49	0.004	Mann-Whitney
Step length (px)	45.50 $\pm$ 2.00	45.11 $\pm$ 0.93	0.847	t-test

Note: SEM = standard error of the mean; CV = coefficient of variation; px = pixels. Angle features are expressed in degrees. Skewness, kurtosis, and the coefficient of variation are dimensionless. Spatial features are expressed in pixel units within the video frame coordinate system and reflect relative positional differences within a standardized recording setup rather than absolute physical distances. Test selection was based on Shapiro-Wilk assessment of normality within each group.

Table 3. Classification performance of three classifiers on the held-out test set.

Model	Accuracy	Sensitivity	Specificity	F1	AUC
LR	0.619 (0.41–0.79)	0.444 (0.19–0.73)	0.750 (0.47–0.91)	0.500	0.676 (0.43–0.92)
RF	0.714 (0.50–0.86)	0.444 (0.19–0.73)	0.917 (0.65–0.99)	0.571	0.815 (0.62–1.00)
SVM	0.810 (0.60–0.92)	0.889 (0.57–0.98)	0.750 (0.47–0.91)	0.800	0.935 (0.80–1.00)

Note: LR = Logistic Regression (Elastic Net); RF = Random Forest; SVM = Support Vector Machine (RBF kernel). Values in parentheses are 95% confidence intervals.

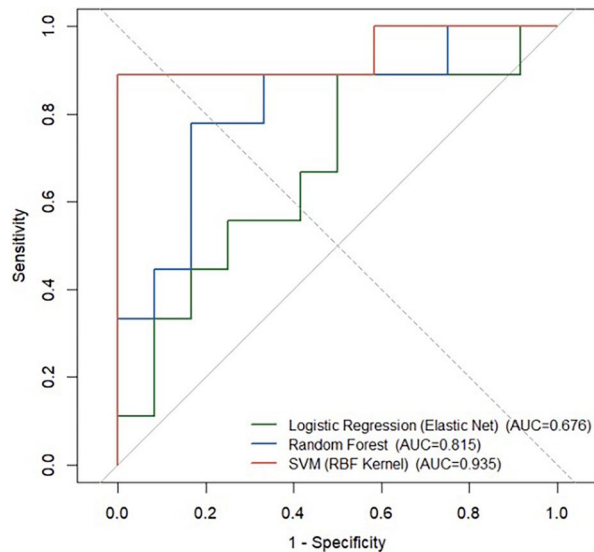


Figure 4. ROC curves for the three classifiers on the held-out test set ($n = 21$). The diagonal reference line indicates chance performance. AUC = area under the curve; LR = logistic regression (elastic net); RF = random forest; SVM = support vector machine (radial basis function kernel).

0.935, accuracy of 0.810, sensitivity of 0.889, and specificity of 0.750 (95% CIs in Table 3). In screening-relevant terms, the SVM correctly identified approximately nine out of every ten autistic children in the test set, while correctly clearing three out of every four non-autistic children; the remaining one in four would be flagged for follow-on evaluation, which is consistent with how a screening tool is expected to operate. These estimates were obtained on a small test set of 21 children including only nine autistic children, so the confidence intervals are wide, and the point estimates should be interpreted as preliminary.

The random forest achieved moderate overall performance ($AUC = 0.815$) but in a very different operating regime: high specificity (0.917) paired with low sensitivity (0.444), meaning the model correctly cleared most non-autistic children but missed more than half of the autistic children in the test set (four of nine correctly identified). Logistic regression performed least effectively ($AUC = 0.676$), suggesting that the relationship between the selected gait features and autism status is not well captured by a single

Table 4. Exploratory SVM performance on the held-out test set by subgroup.

Subgroup	n autistic	n non-autistic	Accuracy	Sensitivity	Specificity
Overall	9	12	0.810	0.889	0.750
By gender ^a					
Male	7	9	0.750	0.857	0.667
Female	1	3	1.000	1.000	1.000
By age band					
3–6 years	3	6	0.778	1.000	0.667
7–9 years	4	4	0.750	0.750	0.750
10–12 years	2	2	1.000	1.000	1.000
By SRS-2 T-score ^b					
≤ 50	0	6	0.500	—	0.500
51–70	3	6	1.000	1.000	1.000
≥ 71	4	0	0.750	0.750	—

Note: Analyses are exploratory and descriptive. Dashes indicate that a class is absent from the subgroup, leaving the metric undefined. Subgroup rows are not mutually exhaustive of the test set; see footnotes. ^aGender rows account for 20 of the 21 test-set children (8 of 9 autistic). One autistic participant identified as non-binary and is not represented in either row, as a single-participant category cannot be reported separately.

^bSRS-2 rows account for 19 of the 21 test-set children (7 of 9 autistic). SRS-2 Total T-scores were unavailable for two autistic participants in the test set, who were recruited through a community camp partner where the measure was not part of the protocol.

linear decision boundary and that the non-linear kernel of the SVM is providing meaningful prediction in this dataset.

Exploratory subgroup performance

Because subgroup sizes in the held-out test set are small, the following analyses are presented as exploratory description rather than as a powered test of differential model performance. Test-set performance of the SVM by gender, age band, and SRS-2 score band is presented in Table 4.

Across age bands, sensitivity was 1.00 in the 3–6 and 10–12-year subgroups, while the 7–9 year band showed balanced but slightly lower performance (sensitivity 0.75, specificity 0.75). The single misclassified autistic child fell in both the 7–9 year and SRS-2 ≥ 71 bands, and all three false positives were male children aged 3 to 7 with SRS-2 scores ≤ 50 . The model performed perfectly in the SRS-2 51–70 band, which contained a mix of autistic and non-autistic children with overlapping symptom profiles, suggesting that the gait features carry signal even where autism-related trait severity is moderate or ambiguous. The lower

specificity in the $\text{SRS-2} \leq 50$ band reflects three false positives among six non-autistic children with low SRS-2 scores.

These patterns must be interpreted with caution. With subgroup sizes ranging from 4 to 16, no autistic children in the $\text{SRS-2} \leq 50$ band, and no non-autistic children in the $\text{SRS-2} \geq 71$ band, several cells cannot support inference, and apparently perfect performance in some subgroups reflects small denominators rather than genuine robustness.

Discussion

This study found that two-dimensional video-based gait analysis, combined with traditional machine learning, can distinguish autistic from non-autistic children with a level of accuracy that warrants further investigation. The SVM, trained on eight interpretable gait features from ordinary video recordings, achieved an AUC of 0.935 on held-out test data. These results are consistent with prior 2D-video gait classification work in autism (Ganai et al. 2025; Kojovic et al. 2021) while extending it to a broader candidate-feature pool with systematic selection across multiple classifiers. The significance of this work extends beyond classification accuracy. At a conceptual level, it provides pilot evidence for adding gait to the portfolio of motor- and behavior-based autism screening signals (Crippa et al. 2015; Kojovic et al. 2021; Krishnappa Babu et al. 2024; Perochon et al. 2023), complementing the social-communication focus of current screeners (Guinchat et al. 2012). At a technological level, it demonstrates that gait analysis can be shifted from expensive laboratory equipment to everyday smartphone videos. At a translational level, it takes a step toward embedding well-established gait findings into a practical screening tool that is objective, language-independent, and usable without specialized equipment.

Limitations

The sample of 72 participants (30 autistic) is modest, the held-out test set contained only 21 children, and all analyses were conducted on a single dataset from one geographic area with limited demographic diversity, so generalizability to racially and ethnically diverse populations remains unknown. The autistic group also skewed more strongly male (73%) than the non-autistic group (64%); because the analysis pool included spatiotemporal and joint-kinematic features that may vary with body proportion and sex

independently of diagnosis, this imbalance is a potential source of confounding that a sample of this size cannot resolve, and sex-balanced sampling or sex-stratified modeling is required in larger validation cohorts. Feature selection was performed on the full sample prior to the held-out test split, so test-set metrics may be modestly optimistic; future work will move feature selection inside a nested cross-validation loop to remove this source of bias.

We did not administer a dedicated adaptive-functioning or sensory-processing instrument—the SRS-2 indexes social, communication, and restricted or repetitive traits and is not a validated measure of either—so we cannot evaluate whether classifier output relates to these dimensions. Age at acquisition of independent walking, global developmental level, and receipt of occupational or physical therapy services were likewise not recorded, although each could shape gait independently of diagnosis. Each child was also recorded in a single session, so the design supports within-session precision but gives no estimate of day-to-day stability. Adding these measures, and repeat recordings on separate occasions, is a priority for the planned validation study.

The autistic group was significantly heavier than the non-autistic group, and weight has been proposed as a confound in this literature (Lum et al. 2020). Two of the eight selected features correlated significantly with body weight: maximum trunk vertical displacement ($r = -0.37$, $p = 0.003$) and step length ($r = 0.56$, $p < 0.001$). Both are expressed in pixel units within the video frame coordinate system, so these associations plausibly reflect body size in the image rather than a weight-specific effect on gait mechanics. The remaining six features, including all four dimensionless shape and variability descriptors, showed no significant association with weight. Future studies should include height and weight as covariates, or match the comparison group on weight, to separate this contribution directly.

We did not collect information on the diagnostic teams or assessment procedures behind our participants' prior diagnoses. In the United States, autism diagnosis requires comprehensive clinical assessment against DSM-5-TR criteria, families often wait years to obtain it, and the process is especially burdensome for those with limited financial resources (Chen et al. 2023; Underwood Carrasco et al. 2026); once secured, most diagnoses (~87%) remain stable as the child ages (Blumberg et al. 2016). Over-diagnosis is rare relative to under-diagnosis, which is more common for children from racial and ethnic minority

backgrounds and for girls (Barbarese et al. 2022; Minutoli et al. 2026; Pham et al. 2022). Residual misclassification in this sample is therefore more likely to be a false negative in the non-autistic group than a false positive in the autistic group. Future studies should record diagnostic provenance directly.

One class of gait variability lies outside our protocol. Four of the eight selected features describe variability within the continuous joint-angle signal, but we did not compute variability across discrete strides—for example the coefficient of variation of stride length or stride time (Lum et al. 2020). With only four gait cycles per participant, such an estimate carries a standard error of approximately 41% of its own value, too imprecise for per-child measurement.

Future directions

Future work should expand the feature space beyond the lower-body kinematic parameters examined here to include whole-body coordination indices and additional variability metrics. Larger, multi-site studies with demographically diverse participants are needed for meaningful external validation. Beyond the descriptive criterion validity provided by the SRS-2 difference between groups in this study, future work should evaluate criterion validity against gold-standard diagnostic instruments such as the ADOS-2 in a larger sample. Investigating whether models developed in school-aged children generalize to younger children in the early-intervention window (ages 2 to 3) is a priority, since developmental gait patterns at those ages differ markedly from those of school-aged children. Gait-based screening will only be clinically useful if it works in children under three, the age range where early intervention does the most good (Guthrie et al. 2023). Gait parameters in toddlers are shaped heavily by overall developmental level and by how recently a child began walking independently, and future work must account for these factors directly rather than treating age as a simple covariate. Whether autistic toddlers specifically can reliably complete even a task this simple is an open empirical question rather than an assumption, and should be established before any screening application is attempted in this age range. Beyond primary screening, this language-independent approach could also contribute to the evaluation of difficult cases in differential diagnosis, for instance in separating autism from developmental language disorder when literacy or communication barriers limit traditional screeners (Buac et al. 2023). Motor impairment risk in autistic children also rises with the severity of social-communication

and cognitive challenges (Bhat 2021); mapping that relationship more closely could sharpen the characterization of the autistic motor profile (Miller et al. 2024).

A practical translational pathway for this approach is a web-based screening platform that processes a caregiver-recorded walking video and returns a probability of autism likelihood within minutes. In a clinical workflow, such a tool could complement parent-report screeners, with referral for formal evaluation prompted when both questionnaire and gait-based signals cross threshold. As a stand-alone secondary screener, it could be deployed when parental questionnaires return ambiguous or borderline results, or in primary-care settings where in-person specialist observation is not feasible. Likely users include pediatricians, school nurses, early-childhood specialists, and caregivers, especially those in low-resource or rural settings, all of whom currently lack an objective motor-domain instrument. Throughout, the tool would function as decision support: it returns a calibrated probability with a confidence interval, not a diagnosis, and the clinician remains the decision-maker.

These results should not be interpreted as evidence of clinical readiness; larger studies with diverse populations are essential before any screening application can be considered. Despite these limitations, the convergence of well-established motor differences in autism, increasingly accessible video-based measurement tools, and effective machine learning methods supports continued investigation of gait-based screening. By adding motor behavior to the screening repertoire, this line of research opens a new pathway for autism detection that complements existing approaches and has the potential to reduce diagnostic delays, particularly for children in underserved communities.

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Ethical approval

All procedures performed in this study involving human participants were approved by the Northern Illinois University Institutional Review Board (Protocol Number: HS23-0046; approved October 13, 2022).

Informed consent

Written informed consent was obtained from the parent or legal guardian of each participant prior to the visit.

Children provided verbal assent appropriate to their developmental level prior to participation. Separate written consent was obtained for the use of video recordings for research purposes.

Generative AI usage statement

During the preparation and revision of this manuscript, the authors used Anthropic's Claude (claude-opus-4-7, claude-opus-5) for language editing, structural feedback, and consistency checks across drafts. The authors reviewed and edited all AI-assisted output, take full responsibility for the final content of the publication, and confirm that no protected health information was shared with the model.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The video data that support the findings of this study are not publicly available due to privacy restrictions involving identifiable footage of minors. De-identified summary data, model code, and trained model weights are available from the corresponding author upon reasonable request, subject to a data-use agreement.

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