Diagnosing Autism Spectrum Disorder in Pediatric Patients via Gait Analysis using ANN and SVM with Electromyography Signals

Rozita Jailani[1]*, Nur Khalidah Zakaria[2], M. N. Mohd Nor[3], Heru Supriyono[4]
Integrative Pharmacogenomics Institute, Universiti Teknologi MARA, 42300, Puncak Alam, Selangor, Malaysia[1]
School of Electrical Engineering-College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia[1, 2]
Politeknik Balik Pulau, Pinang Nirai, Mukim 6, 11000 Balik Pulau, Penang, Malaysia[3]
Department of Electrical Engineering, Universitas Muhammadiyah Surakarta, Indonesia[4]

***Abstract*—Autism Spectrum Disorder (ASD) is a permanent neurological maturation condition that impacts communication, social interaction, and behavior. It is also associated with atypical walking patterns. This study aims to create an automated classification model to distinguish ASD children during walking based on the muscles Electromyography (EMG) signals. The study involved 35 children diagnosed with ASD and an equal number of typically developing (TD) children, all aged between 6 and 13 years. The Trigno Wireless EMG System was used to collect EMG signals from specific muscles in the lower limb (Biceps Femoris - BF, Rectus Femoris - RF, Tibialis Anterior - TA, Gastrocnemius - GAS) and the arm (Biceps Brachii - BB, Triceps Brachii - TB) on the left side. To identify the most significant features influencing walking in ASD children, a statistical analysis using the Mann-Whitney Test was conducted. The dataset contained 42 features derived from the analysis of six muscles across seven distinct walking phases throughout a single gait cycle. Following this, the Mann-Whitney Test was utilized for feature selection, uncovering five significantly distinctive features within the EMG signals between children with ASD and those who were typically developing. The most notable EMG features were subsequently employed in constructing classification models, namely an Artificial Neural Network (ANN) and a Support Vector Machine (SVM), aimed at distinguishing between children with ASD and those who were typically developing. The results indicated that the SVM classifier outperformed the ANN classifier, achieving an accuracy rate of 75%. This discovery shows potential for employing EMG signal analysis and classification model algorithms in diagnosing autism, thereby advancing precision health.**

Keywords*—Autism Spectrum Disorder; Electromyography signals; Artificial Neural Network; Support Vector Machine; precision health

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a lifelong neurodevelopmental condition distinguished by speech impairments, atypical behaviors, and difficulties in social communication. Certain children diagnosed with ASD may display motor-related challenges concerning gross motor skills, encompassing issues with motor coordination, muscle tone, arm movement, postural stability and gait. These motor difficulties are linked to the intricate interplay between the neurotransmitter system and specific brain structures, which influence both basic motor skills and sensory-motor performance [1]. Typically, children with ASD display distinct gait patterns, often characterized by clumsiness [2], subtlety, and a wide base [3-4]. In some cases, children with ASD may exhibit toe-walking tendencies, which are more closely associated with motor behavior than language development. Therefore, early detection of ASD can rely on motor indicators [5-6]. Children with ASD may experience motor delays in gross and fine motor skills, affecting their locomotion [2, 7].

Electromyography (EMG) is an experimental methodology employed in the development, recording, and analysis of myoelectric signals. Its application, particularly in the biomedical field, has grown significantly. EMG-based models have provided accurate results in adjusting musculoskeletal geometry, such as muscle-tendon lengths, velocities, and arm moments for individuals with high-functioning hemiparesis during walking [8]. EMG signal analysis can also measure variations in EMG waveforms during different walking conditions, contributing to human-machine interactions and the adaptability of locomotion activities [9]. Research indicates a notable decrease in the activity of hip adductors and hamstring muscles during walking among individuals with wider pelvises [10].

Gait, the method by which walking occurs, can undergo clinical assessment through various means, such as laboratory tests like surface EMG, force plates, and kinematic assessments. The central nervous system plays a pivotal role in transmitting commands that activate the muscular system, ultimately facilitating movement. Measuring muscular activity through non-invasive EMG is a suitable method for characterizing motor activity [11]. The application of EMG in the rehabilitation of central neurological disorders, including autism and cerebral palsy, has demonstrated successful outcomes [12-13].

The perceptron-based technique employs algorithms rooted in the perceptron concept, encompassing single-layered perceptrons, multi-layered perceptrons, and Radial Basis Function (RBF) networks [14]. Between these, Artificial Neural Networks (ANN), a subtype of multi-layered perceptrons, has gained prominence in the analysis of EMG signals in various applications related to human gait, including classification [15, 16], prediction of gait angles [17, 18], and

*Corresponding Author.

muscle activation [15, 19]. ANN algorithms have been developed to bridge the gap between kinematic movement planning and human muscle activation for normal locomotion. These algorithms adjust parameters such as stance width, stride length, cadence and foot clearance [20]. Wang [15] developed an ANN-based model to address the challenge of accurate muscle activation prediction, showing a strong relationship between EMG signals and joint moments [15]. ANN has been widely used for gait pattern classification [17, 21-22]. Jung [22], for example, applied neural networks to classify gait phases for controlling exoskeleton robots, demonstrating superior performance compared to traditional gait classification methods using foot sensors. ANN has also proven effective in distinguishing between healthy individuals and those with pathological gait, as it can identify relevant parameters specific to classification tasks [17]. Thus, ANN is a valuable tool for gait classification.

The Support Vector Machine (SVM) is a widely employed machine learning technique utilized for data analysis, classification and pattern recognition. SVM algorithms have been applied in numerous studies involving EMG signal analysis [23-26]. SVM has shown potential as a classifier for developing fully automatic EMG signal analysis systems for clinical use. It has successfully identified neuromuscular diseases with a classification accuracy of 100% by combining multi-class SVM algorithms with autoregressive (AR) features [24]. SVM algorithms have also excelled in distinguishing various human activities based on EMG signal data. An SVM classifier utilizing AR-based features attained a recognition rate more than 90% for activities like standing still, walking, running and jumping, and surpassing the performance of conventional SVM classifiers [26]. EMG signals have even been used for hand gesture recognition, with bend resistive sensors and SVM classifiers achieving a classification accuracy of 93.33%, making it suitable for communication by soldiers [27].

Notably, there has been limited attention given to the automated classification of ASD children based on EMG signals. Therefore, this study aims to differentiate between ASD and typically developing (TD) children using EMG signal analysis during walking. The lower limb and arm muscles examined in this study include Biceps Femoris (BF), Rectus Femoris (RF), Tibialis Anterior (TA), Gastrocnemius (GAS), Biceps Brachii (BB), and Triceps Brachii (TB). At the conclusion of this study, two classification models, namely ANN and SVM, were trained to distinguish EMG signals between children with ASD and typically developing children. The research seeks to assist medical practitioners in diagnosing ASD in children based on EMG signals from lower limb and arm muscles during walking, as there is currently no definitive medical test for ASD diagnosis [19].

II. METHODOLOGY

This section provides an in-depth explanation of the proposed classification system illustrated in Fig. 1. The system comprises four key stages: EMG data acquisition, pre-processing techniques, data selection and extraction methods, and the development of the classification model.

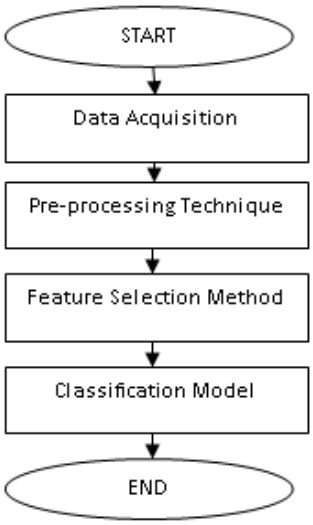

Fig. 1. Overall flowchart.

A. Data Acquisition

In this study, 35 children diagnosed with ASD and 35 typically developing children, aged between 6 and 13 years, with no history of orthopedic surgery, participated. All participants, both ASD and TD, displayed the capability to follow oral guidance given by the researcher. The ASD children were recruited from the National Autism Society of Malaysia (NASOM) center, local kindergarten and primary school in Selangor. The research procedures received ethical approval from the local ethics committee of Universiti Teknologi MARA (UiTM) in Shah Alam, Selangor, Malaysia, from May 29, 2015, to 2023 with updated database. Additionally, all participants were provided with written informed consent forms before participating.

EMG data were collected while the subjects walked naturally at a normal pace. The EMG signals were recorded using the Trigno Wireless EMG System, a product of Delsys Inc. This system is specifically designed for reliable and consistent detection of EMG signals while minimizing noise interference. Each EMG sensor in the system is equipped with a built-in triaxial accelerometer, has a communication radius of 40 meters, and features a rechargeable battery with a minimum runtime of seven hours. The system can transmit data to EMG Works Acquisition and Analysis software and supports up to 16 EMG sensors (measuring 37mm x 26mm x 15mm) and 48 accelerometer analog channels, facilitating integration with Vicon motion capture and data acquisition systems. Furthermore, the system offers full triggering capabilities, expanding the potential for integration with additional measurement technologies.

During data collection, surface electrodes were used, and their placement followed the SENIAM convention system, ensuring that the distance between electrodes did not exceed one-fourth of the muscle fiber length [28]. Specifically, 12 EMG sensors were affixed to the subjects' skin to capture EMG signals from the muscles of BF, RF, TA, GAS, BB, and TB. To secure the electrodes during the experiments, self-adhesive tapes were applied to the skin above the selected muscles, as depicted in Fig. 2.

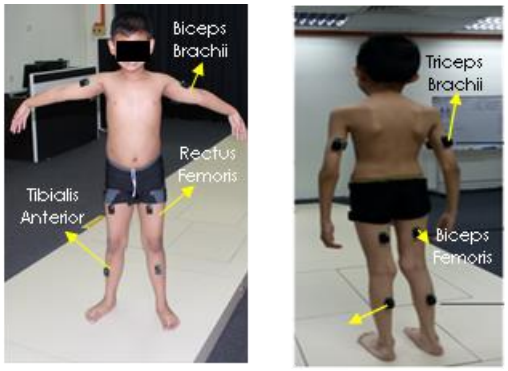

Fig. 2. Electrode placement on subject.

A securely positioned video camera was synchronized with the EMGWorks 4 Acquisition software to allow simultaneous recording of both movement and EMG data. This ensured synchronization in timing between the video camera and the software. To maintain consistency, a sample rate of 2000 Hz was chosen for recording, a rate achievable by all devices in this setup. EMG data for a single gait cycle was extracted and normalized as a percentage of the entire gait cycle duration. In this study, a gait cycle was defined as the duration between two consecutive heel strikes of the same leg. It's important to note that only EMG signals from the left lower limbs and arm muscles were considered for analysis in this study.

B. Pre-processing Techniques

At this stage, the raw EMG signals were normalized to a single complete gait cycle to minimize the influence of environmental noise that might have been present during data collection. Time normalization was selected as the most reliable method to enhance the quality of gait cycle analysis for EMG signal data [29]. It's important to note that each subject had varying time frames due to differences in walking speed and step length. To address this, EMG signal data for each muscle was controlled to fit within one gait cycle, ensuring consistency and obtaining standardized EMG signals for gait analysis.

In this study, a complete gait cycle was defined as the duration from the left foot's initial contact to its terminal swing. This definition was applied due to the generally insignificant differences in gait parameters between the left and right legs during normal walking [30]. The EMG signals obtained via the EMG Works Acquisition software and the duration of one gait cycle from the video camera were synchronized.

Fig. 3 and Fig. 4 illustrate the phases of the gait cycle and arm movements during normal walking, respectively. During walking, the ipsilateral arm and leg exhibit an anti-phase relationship, with the left leg in flexion and external rotation while the left arm is in internal rotation and extension. When one arm moves forward, the corresponding leg and torso move forward, and this relationship alternates between the left and right sides [31]. As walking speed increases, the contribution of active muscles to arm movements increases, while the total energy consumption decreases [31]. A previous study [32] has demonstrated that arm swinging during walking contributes to the stability of human gait.

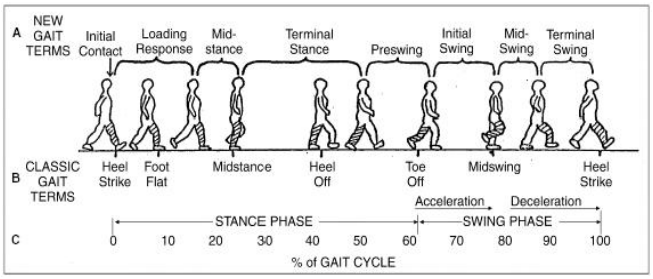

Fig. 3. Phases of one gait cycle.

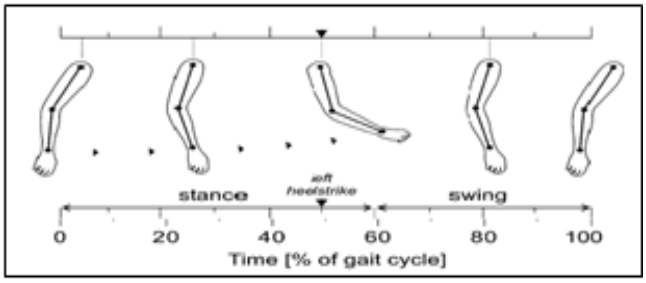

Fig. 4. Arms swing during normal walking [34].

The gait cycle normalization in this study involved two steps. The first step was time-normalizing the EMG signal data for the relevant muscles of all subjects to one gait cycle, expressed as a percentage. The time taken to complete one gait cycle in the recorded video was equated with the time frame of the acquired data. The 100% gait cycle represents the time taken for one complete gait cycle [33]. The second step involved averaging the normalized EMG signal data for the same muscle across all subjects. The normalization process for EMG signal analysis was conducted using Microsoft Excel software version 2013 (Microsoft Corp., USA). This study analyzed the tested muscles across seven gait phases: loading response (LR) spanning 0% to 10% of the gait cycle, mid-stance (MST) covering 10% to 30%, terminal stance (TST) ranging from 30% to 50%, pre-swing (PSW) encompassing 50% to 60%, initial swing (ISW) spanning 60% to 70%, mid-swing (MSW) ranging from 70% to 90%, and terminal swing (TSW) from 90% to 100% of the gait cycle.

C. Feature Selection Method

The feature selection process involved identifying a new set of muscles comprising the most significant features to differentiate between ASD and TD children [34], subsequently enhancing the classification performance. Initially, the normalized EMG data were subjected to an examination of normality using the Shapiro-Wilk test. This test was employed to assess whether the dataset exhibited a normal distribution or not. Given the relatively small number of subjects, the Shapiro-Wilk test is considered an appropriate method to determine the normality of the data. This test is particularly accurate and reliable in assessing the normality of scores [35]. Subsequently, non-parametric testing was applied since the data distribution in this study was found not to be normally distributed [35]. The study utilized the Mann-Whitney test with a 95% confidence interval to explore significant features within the EMG data of muscles including Biceps Brachii (BB), Rectus Femoris (RF), Gastrocnemius (GAS), Biceps Femoris (BF), Tibialis Anterior

(TA), and Triceps Brachii (TB) during walking, comparing children diagnosed with ASD and typically developing children.

D. Classification Model Development

This research presented two classification models: the Artificial Neural Network (ANN) and the Support Vector Machine (SVM); with the aim of distinguishing between ASD walking patterns and normal walking patterns. The computation of these algorithms was carried out using Matlab software version R2014a for evaluation. The input data for both classification models were derived from the significant muscle features that differed between ASD and TD children. The division of input-output data was based on the cross-validation method, where the output represented the classification group for each condition, with '0' indicating ASD and '1' indicating TD children.

One of the most commonly used techniques to assess the performance of the proposed classifier is stratified k-fold cross-validation. In this study, five-fold cross-validation was conducted. This means that the original sample was randomly divided into five equal-sized subsamples. One of these subsamples was used as the training data, while the remaining four subsamples were retained as validation data to test the model. This process was repeated five times, corresponding to the number of folds. Each observation was used for both training and validation, but only once for validation in each fold [36]. It is worth noting that the use of K-fold cross-validation is a reliable method and has the potential to provide meaningful results for estimating expected utilities [37].

For the ANN classification model, the number of hidden neurons in the hidden layer was set to achieve the best accuracy for adjusting the network weights. Scaled Conjugate Gradient (SCG) training algorithm, the optimum number of 10 neurons are found to be the optimum model accuracy. The selection of the network architecture involved testing the performance of the network by varying the number of hidden neurons from 1 to 11 in two-interval increments. The scaled conjugate gradient method was employed to train the network, which updates weight and bias values.

Regarding the SVM classification model, the input data were trained using name-value pair arguments for the kernel function. In this study, the linear kernel function, also known as the dot product, was used to obtain the best accuracy. Subsequently, each row of the sample data was classified using the information in the SVM classifier structure. The performance of both the ANN and SVM classification models was evaluated using a confusion matrix, which included measures such as accuracy, precision, sensitivity, and specificity.

III. Results and Discussion

In this segment, we will examine the acquired results and initiate a discussion. A total of sixty children took part in this study, with 35 diagnosed with ASD and 35 TD children. The demographic information for both the ASD and TD groups is outlined in Table I. Notably, both groups exhibited a similar mean age, with ASD children having a mean age of 8.10 and TD children having a mean age of 9.40. However, the age variation was slightly wider among TD children, ranging from 6.30 to 11.06 years, compared to ASD children, whose ages ranged from 6.30 to 10.50 years. Correspondingly, TD children had a higher mean height and weight compared to ASD children, with mean heights of 128.5 cm and 124.7 cm and mean weights of 30 kg and 28.8 kg, respectively. The range of heights for TD children was more extensive, spanning from 95 cm to 159.5 cm, resulting in a higher standard deviation (SD) of 18.07, compared to ASD children's SD of 13.26. However, the weight variation among both ASD and TD children exhibited a comparable pattern, with standard deviation (SD) values of 11.14 and 11.60, respectively. It is noteworthy to mention that a substantial proportion of the ASD subjects approached by the researcher were boys, as depicted in Fig. 5. Approximately 60% of the ASD children involved in this study were male. This observation may be attributed to the fact that diagnosing autism in boys is often more straightforward than in girls. This finding aligns with previous research, which has consistently shown that ASD is nearly five times more common in boys than in girls [38].

The outcomes of the Mann-Whitney test unveiled noteworthy distinctions ($p < 0.05$) in muscle activation between these two cohorts of children, as succinctly outlined in Table II. Specifically, five muscles were found to be significantly useful in distinguishing between 'Normal' and 'Autism' categories. The p-value for the TA (30%) muscle was found to be 0.017, whereas for the BB the corresponding p-values were 0.021 (10%) and 0.018 (80%), respectively. Meanwhile, the GAS muscle displayed p-values of 0.049 (50%) and 0.034 (60%) respectively. Drawing from the results detailed in Table II, it can be deduced that there exist notable distinctions (highlighted in gray) in the activation of lower limb and arm muscles between ASD and TD children during walking, particularly in the TA, GAS, and BB muscles.

TABLE I. Subjects Demographic Data

Subjects	Age (years)		Height (cm)		Weight (kg)	
	Ave	SD	Ave	SD	Ave	SD
ASD	8.10	2.20	124.5	13.26	27.5	11.14
TD	9.40	2.67	128.5	18.07	30.0	11.60

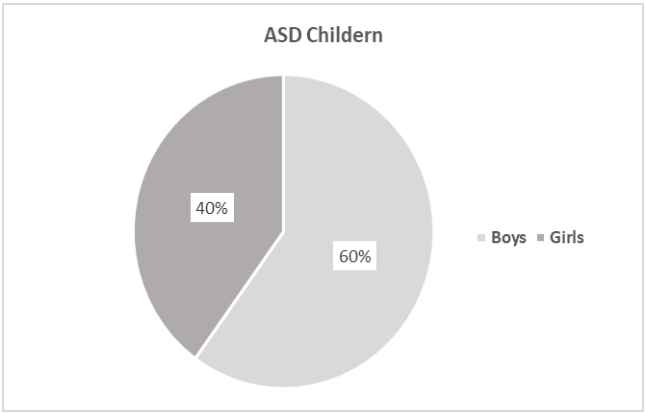

Fig. 5. Gender data for ASD children.

TABLE II. RESULTS FROM MANN-WHITNEY TEST

Gait Cycle	LR 10%	MST 30%	TST 50%	PSW 60%	ISW 80%	MSW 90%	TSW 100%
BF	0.688	0.494	0.495	0.441	0.415	0.321	0.54
RF	0.925	0.803	0.75	1.001	0.651	0.635	0.232
TA	0.974	0.017	0.273	0.534	0.477	0.852	0.69
GAS	0.136	0.162	0.048	0.033	0.305	0.182	0.52
BB	0.02	0.401	0.173	0.864	0.002	0.83	0.491
TB	0.475	0.277	0.964	0.858	0.573	0.682	0.284

The performance of the ANN classifier was assessed using a confusion matrix, as depicted in Table III. The confusion matrix reveals that out of the ASD children group, 3 data points were accurately classified as belonging to the ASD group, and 5 data points from the TD children group were correctly classified as TD. However, there were 3 instances where data from the ASD children group were erroneously classified as TD children, and only 1 data point from the TD children group was incorrectly categorized as ASD children. The accuracy of the SCG ANN classifier is calculated at 66.7%. Additionally, the classifier exhibited a specificity of 91.7%, sensitivity of 79.2%, and precision of 90.5%.

The performance of the SCG ANN classification model was calculated based on the disparity between the actual and predicted gait parameters derived from the EMG signal data. As illustrated in Fig. 6, the x-axis denotes the number of hidden neurons, while the y-axis represents the MSE values. The highest error was observed with four hidden neurons, resulting in an MSE value of 0.9482. In contrast, the lowest error was achieved when using 10 hidden neurons, yielding an MSE value of 0.1542. Notably, in this study, the SCG ANN system with 10 hidden neurons exhibited the most favorable performance among the classification model algorithms. The distribution of error within a neural network serves as a valuable area for exploration and is recommended for determining improved neural network performance criteria and addressing conflicting classification results [39].

TABLE III. CONFUSION MATRIX FOR SCG ANN CLASSIFICATION MODEL

	Positive	Negative
Positive	3 (TP)	1 (FN)
Negative	3 (FP)	5 (TN)

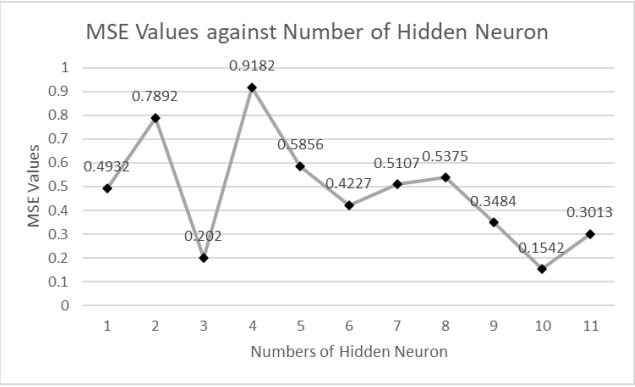

Fig. 6. MSE value in testing performance.

TABLE IV. CONFUSION MATRIX FOR SVM CLASSIFICATION MODEL

	Positive	Negative
Positive	7 (TP)	2 (FN)
Negative	1 (FP)	2 (TN)

The performance of the SVM classifier was assessed using a confusion matrix, as presented in Table IV. The confusion matrix indicates that 7 data points from the ASD children group were accurately classified as belonging to the ASD group, and 2 data points from the TD children group were correctly classified as TD. However, 1 data point from the ASD group was erroneously classified as TD, and 2 data points from the TD group were incorrectly categorized as ASD. With an accuracy of 75%, the SVM classifier demonstrates robust classification capabilities for distinguishing between ASD and TD children. Additionally, the classifier exhibited a specificity of 50%, sensitivity of 87.5%, and precision of 78%.

Fig. 7 provides a comparison of the performance measures of the SCG ANN and SVM classifiers. Notably, the ANN classifier outperformed the SVM classifier in terms of precision and specificity, achieving values of 90.5% and 91.7%, respectively. Conversely, the SVM classifier surpassed the SCG ANN classifier in terms of accuracy and sensitivity, with values of 75% and 87.5%, respectively. It is worth mentioning that specificity is particularly valuable when interpreting positive test results to estimate an individual's probability of having a disease [40]. Overall, both developed classifiers demonstrated impressive performance with consistent rates of accuracy, sensitivity, specificity, and precision.

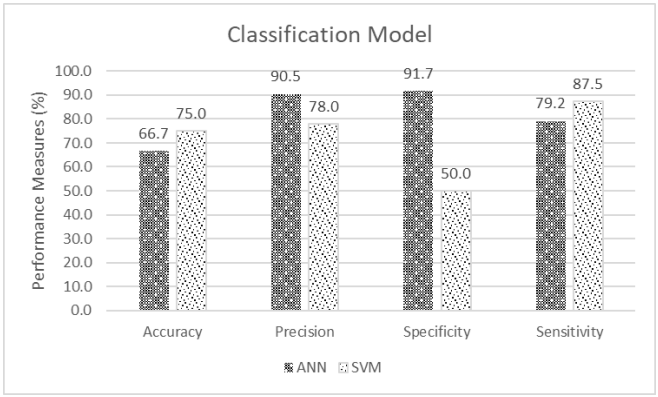

Fig. 7. Comparison of performance measures for ANN and SVM classifier.

As previously mentioned, the primary objective of this investigation was to categorize ASD and TD children by analyzing EMG signals recorded during walking. Despite its inherent challenges, the analysis of EMG data provides valuable insights into diagnosing ASD children through the assessment of muscle activation during walking. In the initial phase of the study, a database of EMG signals for both ASD and TD children during walking was established through the data collection process. The Mann-Whitney test, with a 95% confidence interval, was utilized to scrutinize significant differences in muscle activation among BF, RF, TA, GAS, BB, and TB muscles in both groups of children. The analysis of EMG signals has emerged as a promising diagnostic approach

for identifying autism based on muscle activation patterns during walking.

The subtle motor deficits in individuals with autism can manifest as abnormal gait patterns, with variations in muscle extension being a contributing factor [41]. Difficulties in walking among children with ASD may arise due to heightened variability in velocity and the manifestation of irregularities in stride length and duration [42]. Additionally, a study by [43] demonstrated that movement disorders were observable in ASD children, characterized by irregular steps and vigilant gait during normal walking, as observed in video recordings during experiments. This study has revealed that three muscles—TA, GAS, and BB—were affected during walking in ASD children. The TA muscle, in particular, showed significant activation differences between ASD and TD children [44]. This discovery aligns with earlier research indicating that body movement and arm swing during walking can amplify TA muscle activity [45].

Similarly, while the walking patterns of ASD children may appear relatively normal on the surface, many of them exhibit subtle gait abnormalities that can impact lower limb muscle activation [41]. The BB muscle exhibited significant disparities between ASD and TD children during walking, likely attributable to its role as a primary mover during the concentric phase [45]. Consequently, the BB muscle in ASD children was notably affected and distinct from that in TD children during walking. These results substantiate the study's hypothesis, which proposed that EMG data from ASD children during walking could be precisely classified using SCG ANN and SVM classifiers.

As far as we are aware, our study constitutes the initial exploration into the classification of ASD and TD children based on muscle activation in both lower limb and arm muscles during walking. The results demonstrate that the proposed method successfully classifies ASD and TD children, with high accuracy, specificity, sensitivity, and precision. This research has significant implications for both rehabilitation and clinical applications. The experimental results validate the accomplishment of the study's objectives, and the selected parameters for investigating gait in ASD children during walking have been validated by previous researchers.

The developed classification model system exhibits robust performance, achieving high accuracy rates, specificity, sensitivity, and precision. While this study has succeeded in classifying ASD and TD children, future research may consider classifying the severity of ASD conditions, as suggested by [46]. Additionally, expanding the sample size of ASD participants could further validate the EMG signal patterns observed in this study.

IV. Conclusion

In conclusion, this study has revealed significant differences in muscle activation patterns in the lower limbs and arms of individuals with ASD during walking, focusing on muscles including BF, RF, TA, GAS, BB, and TB. Notably, the TA, GAS, and BB muscles exhibited distinctive features between ASD and typically developing individuals. Two classification models, SCG ANN and SVM, were then introduced to discern these features from the EMG signals. Following classifier training, the SVM model emerged as particularly promising for distinguishing between ASD and TD children. These findings underscore the significant characteristics present in EMG signals between ASD and TD individuals, affirming the efficacy of classification model algorithms in differentiation. This discovery holds substantial potential for automating ASD screening and diagnosis, facilitating the design of more effective treatments and rehabilitation strategies by parents and therapists, thus advancing precision health.

Acknowledgment

The authors wish to thank Institute of Research Management Centre (RMC) and College of Engineering, Universiti Teknologi MARA (UiTM) Shah Alam, Malaysia for the financial support, instrumentation and experimental facilities provided. The authors also express gratitude to the National Autism Society of Malaysia (NASOM), all participants, their families and caretakers for their invaluable contributions to the study.

References

[1] M. L. Cuccaro, L. Nations, J. Brinkley, R. K. Abramson, H. H. Wright, A. Hall, J. Gilbert and M. Pericak-Vance, “A comparison of repetitive behaviors in Aspergers Disorder and high functioning autism.,” Child Psychiatry Hum. Dev., vol. 37, no. 4, pp. 347–60, Apr. 2007.

[2] A. P. Association, Diagnostic and statistical manual of mental disorders (DSM-5®): American Psychiatric Pub, 2013.

[3] M. Shetreat-Klein, S. Shinnar, and I. Rapin, “Abnormalities of joint mobility and gait in children with autism spectrum disorders,” Brain Dev., vol. 36, no. 2, pp. 91–96, 2014.

[4] M. Nobile, P. Perego, L. Piccinini, E. Mani, A. Rossi and M. Bellina, “Further evidence of complex motor dysfunction in drug naive children with autism using automatic motion analysis of gait.,” Autism, vol. 15, no. 3, pp. 263–83, May 2011.

[5] Mukherjee, D., Bhavnani, S., Lockwood Estrin, G., Rao, V., Dasgupta, J., Irfan, H., Chakrabarti, B., Patel, V. and Belmonte, M.K.,. Digital tools for direct assessment of autism risk during early childhood: A systematic review. Autism, 28(1), pp.6-31. 2024.

[6] Athanasiadou, A., Buitelaar, J.K., Brovedani, P., Chorna, O., Fulceri, F., Guzzetta, A. and Scattoni, M.L,. Early motor signs of attention-deficit hyperactivity disorder: A systematic review. European Child & Adolescent Psychiatry, 29, pp.903-916. 2020.

[7] Wang, L. A., Petrulla, V., Zampella, C. J., Waller, R., & Schultz, R. T. Gross motor impairment and its relation to social skills in autism spectrum disorder: A systematic review and two meta-analyses. Psychological bulletin, 148(3-4), 273. 2022.

[8] A. J. Meyer, C. Patten, and B. J. Fregly, “Lower extremity EMG-driven modeling of walking with automated adjustment of musculoskeletal geometry,” PLoS One, vol. 12, no. 7, pp. 1–24, 2017.

[9] F. Sylos-Labini, V. La Scaleia, A. D'Avella, I. Pisotta, F. Tamburella, G. Scivoletto, M. Molinari, S. Wang, L. Wang, E. van Asseldonk, H. van der Kooij, T. Hoellinger, G. Cheron, F. Thorsteinsson, M. Ilzkovitz, J. Gancet, R. Hauffe, F. Zanoy, F. Lacquaniti andf Y. P. Iyanenko, “EMG patterns during assisted walking in the exoskeleton,” Front. Hum. Neurosci., vol. 8, no. June, pp. 1–12, 2014.

[10] C. M. Wall-Scheffler, E. Chumanov, K. Steudel-Numbers, and B. Heiderscheit, “EMG activity across gait and incline: The impact of muscular activity on human morphology,” vol. 143, no. 4, pp. 601–611, 2010.

[11] Li, L., Zhang, L., Cui, H., Zhao, Y., Zhu, C., Fan, Q., & Li, W. Gait and sEMG characteristics of lower limbs in children with unilateral spastic cerebral palsy during walking. Gait & Posture, 108, 177-182, 2024.

[12] Al-Ayyad, M., Owida, H. A., De Fazio, R., Al-Naami, B., & Visconti, P. Electromyography Monitoring Systems in Rehabilitation: A Review of Clinical Applications, Wearable Devices and Signal Acquisition Methodologies. Electronics, 12(7), 1520, 2023.

[13] Sawacha, Z., Spolaor, F., Piątkowska, W.J., Cibin, F., Ciniglio, A., Guiotto, A., Ricca, M., Polli, R. and Murgia, A.. Feasibility and reliability assessment of video-based motion analysis and surface electromyography in children with fragile X during gait. Sensors, 21(14), p.4746. 2021.

[14] S. B. Kotsiantis, "Supervised machine learning: A review of classification techniques," Informatica, vol. 31, pp. 249–268, 2007.

[15] de Jonge, S., W. V. Potters, and C. Verhamme. "Artificial intelligence for automatic classification of needle EMG signals: a scoping review." Clinical Neurophysiology, 2024.

[16] Jiao, Yiran, Rylea Hart, Stacey Reading, and Yanxin Zhang. "Systematic Review of Automatic Post-Stroke Gait Classification Systems." Gait & Posture, 2024.

[17] Liu, S. H., Ting, C. E., Wang, J. J., Chang, C. J., Chen, W., & Sharma, A. K. Estimation of Gait Parameters for Adults with Surface Electromyogram Based on Machine Learning Models. Sensors, 24(3), 734. 2024.

[18] Amrani El Yaakoubi, N., McDonald, C., & Lennon, O. Prediction of Gait Kinematics and Kinetics: A Systematic Review of EMG and EEG Signal Use and Their Contribution to Prediction Accuracy. Bioengineering, 10(10), pp. 1162, 2023.

[19] J. W. Lee and G. K. Lee, "Gait Angle Prediction for Lower Limb Orthotics and Prostheses Using an EMG Signal and Neural Networks," Int. J. Control. Autom. Syst., vol. 3, no. 2, pp. 152–158, 2005.

[20] S. D. Prentice, a E. Patla, and D. a Stacey, "Artificial neural network model for the generation of muscle activation patterns for human locomotion.," J. Electromyogr. Kinesiol., vol. 11, no. 1, pp. 19–30, 2001.

[21] J. Mcbride, S. Zhang, M. Paquette, G. Klipple, E. Byrd, L. Baumgartner and X. Zhao, "Neural Network Analysis of Gait Biomechanical Data for Classification of Knee Osteoarthritis," 1986.

[22] J. Y. Jung, W. Heo, H. Yang, and H. Park, "A neural network-based gait phase classification method using sensors equipped on lower limb exoskeleton robots," Sensors (Switzerland), vol. 15, no. 11, pp. 27738–27759, 2015.

[23] J. Miller, "Walking Mode Classification through Myoelectric and Inertial Sensors for Transtibial Amputees," Master's Thesis, no. University of Washington, 2012.

[24] G. Kaur, A. Arora, and V. Jain, "Multi-class support vector machine classifier in EMG diagnosis," WSEAS Trans. Signal Process., vol. 5, no. 12, pp. 379–389, 2009.

[25] X. Jiang, "EMG based input and control system for lower limb prostheses," pp. 1–48, 2010.

[26] Z. He and L. Jin, "Activity recognition from acceleration data using AR model representation and," SVM, IEEE Int. Conf. Mach. Learn. Cybern., vol. vol, no. July, p. 4pp2245-2250, 2008.

[27] R. Tidwell, S. Akumalla, S. Karlaputi, R. Akl, K. Kavi, and D. Struble, "Evaluating the Feasibility of EMG and Bend Sensors for Classifying Hand Gestures," no. 63, pp. 1–8, 2013.

[28] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of Recommendations for sEMG Sensors and Sensor Placement Procedures," vol. 10, pp. 361–374, 2000.

[29] L. Al Shalabi and Z. Shaaban, "Normalization as a Preprocessing Engine for Data Mining and the Approach of Preference Matrix," 2006.

[30] J. Romkes, A. K. Hell, and R. Brunner, "Changes in muscle activity in children with hemiplegic cerebral palsy while walking with and without ankle – foot orthoses," 2006.

[31] J. P. Ã, "Synthesis of natural arm swing motion in human bipedal walking," vol. 41, pp. 1417–1426, 2008.

[32] S. M. Bruijn, O. G. Meijer, P. J. Beek, J. H. van Dieën, J. H. van Dieen, and J. H. van Dieën, "The effects of arm swing on human gait stability," J. Exp. Biol., vol. 213, no. 23, pp. 3945–3952, 2010.

[33] M. N. M. Nor, N. K. Zakaria, R. Jailani, and N. M. Tahir, "Analysis of EMG Signals During Walking of Healthy Children," Procedia Comput. Sci., vol. 76, no. Iris, pp. 316–322, 2015.

[34] M. N. M. Nor, R. Jailani, and N. M. Tahir. Feature selection of electromyography signals for autism spectrum disorder children during gait using mann-whitney test. J. Teknol., 82(2), pp.113-120. 2020.

[35] A. Field, Discovering Statistics Using SPSS. 2005.

[36] P. Rafaeilzadeh, T. Lei, and H. Liu, "Cross-Validation," in Advances in Oto-Rhino-Laryngology, vol. 71, 2008, pp. 1–9.

[37] A. Vehtari and J. Lampinen, "Bayesian Model Assessment and Comparison Using Cross-Validation Predictive Densities," Neural Comput., vol. 14, no. 10, pp. 2439–2468, 2002.

[38] E. N. Hines, "Rates of Autism Spectrum Disorder Diagnosis by Age and Gender."

[39] J. M. Twomey and A. E. Smith, "Performance Measures , Consistency , and Power for Artificial Neural Network Models *," vol. 21, no. l, pp. 243–258, 1995.

[40] A. K. Akobeng, "Understanding diagnostic tests 1 : sensitivity , specificity and predictive values," pp. 338–341, 2007.

[41] J. A. Vilensky, A. R. Damasio, and R. G. Maurer, "Gait disturbances in patients with autistic behaviour," Arch. Neurol., vol. 38, p. 646-649, 1981.

[42] N. J. Rinehart, B. J Tonge, R. Iansek, J. McGinley, A. V. Brereton, P.G. Enticott and J. L Bradshaw "Gait function in newly diagnosed children with autism: Cerebellar and basal ganglia related motor disorder.," Dev. Med. Child Neurol., vol. 48, no. 10, pp. 819–24, 2006.

[43] P. Teitelbaum, O. Teitelbaum, J. Nye, J. Fryman, and R. G. Maurer, "Movement analysis in infancy may be useful for early diagnosis of autism," Proc. Natl. Acad. Sci., vol. 95, no. 23, pp. 13982–13987, 1998.

[44] T. Ogawa, T. Sato, T. Ogata, S. Yamamoto, and K. Nakazawa, "Rhythmic arm swing enhances patterned locomotor-like muscle activity in passively moved lower extremities," vol. 3, no. 2008, pp. 1–10, 2015.

[45] J. A. Dickie, J. A. Faulkner, M. J. Barnes, and S. D. Lark, "Electromyographic analysis of muscle activation during pull-up variations," J. Electromyogr. Kinesiol., vol. 32, pp. 30–36, 2017.

[46] M. J. Weiss, M. F. Moran, M. E. Parker, and J. T. Foley, "Gait analysis of teenagers and young adults diagnosed with autism and severe verbal communication disorders.," Front. Integr. Neurosci., vol. 7, no. May, p. 33, 2013.