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Research Article

Prediction of POMA-G Score from Spatiotemporal Gait Parameters

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ABSTRACT

The Performance-Oriented Mobility Assessment (POMA) test is a commonly used evaluation tool in rehabilitation and physical therapy to assess an individual's mobility and functional movements. It helps identify areas for improvement by assessing the ability to perform various activities. Experts who are trained in using the POMA test conduct the evaluation, but the results may vary depending on the evaluator. Different evaluators may have different approaches, and even the same evaluator's assessment may differ over time. These variations can affect the reliability of the POMA score. In contrast, gait analysis provides an objective and more reliable way to assess mobility.

In this study, the goal was to predict the gait measurements obtained from the gait portion of the POMA test (POMA-G) using objective spatiotemporal gait parameters. The dataset used for analysis included gait parameters from 44 older adults. The POMA-G scores were rated by two physiotherapists, one of whom was an expert while the other had less experience but was familiar with the test. The study focused on the performance of machine learning based models, including Sequential Minimal Optimization (SMO), K-nearest neighbor(KNN), and Random Forest (RF), in predicting POMA-G scores. The models were trained with selected gait parameters. Results indicated that SMO exhibited the highest R-squared (R^2) values of 0.5676, reflecting its superior predictive capabilities. Moreover, the Intra-class Correlation Coefficients (ICCs) for SMO and RF were found to be 0.859 and 0.891, highlighting their exceptional reliability in mobility assessments. The study also examined the reliability of the physiotherapists' assessments and proposed prediction models.

Introduction

The Performance-Oriented Mobility Assessment (POMA) test is a component of the Tinetti Mobility Test (TMT) and is commonly used in rehabilitation and physical therapy to evaluate an individual's functional movements and activities [1]. It assesses mobility and helps identify areas for improvement. POMA involves various functional tasks, such as walking, climbing stairs, standing on one leg, and reaching for objects [2]. These tests provide valuable information to healthcare professionals for developing personalized treatment plans, tracking progress over time, and assessing the effectiveness of interventions [3]. The scoring criteria for each POMA test may vary, and results are interpreted by healthcare professionals with expertise in mobility impairments [4].

Gait analysis is utilized in biomechanics and physical therapy to study human body movement during walking [5]. It involves using tools and techniques like video cameras, motion capture systems, and specialized software to collect data on gait patterns [6], [7]. Gait analysis provides a detailed picture of joint angles, muscle activity, and other parameters, allowing identification of deviations from a normal gait pattern [8]–[10]. It is particularly useful for individuals with conditions like cerebral palsy or Parkinson's disease, where gait abnormalities can impact mobility [11], [12]. By analyzing these deviations, healthcare professionals can develop personalized treatment plans to improve gait and mobility. Spatiotemporal gait parameters, which include measurements like stride length and cadence, are important for analyzing gait patterns and guiding interventions [13].

POMA evaluations are typically conducted by trained experts to assess mobility and balance. However, the variability in evaluation approaches and individual differences among experts may lead to variations in POMA scores, affecting reliability. In contrast, gait analysis employs objective measurement devices to assess gait parameters, providing more reliable results.

The objective of this study is to predict gait measurements obtained in the POMA test (POMA-G) using objectively obtained spatiotemporal gait parameters. A dataset from [1] is utilized, including gait parameters from 44 older adults (37 women and 7 men) with an average age of 69.98 years. Participants' gait is recorded using three cameras as they walk in a straight line [14]. POMA-G scores are rated by two physiotherapists, one with extensive experience administering the test daily for the past five years and the other familiar with the test but administering it only once a year. The physiotherapists evaluate participant videos twice, with a week-long interval between viewings.

It is proposed in this study to integrate machine learning algorithms including Sequential Minimal Optimization (SMO), K-nearest neighbor (KNN), and Random Forest (RF), to predict POMA-G scores. These algorithms serve as the predictive models, with the ultimate goal of enhancing the accuracy and objectivity of mobility assessments. Two feature selection methods, Relief and Correlation-based Feature Selection, are applied to the dataset to enhance the predictive performance of these machine learning models [15]. In addition to predicting POMA-G scores, this study also assesses the reliability of expert assessment and the proposed prediction models.

The following enumeration summarizes the contributions made by this study to the field.

- The study hints at the possibility of automating mobility assessments by leveraging objective data from gait analysis. This contribution points to a future where assessments can be more objective and less prone to subjectivity.
- The research pioneers the application of predictive models to advance the field of mobility assessment. By using machine learning algorithms to predict POMA-G scores from spatiotemporal gait parameters, it introduces a novel and promising approach to evaluating an individual's functional movements and activities.
- The study contributes to the field of rehabilitation and physical therapy by demonstrating the feasibility of predicting POMA-G scores, which evaluate an individual's functional movements and activities, based on spatiotemporal gait parameters obtained from gait analysis.
- The research evaluates the reliability of prediction models by comparing ratings given by expert and amateur physiotherapists. This contribution highlights the importance of assessing the consistency of human evaluators.

The remainder of the paper is organized as follows:

In the second section, the materials and methods are elaborated. The third section presents the results and findings obtained from the study. In the fourth section, a comprehensive discussion of the results is provided. The paper concludes in the fifth section, summarizing the key insights and implications drawn from this research.

Materials and Methods

In this section, we provide an overview of the methods and data that were used in the experimental studies. The dataset utilized in these experiments is described in detail below. In order to estimate POMA-G score values, three different machine learning algorithms were employed: SMO, KNN, and RF. Additionally, various feature selection techniques were applied to enhance prediction accuracy. Specifically, these methods were used to identify and select the most relevant features from the dataset, which were then incorporated into the model training process.

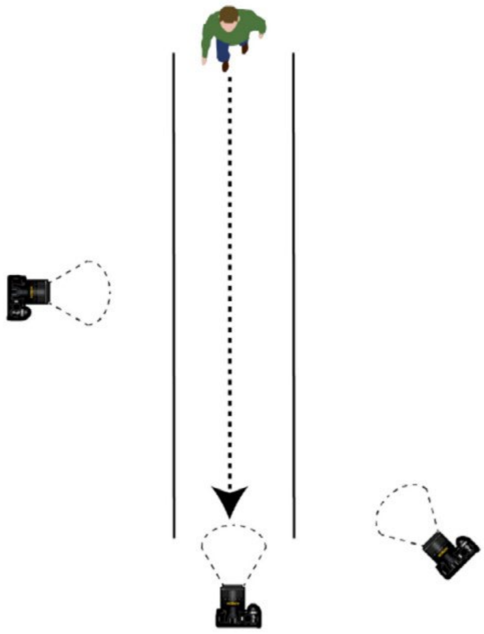

Figure 1. The location of the cameras that were used to record the movements of the participants during the optoelectronic motion-capture trials[1].

Table 1. Spatiotemporal gait parameters provided in the dataset.

Gait Parameters	
Left Cadence	Right Cadence
Left Foot Off	Right Foot Off
Left Walking Speed	Right Walking Speed
Left Single Support	Right Single Support
Left Stride Time	Right Stride Time
Left Double Support	Right Double Support
Left Step Time	Right Step Time
Left Stride Length	Right Stride Length
Left Opposite Foot Off	Right Opposite Foot Off
Left Step Length	Right Step Length
Left Opposite Foot Contact	Right Opposite Foot Contact
Left Step Width	Right Step Width
Left Limp Index	Right Limp Index
Gait Duration After Data Crop	

Dataset

In this study, the dataset provided by [1] is used in the experiments. The study presents a dataset of five parts that focuses on the gait analysis of healthy older adults (37 women and seven men; the average age of 69.98 years, average body mass index of 27.71). Spatiotemporal gait parameters were collected using a Vicon motion analysis system operating at 100 Hz. The optical motion capture system consisted of seven Vantage V5 cameras arranged in a rectangular area measuring 15 meters in length and 6 meters in width. The cameras were mounted on tripods at a height of 1.90 meters above the floor and were configured to sample at a rate of 100 Hz. In addition to the optical motion capture system, three RGB cameras were placed as shown in Figure 1 to capture video footage of the participants walking while wearing reflective markers.

Both the Vicon system and the RGB cameras recorded the participants' movements simultaneously. Spatiotemporal gait parameters obtained from the optical motion capture system are presented in Table 1.

Physiotherapists administered the Short Physical Performance Battery (SPPB) [13], Gait component of the Performance Oriented Mobility Assessment (POMA-G) [2], and the Mini-Mental State Examination (MMSE) [14] tests to 44 participants. Two physiotherapists independently evaluated videos of the test subjects. One of the physiotherapists was an expert who had administered the test daily for the past five years, while the other was familiar with the test but had only administered it once a year. Both physiotherapists evaluated the videos twice, with a week in between each evaluation.

To sum up in the dataset, the records were obtained from 44 adult individuals during five separate sessions, and from each of these records, 27 gait parameters as provided in Table 1 were extracted, resulting in a dataset of dimensions (44×5×27). One of these records was used for training the models, while the remaining were utilized for testing the trained models and conducting the reliability analyses. Additionally, POMA-G scores, collected from both expert and amateur physiotherapists during two sessions (44×2×2) for each adult individual, are also provided in the dataset.

i)Prediction Methods

SMO, KNN, and RF methods have been used to predict POMA-G scores.

Sequential Minimal Optimization (SMO) is an algorithm for training Support Vector Machines (SVM). It works by breaking down the larger problem of training an SVM into smaller sub-problems that are easier to solve [16]. As in this study, it is common to utilize SVMs to train models for regression problems in order to predict continuous output values. SMO works by breaking down the problem of training an SVM into a series of smaller sub-problems. These sub-problems are easier to solve than the original problem, and they can be solved iteratively. The overall goal of SMO is to find the values of the SVM's parameters (alpha) that will result in the best possible model. To do this first selects two alpha values to optimize, then solve for the optimal values of these alpha values using a method called quadratic programming. Once these values have been found, the algorithm moves on to the next pair of alpha values and repeats the process. This continues until all of the alpha values have been optimized, resulting in a trained SVM model. In experimental studies, the model has been trained using a polynomial kernel function.

K-nearest neighbors (KNN) is a non-parametric, instance-based supervised learning method used for classification and regression [17]. In the classification setting, the KNN algorithm works by identifying the K number of training examples that are closest in distance to the test example, and then classifying the test example based on the most common class among those K training examples. In the regression setting, the KNN algorithm makes predictions by averaging the K nearest training examples. In the experimental studies, the parameter 'k' was taken as 3 and the Euclidean function was used to calculate the distances between samples.

Random Forest (RF) algorithm was introduced by Breiman and has been shown to be effective in a variety of classification and regression tasks [18]. It has gained widespread popularity due to its versatility and performance. It is an ensemble learning method that uses multiple decision trees to make predictions [19]. In the experimental studies, the number of trees in the forest was set as 100.

ii)Feature Selection Methods

Two feature selection methods, namely Relief and Correlation were applied to the dataset. The selected features resulting from these methods are presented in Table 2. The following subsections provide a brief explanation of these methods.

Relief feature selection method [20] was proposed by Kira and Rendell in 1992. Relief works by identifying features that are different from one another in the data. It does this by analyzing how well a feature can predict the class of an instance. The idea is that features that are highly predictive of the class are more important, and should be kept in the model [21].

To calculate the importance of a feature, Relief looks at pairs of instances in the data. For each pair, it calculates the difference in the feature values for the two instances. If the feature values are different, the feature is considered important for distinguishing between the two instances. The more pairs of instances that a feature can distinguish between, the more important it is considered to be.

Correlation-based Feature Selection (CFS) is an algorithm to evaluate the worth of each attribute in a dataset. The CFS algorithm calculates the correlation between each attribute and the class attribute, as well as the inter-correlation between each pair of attributes, and uses this information to select a subset of attributes that are highly correlated with the class attribute and are not highly correlated with each other [22]. CFS algorithm can be used in conjunction with a search algorithm, such as best first or Genetic Search, to find the optimal subset of attributes that should be included in the analysis. This can be useful for improving the accuracy of predictive models and for reducing the dimensionality of the data, which can speed up the learning process.

Table 2. Selected gait parameters with Relief and Correlation feature selection methods.

Relief	Correlation
Left Single Support	Right Stride Length
Right Single Support	Left Step Length
Right Foot Off	Left Stride Length
Left Stride Time	Right Step Length
Left Step Time	Right Walking Speed
Left Cadence	Left Walking Speed
Right Stride Time	Right Single Support
Right Step Time	Right Cadence
Right Cadence	Left Cadence
Right Opposite Foot Contact	Left Single Support
Right Double Support	
Gait Duration after data crop	

Experimental Results

In this section, the prediction of POMA-G scores from spatiotemporal gait parameters and the reliability analyses of POMA-G measurements are performed. The Python programming language is employed to perform reliability analyses, data organization, preprocessing, and visualization of results. Additionally, the Weka software [23] is utilized for training predictive models, conducting tests, and selecting features.

The SMO, KNN, and RF methods are utilized to predict POMA-G scores. The prediction methods are trained using the dataset described in Section 2.1, and 10 fold cross-validation is employed to prevent over-fitting during the training phase. Five records are collected for each participant, and spatiotemporal parameters are extracted from each of these records. The parameters obtained from one of the five records are used to train the models, while the parameters from the remaining records are used to test the trained models. The reliability of the models is assessed by using the values obtained during the testing process.

The intra-class correlation coefficient method [24] is employed in the reliability analysis. Amateur and expert physiotherapists assessed the POMA-G scores in two sessions using the same video recording for each participant. The reliability of the physiotherapists and the prediction models was determined by calculating the intra-class correlation coefficients for each.

Quality Metrics

The performance of the prediction models was evaluated using three common metrics: root mean squared error (RMSE), mean absolute error (MAE), and R-squared (R^2). The intra-class correlation coefficient is used in the reliability analyzes of the measurements. These metrics have been widely utilized in previous researches. Explanation and the corresponding formulas for all the metrics employed in the study are provided in this section.

RMSE is a measure of the difference between the predicted values and the true values in a dataset. It is commonly used to evaluate the performance of a model in predicting continuous variables, such as in regression analysis. It is calculated as the square root of the average of the squared differences between the predicted values and the true values. Lower values of RMSE indicate a better fit between the predicted values and the true values.

$$RMSE = \sqrt{\frac{1}{N}\sum_1^N(\hat{y}_i - y_i)^2} \tag{1}$$

MAE is used to evaluate the accuracy of a model's predictions like RMSE. However, while RMSE is the square root of the average squared difference between the predicted and true values, MAE is simply the average absolute difference between the predicted and true values. This means that MAE is less sensitive to outliers than RMSE, as the absolute difference is not squared.

$$MAE = \sum_{i=1}^N |\hat{y}_i - y_i| \tag{2}$$

R-squared (R^2), also known as the coefficient of determination, is a statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variables in a regression model. It is a value between 0 and 1, where a value of 0 indicates that the model explains none of the variance in the dependent variable, and a value of 1 indicates that the model explains all of the variances in the dependent variable.

$$R^2 = 1 - \frac{\sum(\hat{y}_i - y_i)^2}{\sum(\bar{y}_i - y_i)^2} \tag{3}$$

The intra-class correlation coefficient (ICC) is a measure of the consistency of observations within a group. It is used to evaluate the reliability of measurements taken by different raters or judges. The formula for the ICC is:

$$ICC = \frac{\frac{s_B^2}{k}}{\frac{s_B^2}{k} - \frac{s_W^2}{n-k}} \tag{4}$$

where:

- S_B^2 is the between-group variance
- k is the number of groups
- S_W^2 is the within-group variance
- n is the total number of observations

The ICC can take on values between 0 and 1. A value of 0 indicates that there is no consistency among the observations within each group, while a value of 1 indicates perfect consistency.

Results

In this section, the validity and reliability of the proposed models are evaluated using several metrics. To assess the validity of the prediction models, the R^2, MAE, and RMSE are calculated. A low MAE and RMSE value suggests a more accurate prediction, as it reflects a lower error in the prediction. In contrast, a higher R^2 value indicates a stronger correlation, which indicates a better prediction. The reliability of the models is assessed using the ICC. The ICC is also calculated for the ratings made by physiotherapists to compare the reliability of the ratings made by the proposed models.

Table 3. Comparison of the prediction results of models trained using all features versus those trained using the features selected by the relief and correlation feature selection methods.

		R^2	MAE	RMSE
All Features	SMO	0.4575	0.7058	0.8607
	KNN	0.3792	0.6752	0.8557
	RF	0.4745	0.5797	0.7695
Correlation	SMO	0.5676	0.5670	0.7263
	KNN	0.4406	0.6325	0.7989
	RF	0.4576	0.6154	0.7904
Relief	SMO	0.3739	0.6483	0.8676
	KNN	0.2725	0.6838	0.8705
	RF	0.4614	0.5821	0.7760

Spatiotemporal gait parameters were obtained from a single recording session used to train prediction models. The POMA-G scores, as rated by an expert physiotherapist, were used as the ground truth. To prevent overfitting, 10-fold cross-validation method was employed. Three methods, namely SMO, KNN, and RF, were used to predict the POMA-G score. Two different feature selection methods, relief, and correlation feature selection were used to identify the features with the highest correlation to the predicted POMA-G score in order to improve the prediction accuracy. Upon application of feature selection techniques to the original dataset, two additional datasets were created in addition to the original dataset. The prediction methods were trained on these datasets independently, and the performance results for each method were calculated individually.

The prediction results are presented in Table 3. To improve comprehension of the results, the data from this table is also depicted in Figure 2 and 3. These figures allow for a visual comparison of the prediction models in Figure 2, and the feature selection methods in Figure 3.

ICC is a commonly used measure of reliability, particularly for data collected by multiple raters. The ICC scores provided in Figure 4 suggest that expert physiotherapist has higher reliability in their ratings compared to the amateur physiotherapist, as their ICC score is closer to 1.

Discussion

The figures and results presented in Table 3 show that the SMO prediction method combined with the Correlation feature selection method achieved the best R^2 (0.5676), MAE (0.5670), and RMSE (0.7263) values. In terms of R^2, KNN performed poorly on all datasets compared to the other prediction methods. When comparing SMO and RF, SMO produced better results only when the correlation feature selection method was used. Although the best result among all experiments was obtained with the SMO method, the prediction model comparisons presented in Figure 2 show that Random Forest (RF) gave the best result in 6 out of 9 experiments.

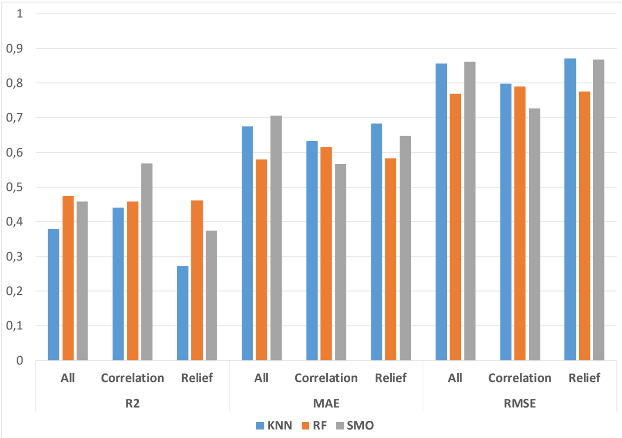

Figure 2. Comparison of the prediction models

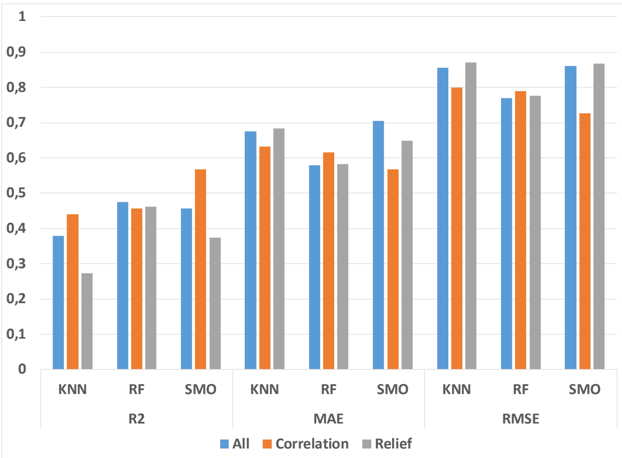

Figure 3. Comparison of the feature selection methods.

The mean absolute error (MAE) and root mean square error (RMSE) are both measures of the average magnitude of the error in the model's predictions. Lower values for both metrics indicate that the model's predictions are closer to the true values. Except for Correlation feature selection, RF mostly has lower values for MAE and RMSE than the other two algorithms, indicating that it has lower prediction errors on average. When the correlation feature selection method was applied to the dataset, the lowest MAE and RMSE results were obtained with the SMO prediction method.

When feature selection is applied, the correlation-based feature selection method improves the performance of all models except RF prediction. On the other hand, the Relief feature selection method does not help much to improve the performance of the models, and all models' performance decreased compared to the model trained with all features except the MAE metric of SMO. It can be seen that with correlation-based feature selection, SMO algorithm improves significantly in terms of R^2, MAE and RMSE, which indicates it's a better choice than the other two algorithms.

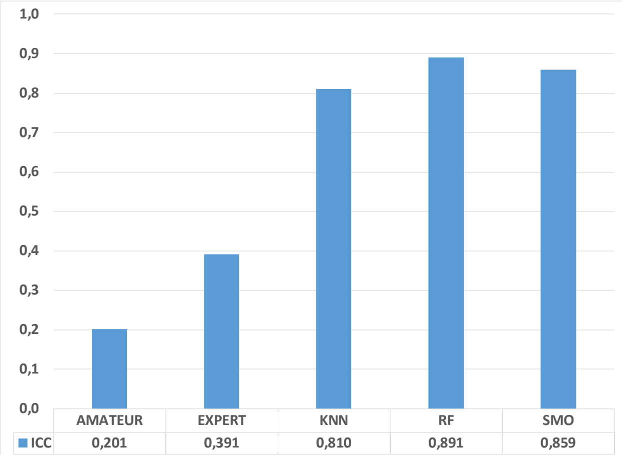

Figure 4. ICC results for the proposed methods' prediction and physiotherapists' ratings.

Based on the Table 3, it seems that the RF algorithm performs generally better than the other two algorithms. When all features are used, the RF algorithm has the highest R^2 value of 0.4745 and the lowest mean absolute error (MAE) of 0.5797, indicating that it has the best overall fit to the data and the lowest prediction errors on average. Additionally, the RMSE of 0.7695 for RF is also lower than the others, indicating that its predictions are less dispersed around the true value. When the correlation-based feature selection method is applied to the dataset, there is an increase in the performance of KNN and SMO. However, when the relief feature selection method is applied it hurts the performance of all the models. Although the relief feature selection method reduces the performance of the model, the performance of RF is still better than the other two models.

When the results in Figure 4 are analyzed, it is seen that there is a moderate level of agreement (0.391) between the ratings given by the experts. The ICC scores for the prediction models, KNN, RF, and SMO, all have much higher ICC scores than the amateur and expert physiotherapists. KNN and SMO have ICC scores of 0.810 and 0.859 respectively, indicating high levels of agreement among the predictions made by the models. Similarly, RF has an ICC score of 0.891, also indicating a high level of agreement among the predictions.

In summary, the ICC values reveal the following:

Amateur and expert groups have lower ICC values, indicating less consistency in measurements within these groups.

KNN, RF and SMO prediction methods have high ICC values, indicating a high degree of agreement and reliability in their predictions in different situations.

ICC values are valuable for assessing the consistency and reliability of measurements or predictions, which is important for understanding the quality and stability of measurements.

Conclusion

This study shows the use of spatiotemporal gait parameters obtained from gait analysis to predict scores on the gait portion of the POMA-G test. The POMA test is used to evaluate an individual's ability to perform functional movements and activities and is commonly used in the field of rehabilitation and physical therapy. SMO, KNN, and RF methods were used to predict POMA-G scores from the gait parameters. 10-fold cross-validation was used to prevent overfitting during the training phase, and feature selection methods were also applied to improve the performance of the models. Among the three prediction models evaluated, the SMO algorithm performed the best results, with the highest R^2 value and the lowest mean absolute error. The experiments also show that the correlation-based feature selection method generally improved the performance of all models, while the Relief feature selection method did not significantly improve the performance.

The study also evaluated the reliability of the expert assessment of POMA-G scores by comparing the scores given by an expert physiotherapist and an amateur physiotherapist. The results show that expert physiotherapists have higher reliability in their ratings compared to amateur physiotherapists, as their ICC score is higher. The expert physiotherapists' ICC score is moderate (0.391) while the ICC scores for the prediction models, all have high levels of agreement among the predictions made by the models.

Overall, the study suggests that spatiotemporal gait parameters obtained from a gait analysis can be used to predict POMA-G scores with a reasonable level of accuracy.

The ultimate goal is to achieve a comprehensive assessment in an automated manner. This study can be regarded as the initial step towards accomplishing this objective. Forthcoming endeavors will involve the utilization of inertial sensors, such as gyroscopes and accelerometers, to acquire additional components of the POMA assessment.

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