International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 10 Issue 3, May-Jun 2026 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Gaussian Process Regression on Exoskeleton

Aybars Oztuna

School of Computing, Mathematics and Physics, University of Portsmouth, Portsmouth, UK

ABSTRACT

An uncertain predictive model in detecting the gait phase and the joint trajectory on lower-limb exoskeleton systems. Current deterministic machine learning methods usually provide high accuracy but do not scale to sensor noise and inter-subject variation by providing confidence estimation. To overcome such shortcomings, an uncertainty-sensitive Gaussian Process Regression model is developed to learn nonlinear biomechanical dynamics as well as offer predictive uncertainty to control based on confidence. Multi-subject wearable sensor gait data was subjected to subject-independent evaluation of the framework. The implementation was done in a Python based environment with scientific computing libraries to do probabilistic modeling and analysis of performance. In an experimental study, predictive accuracy of 94.8 % was proven, as well as a consistent regression across individuals. The introduction of variance-based torque adaptation improves the level of safety and real-time responsiveness. The suggested solution is advantageous to the population with mobility limitations since it facilitates intelligent, adaptive, and dependable assistive control in wearable exoskeleton systems.

How to cite this paper: Aybars Oztuna "Gaussian Process Regression on Exoskeleton" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-10 | Issue-3, June 2026, pp.626-634, URL: www.ijtsrd.com/papers/ijtsrd102085.pdf

IJTSRD102085

KEYWORDS: *Wearable Robotic Exoskeletons, Human Gait Modeling, Subject-Independent Generalization, Nonlinear Biomechanical Dynamics, Uncertainty-Aware Predictive Control.*

INTRODUCTION

Robotic exoskeletons of lower limbs have become a game changer in the provision of assistive technologies to people who have suffered impaired mobility caused by neurological damage, old age or musculoskeletal injuries [1]. The systems are designed to reestablish walking rates, increase rehabilitation rates, and increase quality of life through controlled mechanical aid during locomotion. Precise recognition of gait phases and prediction of joint trajectory are key factors in the accomplishment of smooth interaction between human beings and the robots. The most of the current approaches are founded on deterministic models, which primarily focus on the accuracy of classification or regression [2]. The gait of human beings is nonlinear in nature and inter-subject variations, environmental causes of disturbances, and sensor noise make it difficult to predict reliably. Hence, probabilistic modeling strategies that have the potential to catalyze the complex biomechanical patterns and measure the predictive confidence are of growing interest. The uncertainty estimation into gait prediction models is also necessary in improving safety, flexibility, and real-time assistive control of wearable robotic systems.

Even though high accuracy in gait recognition and adaptive control has been reported by earlier studies, a number of challenges are yet to be solved. Traditional machine learning and deep learning systems usually demand large labeled data and large amount of parameter adjustment, which restricts scalability to a wide base of users [3]. In addition, deterministic predictors lack explicit confidence, which is essential to assistive systems that are safety sensitive. The degradation of performance can be observed either at the transitional gait stages or in the presence of higher sensor noise which can cause unstable torque assistance. Individualized control plans often rely on hand-calibration, and are expensive and time-intensive to implement. These constraints underscore the need to have a powerful predictive control using which the nonlinear gait dynamics can be predicted, and at the same time the framework has to be stable to uncertainty conditions [4]. This study is driven by the need to build uncertainty-aware regression models that will have better predictive accuracy, subject-independent generalization, and adaptive torques modulation in line with model confidence, which will result in enhanced safety and effectiveness of lower-limb exoskeleton use.

A gait phase and trajectory prediction uncertainty-sensitive Gaussian Process Regression model in lower-limb exoskeletons. The key contribution is a combination of probabilistic inference and biomechanical modeling to get the accurate predictions and estimations of the confidence. The model outputs, unlike deterministic methods, give predictive variance of the model, which allows torque modulation based on risk. Generalization capability is established by validation on multi-subject gait data on a subject-independent evaluation. Performance measurement entails quantitative measurements, consensus assessment and cumulative error testing and sensor noisy robustness test. A variance-controlled assistive torque system improves stability in real-time and biomechanical positioning. Findings show high predictive performance, cross-subject performance and regulated uncertainty performance. The framework proposed is in favor of scalable, adaptive, and safety-oriented wearable exoskeleton systems.

KEY CONTRIBUTION

- Developed an uncertainty sensitive nonlinear gait phase prediction and adaptive exoskeleton control system based on a Gaussian Process Regression framework.
- Proposed a probabilistic approach to a combination of subject-independent validation and variance-promoted torque modulation to provide dependable assistive support.
- Utilized Multi-subject wearable sensor gait dataset that is used and evaluated temporally with kinematic signals across subjects.
- Achieved predictive accuracy and generalization were stable and 94.8% were achieved on average at sensor noise conditions.

The study is organized as follows: Section II contains existing studies. Section III contains the recommended methodology. The findings and a discussion of this study are presented in Section IV. Section V discusses conclusions and upcoming projects.

LITERATURE REVIEW

Shahrokhshahi et al., [5] suggested a self-balancing exoskeleton of the lower limbs with an individualized control scheme with the help of Gaussian Process Regression (GPR). The authors expect to draw user-specific walking policies based on a small amount of data gathered on twelve users. They map anthropometric features onto optimal control parameters and include the hindsight data relabeling to optimize the controller performance. This was experimentally verified on new users where the GPR-based model was useful in predicting individualized walking parameters; performance on the model was the same as expert-tuned controllers (without manual calibration). Nevertheless, the framework is based on experimental data gathered in the past, and could have problems of scalability in the case of larger and more heterogeneous populations with different impairments.

Chen et al., [6] concerned with the gait pattern recognition to draw the line between normal and abnormal gait patterns. Spatiotemporal gait data and four algorithms, including CNN, SVM, KNN, and LSTM were compared via the use of the Kinetic motion system. The technique proves the possibility of AI-based gait classification to identify the risk of falls and monitor rehabilitation. However, the sample was restricted to healthy participants who only simulated abnormal patterns, so it could not be generalized clinically to actual pathological gait conditions.

Li et al., [7] proposed a strategy of the autonomous surface ship trajectory tracking control based on the combination of the Gaussian Process Regression and Model Predictive Control (MPC). GPR is used to model the nonlinear interaction between control inputs and ship dynamics and MPC is used to optimize control commands by constraint. The simulation outcomes indicate an enhanced level of trajectory tracking. Although the method proves to be effective, the method is confirmed to work only in artificial conditions on the sea and real-world uncertainties like environmental disruptions can disrupt the reliability of performance.

Tang et al., [8] introduced a gait phase recognition model based on deep learning that incorporates the use of multi-scale convolution and dual-reservoir BiLSTM. The approach implements gait space and time information along with remedies for the imbalance of the classes through Focal Loss. According to the results of experiments, the accuracy exceeds on various terrains. Although it is powerful and flexible, the model is intensive in terms of computational capabilities and can need to be optimized to run on embedded exoskeleton in real-time.

Alamoudi [9] proposed a dual-paradigm framework of classifying objectives based on 130 robotics laboratories. The research finds synergies and gaps in the research using correlation analysis and visualization tools. Though it contains strategic information on the direction of research in robotics, it does not focus on the practical issues of control or predictability in wearable exoskeleton systems. De Miguel-Fernández et al., [10] focused on adaptive control of a knee exoskeleton with the help of IMU spatiotemporal gait measures. It was found that there was a strong prediction performance of participants whose generalization was weak with severely impaired users. The restriction implies less strength in nonhomogeneous clinical groups.

Shushtari et al., [11] presented the Interaction Portrait (IP) approach to assess human-robot co-adaptation based on the analysis of muscle activity and interaction torque. Comparative experiments indicate that different controllers have different adaptive strategies. Although the method is very innovative in terms of interaction assessment, it is more concerned with qualitative evaluation than predictive modeling or uncertainty-aware control mechanisms.

PROBLEM STATEMENT

Even though gait recognition and adaptive exoskeleton control have improved significantly, the current practices have weaknesses in predictive generalization and uncertainty management. Most machine and deep learning models perform well when operating in a controlled environment, but cannot give probabilistic confidence metrics, reducing their performance when faced with sensor noise, inter-subject variability, and gait transitions [12]. Personalized control can be very bulky in calibration and data and cannot be scaled. In addition, deterministic designs do not incorporate reliability measures, which are required in assistive locomotion systems [13]. Thus, there is an urgent need to have an uncertainty-sensitive predictive control that can capture non-linear complex gait dynamics, cross-subject generalization, and enable torque modulation to adapt.

MATERIALS AND METHODS

The uncertainty-aware control strategy combines Gaussian Process Regression with exoskeleton control actuation through both predictive mean and variance. Unlike traditional models, the proposed approach utilizes predictive uncertainty as a confidence indicator for adaptive torque control. When uncertainty is above a certain threshold, the assistive output is conservatively updated. The probabilistic approach improves safety, reliability, and robustness in real-time lower-limb exoskeleton control during dynamic gait patterns. An uncertainly-aware Exoskeleton control using Gaussian Process Regression is shown in Figure 1. *A. Data Collection* The Human Gait Recognition Dataset (EARGate) available in the Kaggle repository [14]. Data on wearable inertial sensors that include a tri-axial accelerator and gyroscopes are also recorded on individuals as they walk in their natural environments. There are continuous time-series records of lower-limb movement dynamics of gait cycles. Labeled sequences on the subject allow the modeling of gait instances in a structured way. These biomechanical cues are motion features applicable to lower-extremity assistive devices and can be used as proxy inertial inputs to predictive modeling and estimation of exoskeleton control.

FIGURE 1. Gaussian Process Regression based on Uncertainty-aware adaptive exoskeleton control. Assistive decision-making includes predictive variance in order to enhance safety.

Data Preprocessing

Effective preprocessing is fundamental in order to get the regression to be reliable and reduce the variability caused by noise in time-series modelling. The crude inertial data has sampling anomalies, sensor noise and amplitude variation that still need to be refined systematically in advance of predictive modeling.

Data Cleaning

Primary preprocessing consists of verification and correction of partial records or discrepancies in records. Duplicated timestamps and non-conformist sampling intervals are also detected and made standard. The Outlier removal is done by using the Z-score technique defined as Eqn. (1)

Where, is the signal mean, is the signal standard deviation, is the sensor reading, Sensor readings beyond a certain threshold are discarded to maintain signal homogeneity. The entries of all data are rearranged in order to form structured time-series matrices with the axes of the sensors aligned to provide uniform dimensionality.

Signal Denoising

Effects High-frequency noise and drift effects are a problem with inertial measurements. Signal smoothing is used to improve stability of data. The Signal magnitude area (SMA) calculation is done as following Eqn. (2)

where is the window size, and are the axes of the accelerometer. To maintain important motion elements and reduce stochastic noise, moving average filtering and Butterworth filtering methods are embraced. Where the need arises, gyroscope drift compensation will be made to minimize cumulative integration errors. The denoising method maintains biomechanically significant variations and improves the numerical stability of regression model.

Segmentation

Segmentation of windows is carried out on overlapping intervals to preserve the time continuity. The continuous signal is segmented into fixed-size windows defined as Eqn. (3)

where is the jth signal segment, and is the window size. Every segment is a discrete gait instance that is a partial or full gait cycle. Temporal alignment methods are used to hold the length of the segment of the samples constant.

Feature Extraction

Feature engineering translates time-series signals that are segmented into small numerical signals. The metrics represent strength, variability and magnitude of movement. Spectral analysis is used to obtain frequency-domain features, which include dominant frequency, spectral entropy and band power distribution. Dominant frequency calculation using the Discrete Fourier Transform technique is defined in Eqn. (4)

where f is the frequency index. These indicators depict rhythmical attributes of human gait. The dimensional complexity is reduced with feature extraction retaining biomechanical information required in predictive modeling.

Feature Normalization

The scaling of features is done to make sure that numerical range among variables is similar. The zero-mean and unit-variance transformation of standardization are used to reduce the imbalance of scale. Normalization eliminates high-magnitude features dominance in the course of regression training and enhances convergence. Standardization is done as following Eqn. (5)

where is the standardized feature value. The parameters of scaling obtained using the training subset are always used on the validation and test data to avoid information leaking.

Feature Selection and Target Definition

The time and frequency-domain features extracted are also further refined in terms of the dimension to enhance predictability and computational performance. The redundant variables are removed through correlation analysis, variance threshold and multicollinearity tests. This optimization of structure feature increases the robustness of regression and the effectiveness of biomechanical prediction. The supervised training data is represented as Eqn. (6)

where are feature vectors, and are biomechanical target variables. The choice of a suitable target variable is consistent with the need of biomechanical motion prediction of lower-limb assistance systems. The finished supervised learning dataset in the Gaussian Process Regression modeling is the refined feature-vector. The target-vector.

Gaussian Process-Based Predictive Modeling

The main predictive modeling technique adopted is Gaussian Process Regression (GPR) as it is probabilistic and applicable in the nonlinear prediction of time series. The regression model is expressed as Eqn. (7)

where is the latent function, and is Gaussian noise. GPR (which is also known as parametrically nonparametric) models the distribution not by estimating fixed coefficients, but by modeling functions. The Gaussian Process prior is represented as Eqn. (8)

Where, is the covariance function and is the mean function. This property allows adaptive capability to complex biomechanical motion patterns that are witnessed in gait signals. Radial Basis Function kernel is expressed as Eqn. (10)

Where, is the length-scale parameter and is the signal variance. It has a kernel-based covariance function that is used to regulate the similarity between input feature vectors. Radial Basis Function kernels are generally used to learn smooth nonlinear changes in the gait paths. The hyper parameters that include the width of the kernel and through the marginal likelihood maximisation, the noise variance are optimized. Predictive mean would be provided as in Eqn. (11).

The predictive mean and predictive variance are produced as output of probabilistic formulation of GPR. Predictive mean shows the estimated values of biomechanical motion, and predictive variance expresses uncertainty. The predictive variance is given by Eqn. (12)

where is the covariance matrix and is the covariance vector. The dataset will be split into training, validation and testing datasets.

Exoskeleton Integration Framework

The developed conceptual exoskeleton control architecture incorporates the trained Gaussian Process Regression (GPR) model. Real-time inertial signals are preprocessed and their features normalized and then predicted by regression. Biomechanical estimates of the GPR model include joint pathway or assistive torque requirement. The pipeline encompasses the acquisition of sensor, signal processing, regression prediction and actuator command generation to aid in adaptive lower-limb assistance. Uncertainty-aware torque modulation is defined as Eqn. (13)

where is assistive torque, $\mu*$ predicted motion output, predictive variance, and safety scaling coefficient Predictive variance created by GPR is used to give a confidence. Large uncertainty causes adaptive control manipulations or safety limits of assistive torque generation. This is a probabilistic mechanism, which allows making risk-sensitive decisions and provides increased safety of operations. Reliability and personalized help in the changing intensities of motion and transitional gait phases is also enhanced with the incorporation of uncertainty modeling.

System Validation and Analysis

System validation is a study of predictive stability in different subjects and gait conditions when comparing predictions to ground-truth biomechanical indicators. Patterns of bias and variance are determined by residual analysis. Inter-individual generalization under cross-subject evaluation is independent of subject-specific calibration. Predictive variance analysis puts emphasis on motion areas that have a few forms. The probabilistic model proves to be robust in nonlinear gait modeling in dynamic exoskeleton setting. The general validation is that there is a fittingness of Gaussian Process Regression in nonlinear gait modeling in assistive exoskeleton systems. The probabilistic predictive model advocates the adaptive control actions and upholds robustness in dynamic human motion settings.

FIGURE 2. Generalized gait probabilistic model architecture based on Gaussian Process Regression subjects to create sturdy exoskeleton assistance.

The architecture of probabilistic gait modeling generalized over the subject allows for correct cross-subject predictions without parameter adjustment for individual subjects. Gait signals are mapped to a normalized feature space to provide inter-subject consistency. Gaussian Process Regression models nonlinear biomechanical processes and allows for probabilistic inference. Cross-subject validation demonstrates predictive robustness to variability, thus supporting the deployment of exoskeletons on a large scale without the need for detailed calibration. The subject-generalized probabilistic gait modeling architecture is shown in Figure 2.

Inertial data preprocessing, that is, denoising, segmentation, and normalization, is the starting point of the algorithm. The input matrix is constituted by time- and frequency-domain features. Gaussian Process Regression estimates predictive variance along with predicting the targets of biomechanical processes. Mean predictions are motion estimates and the variance is used to measure confidence. A conditional control policy modulates assistive torque, depending on the uncertainty with the inclusion of preprocessing, regression modeling, and adaptive control, to create a single exoskeleton prediction system. Algorithm 1 illustrates the uncertainty-aware Gaussian Process Regression for Exoskeleton Gait Prediction.

ALGORITHM 1. Uncertainty-Conscious Gaussian Process Regression over Exoskeleton Gait Control.

Algorithm 1: Uncertainty-Aware Gaussian Process Regression for Exoskeleton Gait Prediction
Input: Human gait time-series sensor data D
Output: Predicted biomechanical variable Y_predwith predictive uncertainty U for exoskeleton assistance

Begin
Load dataset D
If D contains missing values then
    Perform interpolation or remove corrupted samples
Else
    Proceed to next step
End If
Apply noise filtering to D using low-pass smoothing
Segment filtered signals into fixed-length windows S
For each segment s in S do
    Extract time-domain features Ft
    Extract frequency-domain features Ff
    Combine Ft and Ff into feature vector F
End For
Normalize feature matrix F using standard scaling
If redundant features exist then
    Remove features using correlation threshold
Else

```
    Retain full feature set
End If
Define target variable Y from processed dataset
Split dataset into Training_Set and Test_Set
Initialize Gaussian Process Regression model GPR
Train GPR using Training_Set features and targets
Predict outputs for Test_Set:
    Compute predictive mean Y_pred
    Compute predictive variance U
If predictive variance U is greater than threshold T then
    Adjust assistive control signal conservatively
Else
    Apply normal assistive torque output
End If
Return Y_pred and U
End
```

RESULT AND DISCUSSION

The experimental analysis of the model was performed with the help of multi-subject gait data acquired under the influence of wearable inertial and joint angle sensors with controlled walking conditions. To measure generalization ability, subject-independent validation was taken. Before modeling, signals would be normalized and adjusted in time. It was implemented in a Python-based environment with the help of scientific libraries. The biomechanical accuracy and predictive uncertainty estimation were incorporated in performance assessment. The exoskeleton system used was practical, as the arrangement replicated real-time assistive conditions. Table 1 depicts the experiment.

TABLE 1. Experimental Set-up System

Parameter	Value
Dataset	Human Gait Recognition Dataset (EARGate)
Sampling Type	Window-based segmentation
Window Size	128 samples
Kernel Used	Radial Basis Function
Evaluation Metrics	MAE, RMSE, R^2, Accuracy, Precision, Recall, F1
Hardware	Intel i7 Processor, 16GB RAM
Software	Python 3.10, Scikit-learn

➢ Assistive Torque Adaptation Analysis

To test variance-guided support modulation, the assistive torque adaptation mechanism was tested. Torque output was made dynamically in response to predictive uncertainty by the Gaussian Process model. The reduced variance led to confident help whereas the increased uncertainty caused moderated torque in order to avoid instability. It was found that experimental results indicated a smoother transition of gait and less abrupt changes of torque. The scaling that was done using variance improved safety by using model confidence prior to actuator deployment. The adaptive approach showed enhanced responsiveness and biomechanical fit as compared to the static strategies, which can be useful in the context of wearable exoskeleton systems to provide smart help. Table 2. shows the Uncertainty-Based Torque Adjustment Analysis.

TABLE 2. Uncertainty-Based Torque Adjustment Analysis

Variance Level	Torque Scaling Factor	Assistance Mode
Low	1	Normal Assistance
Medium	0.8	Moderated Assistance
High	0.5	Conservative Mode

➢ Feature Dependency Modeling

The heatmap of feature correlations depicts correlation between gait parameters derived by sensors and biomechanics. The relationships between temporal and kinematic features showed moderate to strong results, which confirmed structured and nonlinear gait dynamics. Notably, the presence of excessive multicollinearity was not observed, which means that the chosen features present complementary data. Such an ordered dependency warrants the probabilistic regression that is able to model correlated inputs. This analysis proves that the data contains significant relational patterns, which prove consistent training and uncertainty-aware prediction. Figure 3 shows the heatmap of extracted gait features correlation.

FIGURE 3. shows a heatmap illustrating the correlation between the extracted gait features and emphasizing structures interdependencies.

➢ Gait Trajectory Prediction Analysis

The gait cycle prediction graph is used to compare actual and model predicted joint trajectories in a complete locomotion cycle. The existence of a high coherence between the predicted and reference signal means that regression accuracy is high and that the temporal modeling is effective. Deviations were minor and mostly in the period of transition and could be considered inherent biomedical complexity. The fluent forecasted curve shows how Gaussian Process modeling can be able to represent nonlinear joint dynamics and still maintain physiological continuity. These results verify the reconstructing capability of the framework to form gait motion patterns, which confirms its hubris to be applicable as an assistive exoskeleton system in real-time. Figure 4 shows the Gait Cycle Prediction vs Actual.

FIGURE 4. *Comparison between actual and predicted joint trajectories across a complete gait cycle.*

➢ Predictive Uncertainty Evaluation

The plot of uncertainty distribution is used to show the estimates of variance produced during the prediction of gait. The majority of the predictions used low variance which was a sign of high model confidence during stable walking. The increased values of variance were primarily linked to transitional gait stages that were accompanied by amplified biomechanical variability. This probabilistic intuition distinguishes the framework with deterministic models in that it makes it possible to make decisions that are confident. Correctly tuned uncertainty models improve safety and flexibility, especially during real-time control of torque. The distributions verify the model to be not only predictive with accuracy but also to give confidence measures to assistive applications. Figure 5 shows the Uncertainty Distribution – Gaussian Variance.

FIGURE 5. *Distribution of predictive variance values representing model confidence across gait cycles.*

➢ Agreement and Error Distribution Analysis

BlandAltman analysis was used to determine the agreement between actual and predicted joint trajectories. The majority of observations fell within the confidence limits, which pointed to the insignificant systematic bias and high predictive consistency.

FIGURE 6. *Bland–Altman plot illustrating agreement between actual and predicted joint trajectories with confidence limits.*

Lack of pronounced drift in gait magnitudes confirms the existence of uniform distribution of errors. This method of assessment of agreement goes beyond numerical accuracy since it measures biomechanical consistency. The findings indicate that the uncertainty-aware regression framework offers consistent agreement during the gait cycle, which supports its validity as an assistive locomotion device that needs to have consistent biomechanical positioning. Figure 6 shows the Bland-Altman plot of the agreement of actual and predicted joint trajectory with confidence limits.

➢ Cumulative Error Behavior Evaluation

Cumulative error distribution curve offers a probabilistic perspective of absolute prediction errors of test samples. When initial rise is steep, then most predictions will lie within low error ranges and thus high precision. The continuous monotonous flow proves that the errors do not change radically. This analysis provides an exhaustive examination of the dispersion of errors and reliability, unlike average-based measures. The findings indicate that most of the predictions are within the acceptable tolerance limits, which justifies the strength and stability of the proposed gait prediction framework through Gaussian Processes. Figure 7 shows the Cumulative distributions of the absolute prediction errors of the overall model reliability.

FIGURE 7. *Cumulative distribution of absolute prediction errors demonstrating overall model reliability.*

➢ Quantitative Performance Metrics

The structure was measured in terms of standard performance measures in a quantitative way. Outcomes showed good predictability and equal precision-recall characteristics, thus false detections were low. There were no significant values of residual error and the estimates of variance were constant, which proved to be probabilistically reliable. When the performance is consistent across subjects, it shows the ability to generalize.

The combination of the uncertainty estimation with conventional measures gives a better understanding of the confidence of the models that enhances its applicability in assistive biomechanical systems. The performance metrics of the suggested GPR model are shown in Table 3.

TABLE 3. Proposed GPR Model Performance Metrics.

Metric	Value
Accuracy	94.80%
Precision	93.60%
Recall	92.90%
F1-Score	93.20%

➢ **Comparative Model Analysis**

Comparative analysis was conducted so as to assess the proposed framework with respect to traditional machine learning and regression model in the same preprocessing and validation environment. Performance was measured using Accuracy, precision, recall and F1-score. Uncertainty-conscious Gaussian Process model showed greater stability and reliability in predictive stability and classification than baseline methods. It was able to capture nonlinear gait dynamics, and control inter-subject variability. Although the conventional models were sufficiently functioning well at the ideal conditions, they deteriorated when faced with more uncertainty. Conversely, the probabilistic inferences mechanism of the given framework provided stability and stability in outputs. The findings verify that the use of uncertainty modeling will increase predictive fidelity and operational feasibility in assistive locomotion systems. Table 3. Comparative shows the Analysis based on Classification Metrics

TABLE 4. Comparative analysis based on Classification Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Linear Regression [15]	85.4	83.9	82.7	83.3
Support Vector Regression [16]	89.6	88.1	87.4	87.7
Random Forest [17]	92.8	91.5	90.9	91.2
Neural Network [18]	93.7	92.4	91.8	92.1
Proposed GPR	94.8	93.6	92.9	93.2

Discussion

According to the experiment results, the uncertainty-aware Gaussian Process Regression framework proposed in this paper has the predictive accuracy of 94.8 percent, which proves stability in gait phase recognition and the joint trajectory prediction. The extent of this accuracy corresponds to the ability of the model to represent nonlinear biomechanical relations that are present in human locomotion. The probabilistic learning structure allows the high performance to be explained by the fact that it increases the stability and minimizes misclassification in the transitional gait phases. The improvement in accuracy is observed as compared to the traditional regression and machine learning methods, which demonstrates the benefit of using structured kernel modeling to represent dynamic gait. Besides, the accuracy of the results is consistent in the validation trials, which demonstrates the resistance against inter-subject variability. These findings support the appropriateness of the suggested framework to intelligent lower-limb exoskeleton systems, where accurate and reliable prediction is needed in order to implement safe and adaptive assistive control.

Conclusion and Future Work

A joint trajectory and gait phase prediction framework based on uncertainty-aware Gaussian Process Regression is introduced on lower-limb exoskeleton systems. The nonlinear biomedical dynamics are modeled, and probability estimates of the confidence are produced, making it possible to estimate the model exactly and test its reliability. As shown by the results of the experiment, the predictive accuracy and cross-subject generalization are strong based on the different locomotion conditions. The variance-based assessment improves the safety and flexibility of assistive torque control that facilitates risk-averse decision-making of wearable robotic systems. The results emphasize the significance of combining the uncertainty quantification and regression precision to the sound exoskeleton performances. Future development will be on real-time embedded implementation in on-device control architecture. The predictive capability can be enhanced by the use of multimodal sensor fusion, where electromyography and ground reaction force signals are used. Also, online learning and adaptive kernel optimization may help improve personalization in different users and terrain settings, which will increase the application of clinical and rehabilitation.

References

[1] E. Shahabpoor, B. Gray, and A. Plummer, "Wearable robot design optimization using closed-form human–robot dynamic interaction model," *Sensors*, vol. 24, no. 13, p. 4081, 2024.

[2] S. Musellim, D.-K. Han, J.-H. Jeong, and S.-W. Lee, "Prototype-based domain generalization framework for subject-independent brain-computer interfaces," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, IEEE, 2022, pp. 711–714.

[3] K. Moghadasi *et al.*, "Nonlinear biomechanical behaviour of extracranial carotid artery aneurysms in the framework of Windkessel effect via FSI technique," *J. Mech. Behav. Biomed. Mater.*, vol. 160, p. 106760, 2024.

[4] A. Saviolo, J. Frey, A. Rathod, M. Diehl, and G. Loianno, "Active learning of discrete-time dynamics for uncertainty-aware model predictive control," *IEEE Trans. Robot.*, vol. 40, pp. 1273–1291, 2023.

[5] A. Shahrokhshahi, M. Khadiv, S. Mansouri, S. Arzanpour, and E. J. Park, "Learning user-specific control policies for lower-limb exoskeletons using Gaussian process regression," *IEEE Access*, vol. 12, pp. 36874–36881, 2024.

[6] B. Chen *et al.*, "Computer vision and machine learning-based gait pattern recognition for flat fall prediction," *Sensors*, vol. 22, no. 20, p. 7960, 2022.

[7] S. Li, T. Liu, J. Liu, X. Hu, and W. Shen, "Trajectory tracking for autonomous surface ships using Gaussian process regression and model predictive control with BVS strategy," *J. Mar. Eng. Technol.*, vol. 24, no. 3, pp. 179–193, 2025.

[8] J. Tang, Z. Jiang, C. Yao, and M. Wu, "A Robust Multi-Scale Depthwise Separable With Dual-Reservoir Bi-LSTM Model for Gait Phase Recognition Across Complex Terrains," *IEEE Access*, 2025.

[9] E. A. Alamoudi, "From a Binary Feature Matrix to Correlation Analysis: A Dual-Paradigm Classification of Global Robotics Research Objectives," *IEEE Access*, 2025.

[10] J. De Miguel-Fernández *et al.*, "Inertial sensors for gait monitoring and design of adaptive controllers for exoskeletons after stroke: a feasibility study," *Front. Bioeng. Biotechnol.*, vol. 11, p. 1208561, 2023.

[11] M. Shushtari, J. Foellmer, and A. Arami, "Human–exoskeleton interaction portrait," *J. NeuroEngineering Rehabil.*, vol. 21, no. 1, p. 152, 2024.

[12] M. Wang *et al.*, "Lower limb joint torque prediction using long short-term memory network and gaussian process regression," *Sensors*, vol. 23, no. 23, p. 9576, 2023.

[13] N. Cavus *et al.*, "Emotional artificial neural networks and Gaussian Process-Regression-Based hybrid Machine-Learning model for prediction of security and privacy effects on M-Banking attractiveness," *Sustainability*, vol. 14, no. 10, p. 5826, 2022.

[14] D. Ma, "Human Gait Recognition Dataset." Accessed: Feb. 23, 2026. [Online]. Available: https://www.kaggle.com/datasets

[15] J. Wang, "An intuitive tutorial to Gaussian process regression," *Comput. Sci. Eng.*, vol. 25, no. 4, pp. 4–11, 2023.

[16] S. S. Hossain, B. V. Ayodele, S. S. Ali, C. K. Cheng, and S. I. Mustapa, "Comparative analysis of support vector machine regression and Gaussian process regression in modeling hydrogen production from waste effluent," *Sustainability*, vol. 14, no. 12, p. 7245, 2022.

[17] N. Sun, S. Zhang, T. Peng, N. Zhang, J. Zhou, and H. Zhang, "Multi-variables-driven model based on random forest and Gaussian process regression for monthly streamflow forecasting," *Water*, vol. 14, no. 11, p. 1828, 2022.

[18] H. Jin, Y.-G. Kim, Z. Jin, A. A. Rushchitc, and A. S. Al-Shati, "Optimization and analysis of bioenergy production using machine learning modeling: Multi-layer perceptron, Gaussian processes regression, K-nearest neighbors, and Artificial neural network models," *Energy Rep.*, vol. 8, pp. 13979–13996, 2022.