



Machine Learning for Classification of Locomotor Performance from Electromyographic and Kinetic Gait Parameters

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ABSTRACT: Gait is a complex motor activity that reflects the interaction between neuromuscular control and mechanical loading. This study evaluated the ability of electromyographic (EMG) and kinetic gait parameters to classify observations according to a study-specific index of locomotor performance. A multimodal gait dataset comprising motion-capture, ground reaction force (GRF), and surface EMG measurements was analyzed. EMG features derived from the gluteus maximus and soleus muscles included root mean square (RMS), integrated EMG (iEMG), median frequency (MDF), and a muscle co-contraction ratio. Kinetic features included peak and mean vertical GRF, force impulse, GRF asymmetry, center-of-pressure (COP) path length, and COP velocity. A study-specific Performance Index was constructed from normalized cadence, GRF, COP stability, and asymmetry components and used to categorize observations into Low, Medium, and High performance classes. A total of 1,143 observations were analyzed using a stratified 70:30 training–testing split. Random Forest and XGBoost were applied for EMG-based classification and feature assessment, whereas Random Forest, XGBoost, Support Vector Machine (SVM), and Nearest Mean were evaluated for kinetic-based classification. SHapley Additive exPlanations (SHAP) were used to interpret model predictions, while Spearman correlation analysis was performed to examine EMG–kinetic relationships. The EMG-based Random Forest and XGBoost models both achieved accuracies exceeding 99%. For kinetic data, SVM achieved the highest accuracy (93.59%), followed by Random Forest and XGBoost (90.38% each), whereas Nearest Mean achieved 70.55%. Soleus iEMG was among the most informative EMG features, while GRF magnitude and force impulse were the dominant kinetic features. The strongest EMG–kinetic association was observed between gluteus maximus RMS and right-limb force impulse ($r = -0.421$). Overall, the findings demonstrate the complementary value of neuromuscular and kinetic information for the study-specific classification of locomotor performance.

KEYWORDS: Biomechanical signals; muscle activation; ground reaction forces; model interpretability; movement analysis

1. Introduction

Human gait is a complex, repetitive motor behavior resulting from the coordinated action of the musculoskeletal, neuromuscular, and sensory systems. Quantitative gait analysis enables this behavior to be characterized using objective temporal, spatial, kinematic, kinetic, and muscle-activation variables. Walking speed is one of the most widely used global indicators and has been described as a functional “vital sign” because of its association with mobility, functional status, and health outcomes [1, 2]. However, gait performance cannot be adequately represented by a single variable, as gait rhythm, variability, symmetry, loading, balance, and muscle activation provide complementary information about locomotor function [3–5].

Instrumented gait analysis traditionally combines three-dimensional (3D) motion capture, force plates, and surface electromyography (EMG). Marker-based motion capture provides detailed trajectories of body segments and joint movements, whereas force plates quantify ground reaction forces (GRFs) and the center of pressure (COP). Surface EMG provides a non-invasive measurement of muscle electrical activity and therefore complements mechanical measurements with information about neuromuscular control [6–9]. The integration of kinematic, kinetic, and EMG measurements is particularly valuable because the same gait event can be characterized simultaneously in terms of movement, external loading, and muscle activation [6, 8].

Kinetic measurements are particularly relevant when the objective is to characterize the mechanical interaction between the body and the ground. GRFs are routinely used to quantify loading during gait, while force-impulse measures describe the accumulated effect of force over time [10, 11]. COP-based measures provide additional information about the trajectory and control of the point of application of the resultant ground force and have been investigated as indicators of gait stability and age-related changes [12]. Bilateral comparisons are also important because gait is not perfectly symmetric, even in healthy individuals, and the magnitude and interpretation of asymmetry depend on the selected variable and calculation method [13, 14].

EMG provides complementary information on neuromuscular activity. The amplitude and frequency characteristics of EMG signals can be summarized using measures such as root mean square (RMS), integrated electromyography (iEMG), and median frequency (MDF). These descriptors have been widely used to quantify the intensity and spectral characteristics of muscle activation, although their interpretation depends on electrode placement, signal processing, normalization, cross-talk, and the specific movement task [6, 15]. Reviews of surface EMG in gait analysis emphasize that muscle selection, filtering, normalization, cross-talk, and activation timing are important methodological considerations when extracting meaningful features [6, 7]. The gluteus maximus and soleus are of particular biomechanical interest because they contribute to lower-limb control and force generation associated with support and forward progression during walking [16, 17].

The increasing availability of multimodal biomechanical datasets provides opportunities to move beyond the interpretation of isolated gait parameters. The dataset used in the present study was established by Schreiber and Moissenet and combines 3D motion capture, GRFs, and EMG recordings acquired during walking at different speeds [18]. Such multimodal data are suitable for investigating relationships between neuromuscular activity and external mechanical loading. However, they also generate high-dimensional feature spaces that can be

challenging to analyze using conventional statistical approaches, particularly when the objective is classification.

Machine learning (ML) has consequently become an increasingly important tool in human movement biomechanics. Reviews have reported applications including gait-pattern classification, disease recognition, activity recognition, rehabilitation assessment, and prediction of biomechanical variables [19–22]. Support Vector Machine (SVM), Random Forest, and other supervised learning methods have frequently been applied to gait data, with their reported performance strongly influenced by the dataset, target definition, feature representation, and validation strategy [19, 20]. Importantly, methodological reviews have emphasized that high classification accuracy alone is insufficient to establish the usefulness of a biomechanical model. The construction of training and test sets, treatment of repeated measurements, feature selection, and interpretation of model predictions can substantially influence model reliability and generalizability [23].

Explainable artificial intelligence (XAI) methods provide an additional perspective by enabling researchers to identify the input variables that contribute to model predictions. SHapley Additive exPlanations (SHAP), based on Shapley-value concepts from cooperative game theory, provide a unified framework for attributing model outputs to individual features [24]. Recent systematic reviews of XAI in gait analysis have demonstrated the growing use of SHAP and related methods while emphasizing the need for careful validation and biomechanical interpretation of model explanations [25]. This consideration is particularly important in multimodal gait analysis, where a highly accurate classifier may still be difficult to interpret physiologically.

Despite the rapid development of machine-learning methods for gait analysis, an important methodological challenge remains: there is no single universally accepted multidimensional scalar measure that directly represents overall locomotor performance across heterogeneous biomechanical variables. Furthermore, supervised classification requires a clearly defined target variable. In the present study, this challenge was addressed by constructing a study-specific Performance Index from four normalized components representing cadence, GRF characteristics, COP stability, and gait asymmetry. The index was used solely to define three approximately balanced performance classes and was not intended to represent a clinically validated measure of physical fitness or locomotor ability.

Accordingly, this study aimed to develop and evaluate a machine-learning framework for classifying study-defined levels of locomotor performance using EMG and kinetic gait parameters. The specific objectives were to (1) construct a multidimensional Performance Index from selected gait variables; (2) compare supervised classifiers using EMG- and kinetic-based feature sets; (3) identify the parameters most informative for classification using tree-based feature importance and SHAP analysis; and (4) quantify relationships between EMG-derived and kinetic variables using correlation analysis. The study also included a baseline comparison with a simple Nearest Mean classifier and identified methodological directions for subsequent analyses stratified by walking speed.

2. Materials and Methods

2.1. Dataset and Data Structure.

The analysis was based on the multimodal gait dataset developed by Schreiber and Moissenet [8]. The original dataset contains synchronized three-dimensional (3D) motion-capture trajectories, 3D ground reaction forces (GRFs) and moments, and surface electromyography (EMG) recordings acquired during walking under five speed conditions. The original study included 52 healthy, injury-free adult participants and provided 1,143 available gait trials [8]. In the present study, all 1,143 observations were included in the modelling dataset. The multimodal structure of the dataset and the measurement modalities considered in the present analysis are summarized in Figure 1. The data were stored in C3D biomechanical data files, which contain synchronized motion-analysis measurements. The dataset comprised trajectories from 52 reflective markers, GRF and moment measurements, surface EMG signals from eight muscles of the right leg, and gait-event metadata. The recorded muscles were the gluteus maximus, gluteus medius, rectus femoris, vastus medialis, semitendinosus, medial gastrocnemius, soleus, and tibialis anterior.

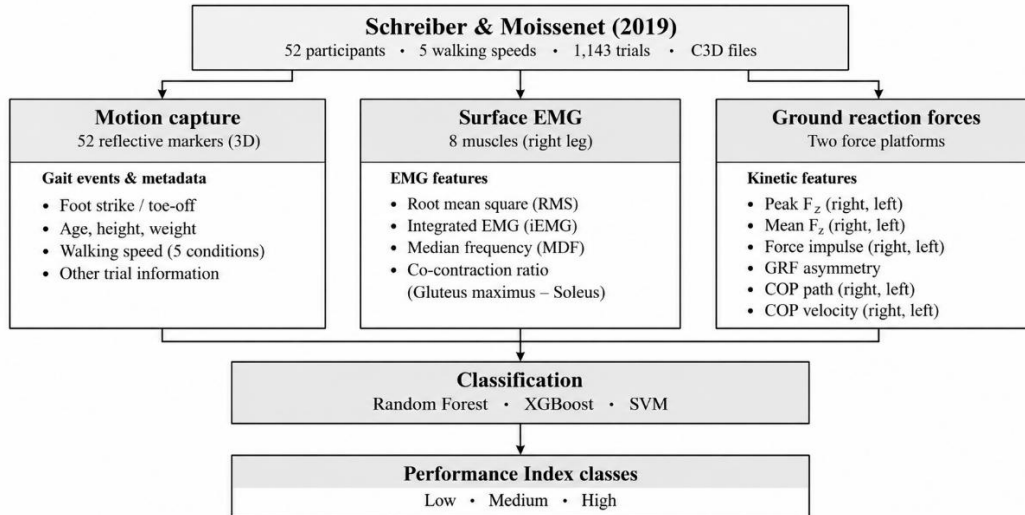


Figure 1. Overview of the Multimodal Dataset and Measurement Modalities Used in the Study.

2.2. Signal Preprocessing and Feature Extraction.

According to the processing procedures reported for the analyzed dataset [8], marker trajectories were filtered using a fourth-order low-pass Butterworth filter with a cutoff frequency of 6 Hz. GRF and moment signals were filtered using a second-order low-pass Butterworth filter with a cutoff frequency of 15 Hz, and vertical force values below 5 N were set to zero. EMG signals were band-pass filtered between 30 and 300 Hz using a fourth-order Butterworth filter, followed by rectification and envelope extraction. The present EMG analysis focused on the gluteus maximus and soleus muscles. A representative soleus EMG signal is presented in Figure 2 to illustrate the type of muscle-activation signal used for subsequent feature extraction. EMG features included root mean square (RMS), integrated electromyography (iEMG), median frequency (MDF), and the gluteus maximus–soleus co-contraction ratio. RMS was used to characterize the amplitude of muscle activation, whereas iEMG represented cumulative muscle activity. MDF was included as a frequency-domain

descriptor, while the co-contraction ratio was used to characterize the simultaneous activation of the two selected muscles. Kinetic features were extracted from the vertical component of the GRF and center-of-pressure (COP) data. Eleven kinetic variables were included: Peak_Fz_Right, Peak_Fz_Left, Mean_Fz_Right, Mean_Fz_Left, Impulse_Right, Impulse_Left, GRF_Asymmetry, COP_Path_Right, COP_Path_Left, COP_Velocity_Right, and COP_Velocity_Left. These variables were selected to represent force magnitude, cumulative loading, bilateral asymmetry, and COP-related characteristics of gait.

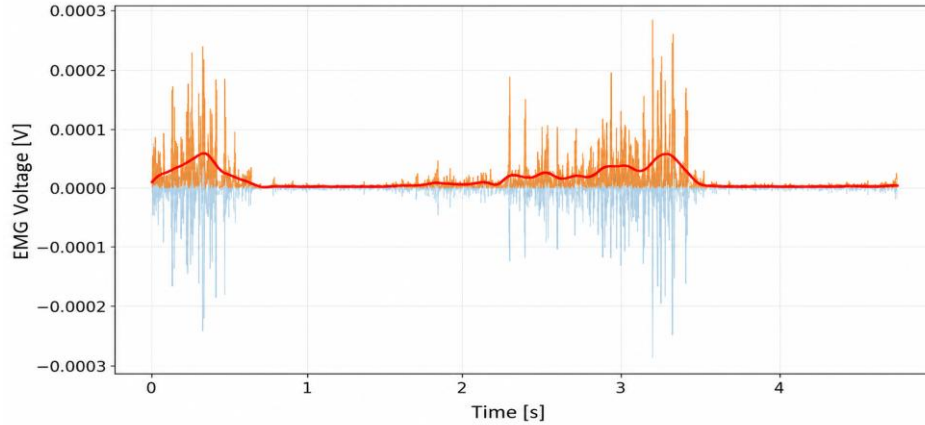


Figure 2. EMG Signal Recorded from the Soleus Muscle of a Representative Sample.

2.3. Construction of the Performance Index.

A study-specific Performance Index was constructed to provide a common target variable for grouping observations according to their biomechanical characteristics. Four normalized components were considered: Cadence Score, GRF Score, COP Stability Score, and Asymmetry Score. The components were normalized to a common scale and combined using their arithmetic mean. Higher normalized scores represented characteristics interpreted as more favorable for locomotor performance, whereas inverse normalization was applied to asymmetry-related variables so that greater asymmetry did not produce a higher Performance Index. The resulting Performance Index was divided into three approximately balanced classes using tertile-based quantiles: Low, Medium, and High. The ranges of the four normalized components corresponding to these classes are summarized in Table 1. The Performance Index was defined specifically for the present analysis as an auxiliary classification target and should not be interpreted as a clinically validated or universal measure of physical fitness or locomotor ability.

Table 1. Ranges of the normalized Performance Index components for the Low, Medium, and High classes.

Class	Cadence (steps/min)	GRF Score	COP Stability Score	Asymmetry Score
Low	87.25–95.75	0.29–0.48	0.19–0.42	0.27–0.46
Medium	96.00–106.50	0.49–0.66	0.43–0.67	0.47–0.69
High	107.00–118.00	0.67–0.86	0.68–0.89	0.70–0.91

2.4. Machine-Learning Classification.

A total of 1,143 observations were divided into training and test sets using a stratified 70:30 split, resulting in 800 training observations and 343 test observations while preserving approximately similar class proportions. The Performance Index class was used as the target

variable for classification. For the EMG-based analysis, Random Forest and XGBoost algorithms [26, 27] were applied to classify observations into the Low, Medium, and High Performance Index classes and to identify informative EMG features. For the kinetic analysis, Random Forest, XGBoost, Support Vector Machine (SVM) [28], and a Nearest Mean classifier were evaluated. The Random Forest, XGBoost, and SVM models used the same set of 11 kinetic input features, allowing their classification performance to be compared under a common feature representation. For the Nearest Mean classifier, a four-dimensional representation comprising the Cadence Score, GRF Score, COP Stability Score, and Asymmetry Score was used. Class centroids were calculated from the training data, and each test observation was assigned to the class with the smallest Manhattan distance to the corresponding centroid. Because this baseline used the four components from which the Performance Index was constructed, its results were treated as a reference rather than as a directly equivalent comparison with models based on independent EMG or kinetic feature sets. The computational analysis was conducted in Python using the Pyomeca, SciPy, NumPy, and pandas libraries.

2.5. Feature Interpretation and Correlation Analysis.

Feature interpretation was performed to identify the biomechanical variables contributing most strongly to classification. Random Forest feature importance was first used to rank the EMG-derived variables according to their contribution to the tree-based model. The resulting feature-importance distribution is presented in Figure 3. SHapley Additive exPlanations (SHAP) were subsequently applied to provide additional information on the magnitude and direction of individual feature contributions to model predictions.

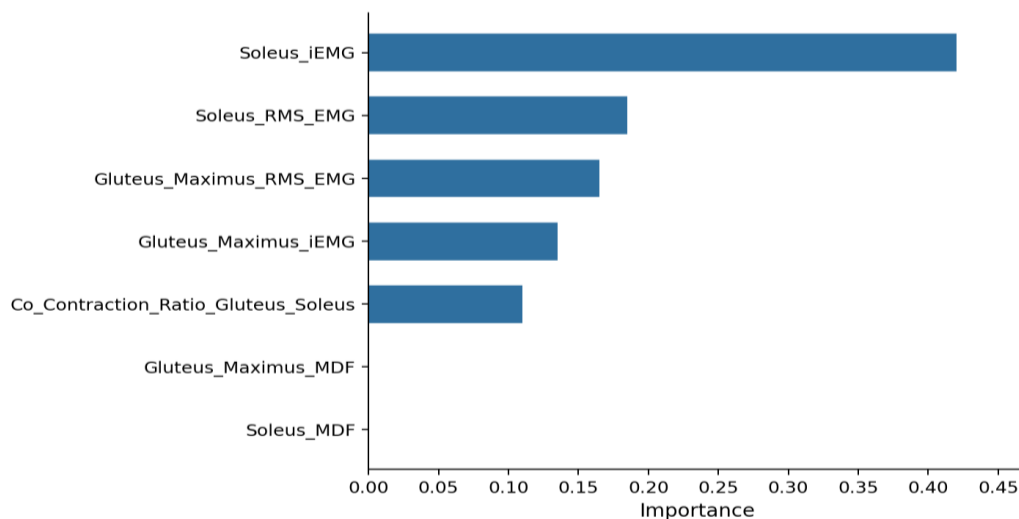


Figure 3. Random Forest Feature Importance For The Selected EMG-Derived Parameters.

Correlation analyses were performed to investigate associations among the extracted biomechanical variables. Pearson correlation was used for the exploratory analysis among EMG-derived features, whereas Spearman rank correlation was used to evaluate associations between EMG and kinetic parameters. The EMG–kinetic analysis included RMS, iEMG, MDF, and co-contraction features derived from the gluteus maximus and soleus, together with GRF magnitude, force impulse, GRF asymmetry, and COP-related variables.

3. Results

3.1. EMG-Based Analysis.

The EMG-based analysis demonstrated that the extracted neuromuscular features contained substantial discriminative information for distinguishing the study-defined locomotor performance classes. Both Random Forest and XGBoost achieved classification accuracies exceeding 99%, indicating that the selected EMG descriptors effectively differentiated the predefined groups within the analysed dataset. Feature-importance and SHAP analyses provided further insight into the variables contributing most strongly to model predictions. Both approaches consistently identified soleus-derived features as particularly informative. Soleus integrated electromyography (iEMG) emerged as one of the most influential variables, while soleus root mean square (RMS) also contributed substantially to class discrimination. This consistency across complementary interpretability approaches strengthens the evidence that features representing the magnitude and cumulative activity of the soleus played an important role in the classification process. Exploratory correlation analysis further revealed substantial redundancy among amplitude-related EMG features obtained from the same muscle. For the gluteus maximus, correlations among mean, RMS, and peak EMG were approximately 0.93–0.99, indicating that these variables captured highly overlapping aspects of muscle activation. Such strong correlations suggest that future models could potentially achieve comparable performance using a more parsimonious feature set, thereby reducing model complexity and redundancy. In contrast, median frequency (MDF) showed zero feature importance in the reported Random Forest analysis. Because this result coincided with limited variability in the MDF values, it should not be interpreted as evidence that frequency-domain EMG characteristics are inherently uninformative. Instead, the calculation and preprocessing of MDF warrant further evaluation.

3.2. Kinetic Analysis.

The kinetic analysis was conducted to determine which ground-reaction-force (GRF), force-impulse, asymmetry, and centre-of-pressure (COP) characteristics contributed most strongly to the classification of locomotor performance. The feature vector consisted of 11 variables: Peak_Fz_Right, Peak_Fz_Left, Mean_Fz_Right, Mean_Fz_Left, Impulse_Right, Impulse_Left, GRF_Asymmetry, COP_Path_Right, COP_Path_Left, COP_Velocity_Right, and COP_Velocity_Left. The feature-importance and SHAP analyses indicated that variables representing GRF magnitude and force impulse contributed more strongly to the classification process than asymmetry and COP trajectory measures. Importantly, the two interpretability approaches produced broadly consistent patterns, strengthening confidence in the identification of the principal kinetic predictors. Figure 4 summarizes the relative contribution of the kinetic variables according to the feature-importance and SHAP analyses. The predominance of GRF- and impulse-related variables suggests that overall mechanical loading characteristics contained greater discriminative information for the predefined performance classes than spatial COP behaviour or bilateral asymmetry. However, this pattern should be interpreted within the context of the healthy, injury-free study population, in which pronounced gait asymmetries were unlikely to occur.

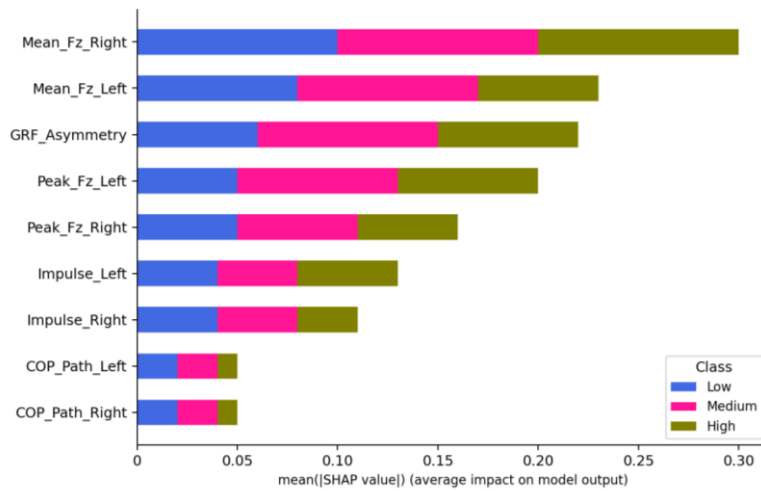


Figure 4. Feature Importance and SHAP Interpretation for the Kinetic-Data Classifier.

3.3. Comparison of Classifiers.

To evaluate whether classification performance depended on the modelling approach, four classifiers with different decision structures were compared using the kinetic feature set. Table 2 summarizes the classification accuracies obtained using Random Forest, XGBoost, Support Vector Machine (SVM), and the Nearest Mean reference method. Among the evaluated approaches, SVM achieved the highest classification accuracy at 93.59%. Random Forest and XGBoost produced identical accuracies of 90.38%, indicating comparable performance of the two tree-based ensemble approaches for the selected kinetic features. In contrast, the Nearest Mean method achieved an accuracy of 70.55%, substantially lower than those of the three machine-learning classifiers. The approximately 20–23 percentage-point difference between the Nearest Mean method and the machine-learning approaches suggests that the predefined classes were not adequately separated by simple proximity to class centroids and that more flexible decision boundaries were beneficial for discriminating observations within the multidimensional kinetic feature space.

Table 2. Classification Accuracy Of The Evaluated Machine-Learning And Reference Methods.

Classifier	Accuracy (%)
Random Forest	90.38
XGBoost	90.38
Support Vector Machine	93.59
Nearest Mean	70.55

3.4. EMG–Kinetic Relationships.

To examine whether neuromuscular activation and external mechanical loading provided overlapping or complementary biomechanical information, Spearman correlation analysis was performed between the selected EMG-derived and kinetic variables. Figure 5 presents the resulting correlation matrix and illustrates both the direction and magnitude of the associations between the two measurement modalities. The strongest association was observed between gluteus maximus RMS and right-limb force impulse (Spearman $r = -0.421$), followed by the association between gluteus maximus RMS and left-limb force impulse ($r = -0.318$). Soleus RMS also exhibited negative relationships with right- and left-limb force impulse ($r = -0.250$ and -0.220 , respectively). Conversely, gluteus maximus MDF showed weaker positive

associations with force impulse, with coefficients of $r = 0.243$ for the right limb and $r = 0.210$ for the left limb. Overall, the observed correlations were weak to moderate rather than strong, indicating that EMG-derived and kinetic parameters captured related but distinct components of locomotor behaviour. Thus, neuromuscular activity could not be considered interchangeable with external mechanical loading. Instead, the correlation structure supports the complementary value of combining EMG and kinetic measurements in multimodal gait analysis.

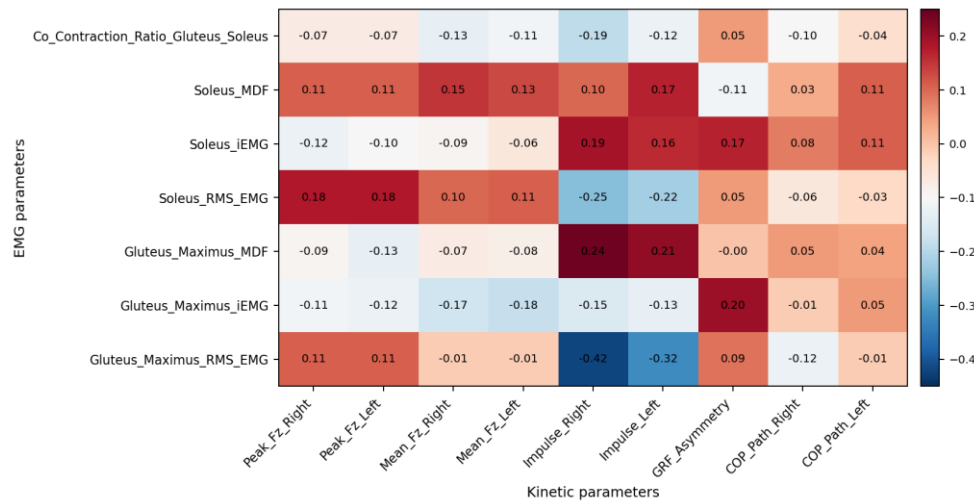


Figure 5. Spearman Correlation Matrix Between EMG-Derived and Kinetic Parameters.

4. Discussion

4.1. Main Findings.

The main finding of the present study was that both neuromuscular and kinetic measurements contained sufficient information to distinguish the study-defined levels of locomotor performance. The EMG-based Random Forest and XGBoost models both achieved accuracies exceeding 99%, whereas the best-performing kinetic model, SVM, achieved an accuracy of 93.59%. This difference indicated that the selected EMG features contained substantial discriminative information for the adopted target grouping. Previous reviews of machine-learning applications in gait analysis have shown that classification performance varies considerably across datasets and depends on target definition, feature representation, sample characteristics, and validation strategy [3, 4]. Therefore, the high accuracy obtained in the present study should be interpreted within the context of the specific dataset and classification framework rather than as evidence that EMG-based classification is universally superior to kinetic classification.

The very high performance of the EMG-based models may also have been influenced by the construction of the target variable. The Performance Index combined cadence, GRF-related characteristics, COP stability, and gait asymmetry, whereas the EMG feature set represented neuromuscular activity recorded during the same walking trials. Because the classes were derived from a multidimensional biomechanical index rather than an independent clinical diagnosis, strong associations between the input features and the target classes were possible without necessarily implying clinical diagnostic validity. This distinction is particularly important when interpreting machine-learning accuracy in biomechanics, as methodological reviews have emphasized the influence of data splitting, repeated observations, feature

selection, and validation strategies on apparent model performance [7]. Accordingly, differences in accuracy between the EMG-based and kinetic models should not be interpreted as a direct comparison of the intrinsic predictive value of the two modalities.

4.2. Importance of Soleus-Derived EMG Features.

Soleus iEMG was identified as one of the most informative EMG variables, with soleus RMS also making a substantial contribution to classification. This finding is biomechanically plausible because the soleus is a major plantar-flexor muscle involved in stance-phase support and forward progression. Muscle and joint functions during locomotion depend on coordinated activation of the plantar-flexor musculature to regulate ankle mechanics and transmit forces during stance [12]. The present findings therefore suggest that the cumulative magnitude of soleus activation contained information relevant to the study-defined grouping of gait observations. The prominence of iEMG and RMS further indicated that amplitude- and cumulative-activity descriptors provided useful discriminative information within the present dataset, whereas MDF did not contribute to the reported Random Forest model. Because the MDF features exhibited limited variability, this finding should not be interpreted as evidence that frequency-domain characteristics are generally less informative for gait classification. Moreover, surface EMG amplitude is influenced by several methodological factors, including electrode placement, filtering, signal normalization, cross-talk, and other signal-processing procedures [9–11]. These factors should therefore be considered when interpreting the relative importance of individual EMG features. From a physiological and modelling perspective, these findings are relevant because they indicate that a relatively small set of physiologically meaningful EMG descriptors may contain substantial information for study-specific locomotor classification. Nevertheless, feature importance should not be interpreted as evidence of a causal relationship. Specifically, the present analysis does not demonstrate that increased or decreased soleus activation causes a higher or lower Performance Index. Rather, feature importance reflects the statistical contribution of individual variables to class discrimination within the fitted model.

4.3. Kinetic Feature Importance: Ground Reaction Force Loading versus COP and Asymmetry.

The kinetic analysis revealed a different but complementary pattern of feature importance. Variables describing the magnitude of ground reaction forces and force impulse were among the most informative predictors, whereas asymmetry and COP-related variables showed comparatively lower importance. GRF directly represents the external mechanical interaction between the body and the ground, while force impulse integrates force over time [14, 15]. The high importance of these variables was therefore consistent with the mechanical components incorporated into the Performance Index and suggested that overall loading characteristics were more discriminative for the adopted classes than the spatial trajectory of the centre of pressure. The lower importance of COP-related variables should not be interpreted as evidence that COP is unimportant for gait control. COP measures have been widely used to characterize changes in gait and postural control, including age-related changes [16]. Rather, the present findings indicate that COP-related variation was less useful for distinguishing the three predefined classes within this particular dataset. Because the dataset comprised healthy, injury-free adults [8], pronounced pathological deviations in COP behaviour or bilateral loading were not

expected. The relative homogeneity of the study population may therefore have reduced the discriminative contribution of these features compared with variables representing overall force magnitude.

An additional methodological consideration concerns the relationship between the kinetic predictors and the construction of the Performance Index. Because GRF-, COP-, and asymmetry-related components were used to construct the target index, an inherent overlap existed between some predictor variables and the target definition. Consequently, the relatively high kinetic classification accuracy should be interpreted as evidence that the selected kinetic variables effectively discriminated the predefined index classes rather than as evidence of independent prediction of locomotor performance. This overlap was less pronounced for the EMG-based models because EMG features were not directly incorporated into the construction of the Performance Index. A similar interpretation applies to gait asymmetry. Human gait is not perfectly symmetrical, even among healthy individuals, and the magnitude of asymmetry varies according to the selected biomechanical variable and calculation method [17, 18]. The relatively low importance of the asymmetry measure in the present analysis may therefore reflect the limited range of clinically meaningful asymmetry within the study population rather than an absence of relevant bilateral information. Asymmetry may become more informative in populations with neurological, musculoskeletal, or other locomotor impairments; however, the present dataset did not allow this hypothesis to be tested.

4.4. Comparison of Classifiers and the Role of Nonlinear Decision Structures.

Among the kinetic models, SVM achieved the highest classification accuracy (93.59%), followed by Random Forest and XGBoost, both of which achieved 90.38%. This result is consistent with previous research showing that SVM is among the most frequently applied classifiers in gait-analysis studies and can perform effectively with structured biomechanical feature sets [3, 4]. Recent machine-learning-based gait studies have likewise identified SVM as an established classification approach. Nevertheless, the present finding should be interpreted as a characteristic of the tested feature space, dataset, and model configuration rather than as evidence that SVM is universally superior to tree-based methods. Differences in feature representation, hyperparameter selection, sample composition, and validation strategy can substantially influence classifier performance [7]. The substantially lower accuracy of the Nearest Mean classifier (70.55%) provided an informative methodological reference. The target classes were constructed from four normalized components and subsequently represented by class centroids for the Nearest Mean analysis. This approach assumes that proximity to a class centre is sufficient to discriminate among observations. However, the kinetic feature space comprised multiple variables representing force magnitude, impulse, asymmetry, and COP behaviour, and the resulting class distributions were not necessarily compact or approximately spherical. In contrast, SVM and tree-based models can accommodate more complex decision boundaries and interactions among variables. The difference between the Nearest Mean classifier and the machine-learning models therefore suggests that class discrimination was not adequately represented by simple centroid-based distances. From an engineering perspective, these findings support the comparison of models with substantially different underlying assumptions rather than reliance on a single classification algorithm. They also illustrate why the accuracy of the best-performing model should be interpreted alongside an appropriate reference method. Such comparisons provide

information not only about predictive performance but also about the potential complexity and structure of the underlying feature space.

4.5. Relationships Between EMG and Kinetic Variables.

The strongest EMG–kinetic association was observed between gluteus maximus RMS and right-limb force impulse (Spearman $r = -0.421$), followed by the association between gluteus maximus RMS and left-limb force impulse ($r = -0.318$). Soleus RMS also showed negative relationships with force impulse, whereas gluteus maximus MDF exhibited weaker positive relationships with impulse. Overall, the observed correlations were weak to moderate, indicating that EMG and kinetic measurements represented related but non-identical components of the locomotor system. Surface EMG measures the electrical activity associated with muscle activation, whereas GRF-derived variables quantify the resulting external mechanical interaction between the body and its environment. Consequently, a strong one-to-one relationship between EMG amplitude and GRF magnitude would not necessarily be expected. The mechanical output of a muscle depends not only on activation amplitude but also on activation timing, muscle–tendon properties, joint configuration, contributions from other muscles, and whole-body dynamics [12]. The moderate relationship between gluteus maximus RMS and force impulse may therefore indicate that hip-extensor activation was associated with the mechanical loading accumulated during gait, while a substantial proportion of the variation was attributable to other biomechanical factors. This interpretation is also consistent with previous evidence indicating that gluteal muscle activation and vertical GRF are related during gait but represent distinct aspects of locomotor mechanics. These findings have important implications for multimodal gait analysis. The relatively modest correlations do not weaken the rationale for combining EMG and kinetic measurements; instead, they indicate that the two modalities provide partially independent and potentially complementary information. A future multimodal classifier could therefore integrate neuromuscular and mechanical descriptors simultaneously rather than treating one modality as a substitute for the other. Such an approach would be consistent with the broader application of multimodal measurements in quantitative gait analysis, in which movement, external loading, and muscle activation provide complementary descriptions of the same gait event [9, 19].

4.6. Scientific Significance and Implications.

Taken together, the findings support the use of multimodal biomechanical information as an engineering framework for study-specific locomotor classification. The EMG analysis highlighted the discriminative contribution of soleus-related activation features, whereas the kinetic analysis emphasized GRF magnitude and force impulse. At the same time, the weak-to-moderate relationships between EMG and kinetic parameters indicated that the two modalities should not be considered interchangeable. Instead, the findings provide evidence that neuromuscular and mechanical measurements contribute complementary information to the classification of locomotor behaviour. The practical significance of the present study is primarily methodological rather than clinical. The analytical framework demonstrates how feature importance, SHAP interpretation, classifier comparison, and correlation analysis can be integrated to move beyond the reporting of a single classification-accuracy value. This approach is particularly relevant to explainable machine learning in gait analysis, where predictive performance should be considered alongside physiological interpretation and

appropriate validation [1, 2]. The proposed framework may therefore provide a useful baseline for future analyses in which the same feature sets are evaluated using subject-wise validation, speed-stratified modelling, and independent populations.

4.7. Limitations and Future Directions.

Several limitations should be considered when interpreting the present findings. First, the Performance Index was an original, study-specific construct and had not been independently validated as a measure of physical fitness. Consequently, the reported classification accuracies should be interpreted as measures of the ability to distinguish the adopted biomechanical groupings rather than as diagnostic accuracy for human physical fitness. Second, the analysis was based on trial-level observations from a multimodal dataset containing repeated trials from the same participants [8]. If observations from the same participant were included in both the training and test sets, model performance may have been partly influenced by participant-specific characteristics. Future analyses should therefore implement subject-wise cross-validation or participant-level data splitting to provide a more stringent assessment of model generalizability to previously unseen individuals. Third, walking speed was not analysed as an independent modelling factor, although the source dataset explicitly included several walking-speed conditions [8]. Because walking speed can influence both muscle activation and kinetic characteristics, future studies should evaluate the different speed conditions separately and determine whether feature importance and classifier performance remain stable across walking speeds. Finally, the EMG analysis revealed substantial redundancy among amplitude-related features, while MDF showed no feature importance in the reported Random Forest analysis. Future studies should therefore evaluate dimensionality reduction or feature-selection strategies, reassess MDF preprocessing, and determine whether a more parsimonious feature set can maintain comparable classification performance. Independent validation using new participants and, ultimately, clinically characterized populations will also be necessary before the proposed framework can be considered for broader biomechanical or clinical applications. Furthermore, the overlap between the kinetic input variables and the components used to construct the Performance Index limits the interpretation of kinetic classification as an independent prediction problem. Future studies should therefore consider outcome variables defined independently of the predictor set, such as externally validated functional or clinical measures.

5. Conclusions

The results indicate that the proposed processing framework can distinguish study-defined levels of locomotor performance using biomechanical gait data. EMG-derived features showed very high classification performance, while kinetic variables also enabled accurate classification, with SVM reaching 93.59%. The analyses consistently highlighted soleus-related EMG features and ground-reaction-force parameters as informative variables. The findings support multimodal biomechanical analysis as a promising engineering approach for quantitative assessment of locomotor behaviour, while the study-specific nature of the Performance Index prevents its interpretation as a validated clinical measure. The next methodological step should be subject-wise validation, explicit modelling of walking speed, and testing on independent populations.

Author Contributions

Conceptualization: Maria Gołdasz; Methodology: Maria Gołdasz; Data processing: Maria Gołdasz, Feature extraction: Maria Gołdasz; Machine-learning Analysis: Maria Gołdasz; Interpretation of Results, Visualization and Manuscript Preparation: Maria Gołdasz.

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Conflict of interest

No conflict of interest was reported by the author.

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