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Autism Spectrum Disorder and Normal Gait Classification Using Machine Learning Approach

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ABSTRACT: Previous studies have reported that children with autism spectrum disorder (ASD) demonstrate unusual movement and irregular gait patterns during daily walking. Automated classification of normal and abnormal gait can be used as an effective method to provide accurate detection of ASD gait. This study aims to employ machine learning approaches to distinguish between children with ASD and healthy controls by utilizing gait characteristics extracted from three-dimensional (3D) kinematic and kinetic gait data. The gait data of 30 children with ASD and 30 healthy controls were acquired using 3D gait analysis during walking. Time-series parameterization techniques were applied to the 3D kinematic and kinetic waveforms to obtain valuable gait features. Further, statistical feature selection approaches were used to determine the dominating gait features. In this study, four machine learning classifiers were trained to distinguish between ASD and normal gait patterns based on the selected dominant gait features to highlight the effectiveness of different machine learning classifiers in establishing an accurate gait classification. The four machine learning classifiers involved in this study were Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Support Vector Machines (SVMs), and Artificial Neural Networks (ANN). The findings show that the ANN classifier with the combination of six dominant gait features demonstrated an optimum classification performance, achieving an accuracy of 98.3%, sensitivity of 96.7%, and specificity of 100%. These outstanding findings highlight the potential of the ANN classifier as a valuable tool for supporting the diagnosis of ASD gait and evaluating the effectiveness of post-therapy treatments.

1. INTRODUCTION

Autism spectrum disorder (ASD) is a pervasive neurological condition that has a lifelong impact on an individual’s brain growth, functional capabilities, and quality of life [1]. Children with ASD frequently have difficulties with social interaction, and social communication, as well as demonstrate limited and recurring behaviors, which can significantly influence their social and cognitive abilities [1], [2]. According to studies, the prevalence of ASD is on the rise worldwide, with approximately 1 in 68 children being diagnosed with the disorder [3], [4].

Children diagnosed with ASD were discovered to demonstrate unusual movement and atypical gait during walking [5]–[8]. In recent years, there have been increasing studies underlining movement abnormalities and gait deviations as a significant impairment to the focus signs linked with ASD [9]–[13]. It has been observed that persons with ASD often exhibit various symptoms of significant impairments in movement and gait difficulties. These include an unbalanced gait, irregular coordination [14], postural control, and significant changes in lower-limb joint kinematics and kinetics gait [7], [9], [15], [16]. These atypical gait patterns were frequently observed in children with ASD during their normal walking.

Until now, there has been no direct clinical test for identifying ASD. In clinical practice, the diagnosis is typically reliant on assessments of developmental history as well as evaluations of behavioral and motor symptoms [4]. Typically, this process led to manual interpretations that were time-consuming and frequently involved subjective and imprecise assessments [4], [17].

The three-dimensional gait analysis (3DGA) using the leading-edge motion capture and analysis system provides novel perspectives in comprehensively understanding human gait patterns. This advanced technology in motion analysis opens up opportunities for the development of automated gait classification methods [18]. Current 3DGA provides a large amount of gait data, for example, 3D joint kinematics and 3D joint kinetics data that are laborious and difficult to interpret. These high-dimensionality data can be reduced using appropriate feature extraction and feature selection techniques. The extensive body of research in gait analysis has predominantly been based on statistical techniques due to their clear advantage of providing deeper insights into specific gait features and ensuring widespread acceptance in clinical settings [19].

On the other hand, machine learning has the ability to explore, recognize data, and make decisions based on only the input data. Machine learning can analyze large datasets, perform pattern classification tasks, and provide accurate results by identifying specific patterns [4]. Machine learning classifiers have been widely explored to solve numerous pattern recognition and classification problems especially in rehabilitation engineering and gait applications [20].

In the gait analysis research field, machine learning approaches have been employed to automatically recognize and classify various types of normal and abnormal gait patterns [21]. These applications extend to diverse gait conditions such as in cerebral palsy children [22], post-stroke cases [23], and individuals affected by Parkinson's disease [24].

So far, however, limited research has focused on employing machine learning techniques based on 3D gait analysis for ASD gait classification. Therefore, this study aims to employ machine learning classifiers to classify children with ASD and healthy controls by utilizing gait features extracted from 3DGA data. This research work addresses the limitations of prior studies by examining novel features extracted from 3D kinematics and kinetics gait data.

In the search for the optimal ASD classification models, this study delves into the exploration of multiple machine learning classifiers to identify the most effective classification performance. To achieve this, the present study expands the scope of investigation by employing a dataset-classifier fusion approach to determine the ideal combination of dataset and classifier that yields accurate ASD gait classification outcomes. The anticipated outcome of this approach is the development of an optimal classification model for distinguishing between ASD and normal gait patterns.

2. METHODOLOGY

The current study represents an extension of the previous research work conducted by Hasan et al. [25]–[29]. Figure 1 illustrates the research design employed in the earlier study for classifying ASD and normal gait, consisting of five stages. In this enhanced study, four types of machine learning classification methods were employed to perform the recognition task in differentiating between the walking patterns of children with ASD and typically developing children. Before the classification stage, two types of statistical feature selection techniques are utilized to determine the prominent gait features that will serve as the input data for the development of the classification models.

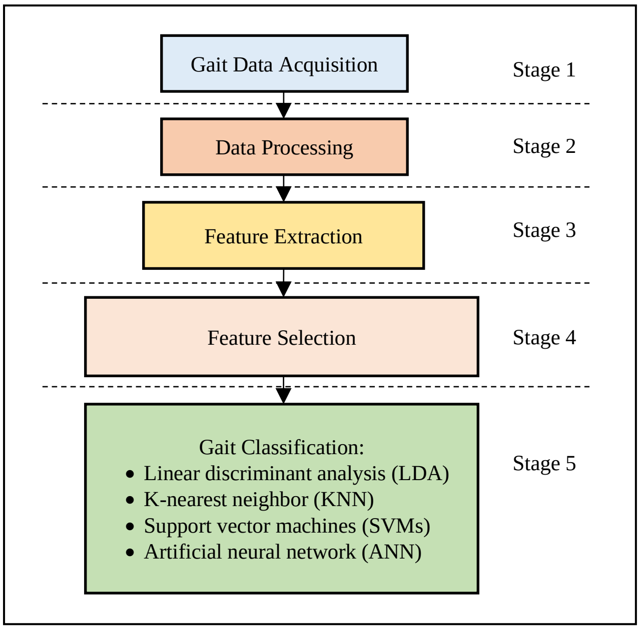

Figure 1: The research design for ASD gait classification using machine learning approaches.

A. Gait Data Acquisition

The current study utilized the gait data that was previously obtained from two groups of subjects, namely the ASD group and the typically developing group. The ASD group consisted of 30 children who had previously been diagnosed with mild ASD, and the control group was represented by 30 typically developing children.

The gait data was previously acquired using 3DGA equipped in the Human Motion Gait Analysis Laboratory at UiTM Shah Alam, Selangor [25]. Kinematic data were obtained using a state-of-the-art 3D motion capture system with eight optical cameras (Vicon Motion Systems Ltd., Oxford, United Kingdom). The gait trial was recorded using the motion capture system at a sampling frequency of 100 Hz. The function of the motion capture system is to trace and capture the 3D trajectories of the retroreflective markers placed on the specific anatomical bony landmarks of the subject's skin.

Two force plates (Advanced Mechanical Technology Inc. (AMTI), MA, USA) were used to collect kinetic gait data. All subjects were instructed to perform a straight barefoot walk with their walking speed along the walkway located in the laboratory. During the data collection process, a valid gait trial was carefully monitored using a motion analysis system to obtain a valid gait trial. Figure 2 shows a valid gait trial with clean foot contact on each force plate. A valid gait trial is important to be used as a reference for the determination of gait event detection.

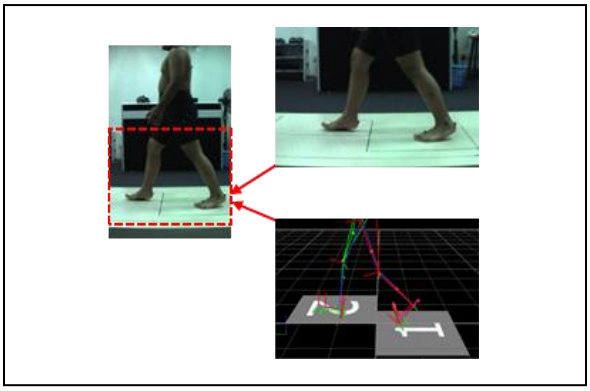

Figure 2: A valid gait trial with a single foot contact on each force plate.

Figure 3 shows the corresponding reconstructed stick figure diagram during a valid foot contact on every force plate analyzed using the Vicon Motion analysis software (Vicon, Oxford, UK).

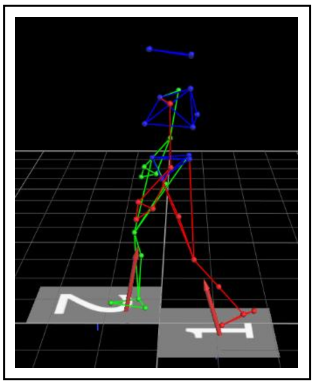

Figure 3: The reconstructed stick figure with a valid foot contact on each force plate.

The following step was the gait events detection. Gait events such as foot-strike and foot-off events for each foot were important to be used in the selection of the region of interest for each valid gait trial. This was because only the kinematic and kinetic data in the region of interest will be extracted for further data analysis. These gait data were then normalized to facilitate significant data comparison between subjects. The gait data normalization is necessary to eliminate the variability of certain parameters due to several related factors such as different heights, leg lengths, and body masses among the subjects.

B. Feature Extraction

Feature extraction is the subsequent stage after processing the gait data. This stage involves the process of extracting and identifying the important gait features and reducing the size of the gait data [30]. This study adopted time-series waveform parameterization techniques to extract meaningful gait features from the processed time-series gait data. The gait features were extracted from the temporal-spatial, lower-limb joint kinematic and kinetic gait patterns.

In this study, the 3D kinematic and 3D kinetic gait features were extracted from the joint angles, joint moments, and joint powers at the ankle, knee, and hip joints. The gait feature extraction was performed using waveform parameterization methods. Similar methods were applied to the 3D ground reaction forces (GRF) data. The gait feature extraction methods from the 3D GRF data were previously reported by Hasan et al. in [7].

C. Feature Selection

In general, all the extracted features can be utilized as input data for the classification stage. However, there are instances where certain features may consist of redundant and less significant information, which can decline the performance of the classifier and result in lower classification results.

Hence, two filter-type of feature selection methods were employed in the present study to determine the most discriminatory features from the overall extracted gait features. The two statistical methods involved are statistical hypothesis tests which include an independent t-test and Mann-Whitney U test (TMWU)), and the stepwise method of discriminant analysis (SWDA). Both methods were employed due to the successful applications in previous research [16], [31].

To study the effectiveness of the two feature selection methods, the feature selection process was conducted using three approaches. The first approach involved the assessment of the overall extracted gait features using the TMWU tests to determine the significant gait features. These significant gait features were grouped as the RAW-TMWU dataset. In the second approach, the SWDA method was used to select the dominant gait features from the original RAW dataset. These dominant gait features were categorized as the RAW-SWDA dataset. Finally, the third approach was by applying both feature selection methods. In this approach, the selected dominant gait features were gathered as the RAW-TMWU-SWDA dataset.

C. Gait Classification

To distinguish between ASD and normal gait patterns, four machine learning classifiers were evaluated using four different sets of gait data. The goal was to identify the most effective gait classification model that achieves the highest classification performance. Figure 4 shows the four input datasets and the types of machine learning classifiers employed for ASD gait classification.

Further, the four machine learning models being examined in this study were Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Support Vector Machines (SVMs), and Artificial Neural Networks (ANN).

LDA and KNN classifiers were used as a baseline for comparison because both classifiers are simple and easy to be implemented [32]. The 10-fold cross-validation method is applied to all models that are being trained to assess and compare the classification performance for each classifier using different combinations of training and testing datasets.

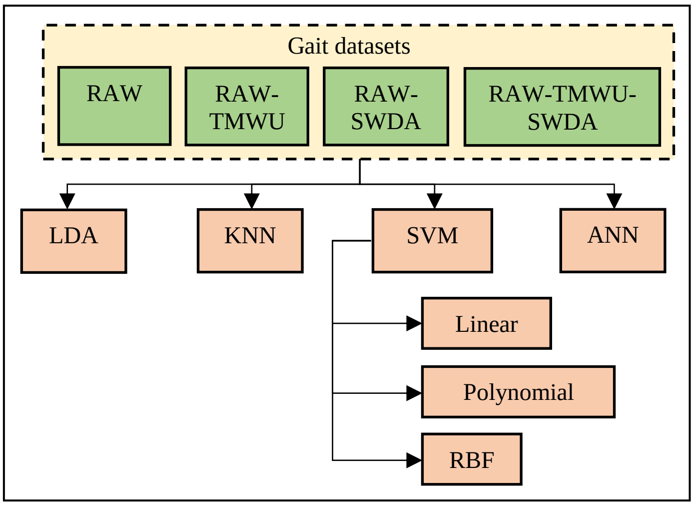

Figure 4: The gait datasets and machine learning classifiers for ASD gait classification.

As for the ANN and SVM classifiers, this study applied a grid search strategy to optimize the internal model parameters. In the modelling of an SVM classifier, three kernel functions were investigated. The three SVM kernels, namely linear, polynomial, and radial basis function (RBF) were analyzed for the optimization of the SVM classification model. The training process of the SVM classifier begins by choosing a kernel function and varying its associated kernel parameters as well as properly tuning the value of regularization parameter C to attain the best SVM classification model.

In contrast, the classification model for ANN was investigated using a feed-forward neural network with three layers. The number of input neurons for model development was determined based on the number of input features to be fed into the network. Meanwhile, the output layer consisted of two neurons which represent the number of class labels corresponding to ASD and normal groups. In the testing phase, the hidden layer's neuron number was varied from 1 to 50. Due to its fast-learning time performance, the ANN classifier was trained using the scaled conjugate gradient (SCG) backpropagation training function.

Further, this study also employed a 10-fold cross-validation method to assess and compare the classification performance for each classifier using different combinations of training and testing datasets. In this case, the overall dataset was randomly divided into ten equal folds with nine folds used as training data, and one fold was used for the model testing. The results from the ten testing folds were then averaged to produce the final classification accuracy for each classification model. Finally, the measurement of classification performance was evaluated using three performance measures, i.e. accuracy, sensitivity, and specificity.

Table 1 shows the confusion matrix for two actual groups of gait classification which is ASD (positive) and control (negative). The table also shows the four different possible gait predictions.

Table 1 Confusion Matrix for Classification of ASD and control gait

		Predicted group	
		ASD (Positive)	Control (Negative)
Actual group	ASD (Positive)	True positive (TP)	False negative (FN)
	Control (Negative)	False positive (FP)	True negative (TN)

3. RESULTS AND DISCUSSION

This section presents and discusses the classification results obtained from the proposed feature extraction, feature selection and classification methods. In brief, following the time-series parameterization techniques, a total of 86 gait features were extracted as potential gait features. After data filtering using TMWU tests, a total of 26 features (RAW-TMWU) were found to be statistically significant for group differentiation, while 7 features were found to be dominant from the SWDA test (RAW-SWDA). For the RAW-TMWU-SWDA, it resulted in 6 dominant features which were contributed by the knee joint moments, 3D ground reaction forces, and the ankle plantarflexion.

Table 2 presents a summary of the classification performance outcomes, including accuracy, sensitivity, and specificity, when comparing various machine learning classifiers using the RAW-TMWU-SWDA dataset as input. The significant classification performance of the machine learning models was demonstrated through the presentation of these results, specifically when utilizing the RAW-TMWU-SWDA input dataset. Based on the 10-fold cross-validation outcomes depicted in Table 2, it is evident that the fusion of the RAW-TMWU-SWDA dataset and the ANN-SCG classification model outperformed other classification models, achieving an accuracy of 98.3%, sensitivity of 96.7%, and specificity of 100.0%.

Additionally, the classification performance results of different classification models for the six machine learning classifiers using the RAW-TMWU-SWDA dataset input features are graphically shown in a clustered column chart as shown in Figure 5. As illustrated in the chart, among the six classifiers, the ANN-SCG classifier was able to effectively differentiate the gait patterns of ASD from the normal control gait with the utmost performance rates. The promising results indicated that the ANN-SCG classification model was highly accurate in the differentiation of ASD gait and normal gait patterns compared to other examined models.

Table 2 Classification Performance Results of Different Classification Models using the RAW-TMWU-SWDA Input Dataset

Classifier	**Classification Performance**		
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**
LDA	88.3	86.7	90.0
KNN	90.0	86.7	93.3
SVMLin	88.3	83.3	93.3
SVMPoly	85.0	80.0	90.0
SVMRBF	93.3	96.7	90.0
ANN-SCG	**98.3**	**96.7**	**100.0**

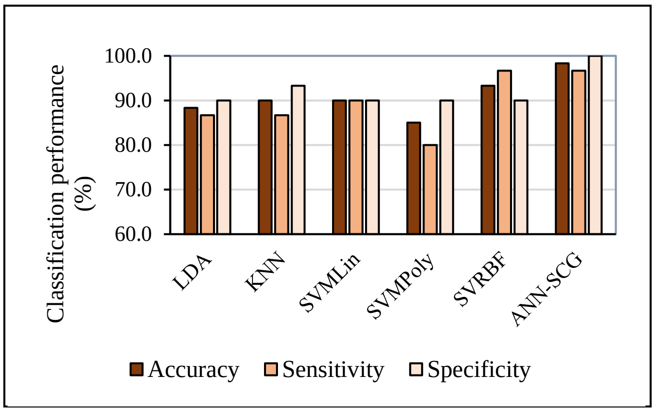

Figure 5: Performance comparison of six machine learning classification models using RAW-TMWU-SWDA input dataset.

4. CONCLUSION

In this research work, an improved objective approach for the effective categorization of ASD and normal gait based on the dominant gait features obtained using 3D gait analysis has been successfully achieved. By applying stepwise discriminant analysis for the feature selection technique, this work was able to significantly reduce the number of gait features as the prominent diagnostic biomarkers. Further, in the search for the optimum ASD gait classification model, the dataset-classifier fusion strategy was able to determine the combination of dataset and classifier that produces the best classification performance. In this case, the combination of the RAW-TMWU-SWDA dataset and the ANN-SCG classifier outperformed the other classification models with 98.3% accuracy, 96.7% sensitivity, and 100% specificity. The outcomes of the study suggest that the dominant gait features selected using both statistical feature selection techniques provide useful information regarding the abnormal gait characteristics observed in the walking pattern of children with ASD. In summary, this study demonstrated that the proposed feature selection techniques and the application of machine learning classification models based on the dataset-classifier fusion method can facilitate greater comprehension of gait patterns in children with ASD. It is also expected that the novel findings from this study could provide valuable insights for medical practitioners and physiotherapists in optimizing post-therapy treatments and improving the functionality and quality of life for persons with ASD.

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