Prediction of Optimal Walking Speed for Powered and Passive Prostheses to Improve long-term Gait Stability

Dhanalakshmi M[a], Saranya S[b], Bhavya Natarajan[c], Swethashri S S[d], Shreeda R[e]

Department of Biomedical Engineering, Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam, India- 603110

[a]dhanalakshmim@ssn.edu.in,[b] ssaranya@ssn.edu.in, [c]bhavya2010969@ssn.edu.in,[d]swethashri2010218@ssn.edu.in, [e]shreeda2011008@ssn.edu.in

Abstract: This study explores the effects of powered versus passive prosthetic knees on gait biomechanics in transfemoral amputees with unilateral left leg amputation. Knee joint Kinetics during gait viz., Joint moment, Joint power and Ground reaction forces of the affected and unaffected legs were analyzed. Significant variations in hip joint activity were noted, highlighting compensatory adjustments in the intact limb. For the choice of prosthetics and optimal walking speeds (slow, medium and fast), machine learning techniques such as Long Short-Term Memory (LSTM) networks, Random Forests (RF), and Support Vector Machines (SVM) were employed and the results were compared. The LSTM model achieved an accuracy of 97% in predicting prosthetic type and walking speed, surpassing the 94% accuracy of SVM and the 95% accuracy of RF models. These results underscore the importance of personalized prosthetic solutions to improve gait efficiency and reduce compensatory movements, thereby enhancing long-term mobility and comfort.

Keywords: Transfemoral prosthesis, walking speed, Kinetics, Kinematics, Gait

1. Introduction

A staggering statistic from the World Health Organization reveals that roughly 1.5 million people undergo amputation procedures every year, with a significant number involving the lower limbs. Among these, transfemoral amputation, the removal of the leg above the knee joint, presents a formidable challenge for individuals. Transfemoral amputation can lead to a multitude of physical limitations such as maintaining a steady posture and navigating uneven terrain becomes more challenging due to the loss of a limb and the altered biomechanics of walking. a significant decrease in walking speed and tiredness. The altered gait patterns and reduced balance can lead to a higher risk of falls and subsequent injuries. The body attempts to compensate for the missing limb, leading to changes in gait patterns that can put undue stress on other joints. Transfemoral amputation disrupts the body's natural biomechanics of walking. The missing limb and disrupted musculature significantly impact balance, stability, and overall gait efficiency. People with transfemoral amputations often experience a shorter stride length, decreased walking speed, and altered joint movements compared to unimpaired individuals. Additionally, the lack of sensory feedback from the missing limb can further complicate gait control and coordination.

Prosthetic limbs play a vital role in helping individuals with transfemoral amputation regain mobility. There are two main categories of prostheses: passive and powered. Passive Prosthetic Limbs: These are the more traditional type of prosthesis. They rely on the user's remaining musculature and balance to function. Passive prosthetics are typically lighter and less expensive than powered alternatives. However, they lack the ability to actively replicate natural muscle function during walking. This limitation can lead to gait compensations, where individuals adjust their walking patterns to maintain balance and stability. These compensations, while necessary for short-term walking, can put undue stress on the unaffected limb over time, potentially increasing the risk of secondary musculoskeletal problems. Powered Prosthetic Limbs: These technologically advanced prostheses are equipped with motors, sensors, and microprocessors. They aim to address the limitations of passive prostheses by mimicking natural joint movements and providing dynamic support during walking. Powered prosthetics can sense the user's gait and adjust their resistance or assistance, accordingly, potentially leading to a more natural and efficient gait pattern. However, powered prostheses are typically heavier, more expensive, and require more maintenance compared to passive options.

Traditional passive prostheses lack the ability to actively replicate natural muscle function during walking. This can lead to gait compensations in the unaffected limb to maintain balance and stability. These compensations can put undue stress on the sound limb, potentially increasing the risk of secondary musculoskeletal problems. Powered prostheses, equipped with motors and sensors, aim to address these limitations by mimicking natural joint movements and providing dynamic support. However, choosing the most suitable prosthetic type and optimizing walking speed for each individual amputee requires a comprehensive understanding of their biomechanical gait patterns.

In previous studies, the researchers examined the influence of prosthetic design on knee joint mechanics in transtibial and transfemoral amputees. Researchers explored whether prosthetic feet with increased push-off force could reduce stress on the knee joint, potentially mitigating the risk of osteoarthritis [1]. Few other research explores the link between prosthetic design and the development of knee osteoarthritis in young, unilateral transtibial amputees [2, 3, 4]. It compares passive and powered ankle-foot prostheses, investigating their influence on limb loading during walking. While powered prostheses offered push-off assistance and potentially mitigated some risk factors for knee osteoarthritis in the sound limb during early stages of prosthetic use, further studies are needed to understand their long-term effects and effectiveness across different amputee populations.

Since machine learning is an advancement in research, many researchers used machine learning techniques for studying gait phases and different walking speeds [5, 6, 7]. In [8], machine learning technique is used to estimate gait phases in robotic transfemoral prostheses for different walking speeds. Two sensor setups are tested: one with just IMUs and another with added heel force sensors. Both setups achieved accurate gait phase estimation in healthy subjects at various speeds. However, including heel force data improved heel-strike detection accuracy. Future research should involve amputees and explore additional sensors for even more robust gait estimation in prosthetic control.
Even though there is research on gait pattern prediction and classification, only few focus on foot pressure [9]. In [9], the findings show amputees put more pressure on their forefoot and midfoot compared to healthy individuals, suggesting compensatory gait mechanisms. Fall detection, shock absorption and balance controlling are also key aspects in designing prosthesis [10, 11, 12]. While walking, the influence of prosthetic foot compliance on joint kinetics and kinematics during walking in transtibial amputees. It enhances energy storage and release, leading to more natural gait patterns and reduced biomechanical stress on residual limb tissues [13].

The present work aims in improving gait function in transfemoral amputees through a comprehensive investigation of biomechanics and the development of a personalized prosthetic solution.analyzing and comparing key biomechanical parameters, such as joint angle, power output, and moments, Ground reaction force (GRF) during gait using both powered and passive prostheses in transfemoral amputees. Then to investigate the presence and nature of gait compensations developed in the unaffected limb of transfemoral amputees. This may include analyzing differences in joint kinematics and kinetics compared to the unaffected limb in healthy individuals. Finally to develop machine learning models using Long Short-Term Memory (LSTM) networks, Random Forest and Support vector Machine networks and accurately predict the optimal prosthetic type and ideal walking speed based on an individual's biomechanical data.

2. Materials and Methods

In this study, a multidisciplinary approach is adopted to analyze and optimize prosthetic knee performance in transfemoral amputees using advanced machine learning techniques and biomechanical analysis. The research utilizes a combination of motion capture and force plate measurements from the Murphy dataset to gather comprehensive gait data. These data were processed and segmented into meaningful features, including joint angles, knee adduction moments and ground reaction forces (GRF). The study utilized Long Short-Term Memory (LSTM) networks, Random Forests (RF), and Support Vector Machines (SVM) to model the relationship between these features and the effectiveness of powered versus passive prosthetic knees. Statistical methods were applied to assess the significance of observed differences in gait mechanics, with a particular focus on identifying compensatory strategies in the intact limb. This integrated approach aimed to provide personalized prosthetic recommendations to improve gait efficiency and reduce the long-term health risks associated with compensatory movements.

2.1. Dataset and Experimental protocol

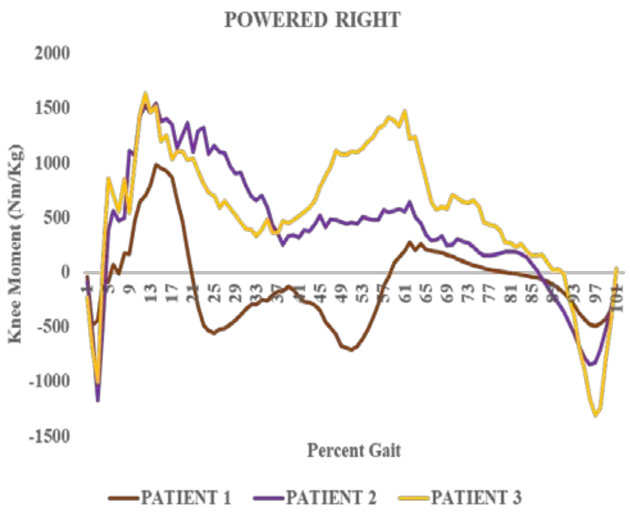
Murphy dataset [25] that investigates the impact of prosthetic leg designs and walking speeds on individuals with transfemoral amputations. Three participants each walked on a treadmill at slow, normal, and fast speeds using two types of prosthetic legs: a passive everyday model and an advanced powered one. In this study, 18 recordings (3 individuals × 2 leg types × 3 speeds) have been utilized. Motion capture tracked their leg movements and force plates measure ground forces.. Recordings were segmented into individual strides based on heel contact and standardized for comparison. The dataset offers insights into how prosthetic design and walking speed influence gait in this population.

2.2. Analysis on Knee Kinematics and Kinetics

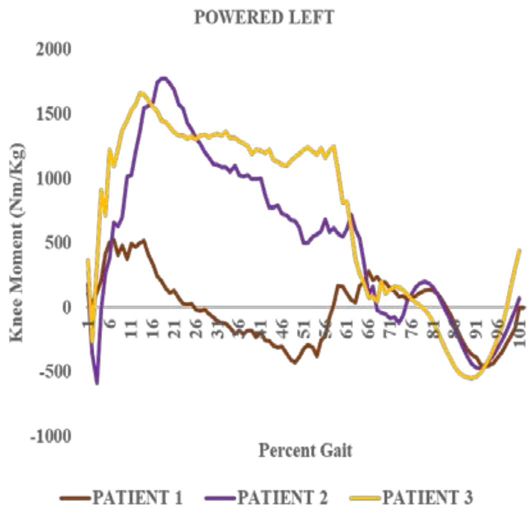
The data processing: legs were categorized (left/right), strides were segmented by heel contacts, and time normalization is applied to standardize stride durations to 100 data points per participant. Segregation into stance and swing phases enabled focused analysis of gait cycle components. ??Visualizations of knee adduction moment, knee joint power and ground reaction forces (GRF) graphically explore the relationships and patterns, guiding further detailed investigation.

2.2.1. Knee Adduction Moment

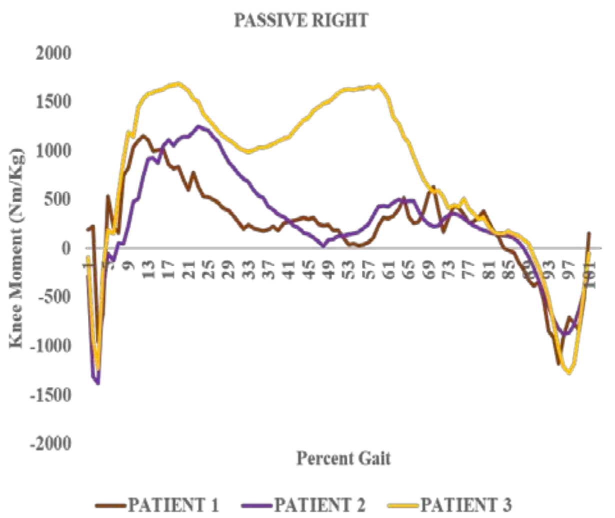
The knee external adduction moment across all three participants (Subject 1, 2, and 3) were plotted in Figure 1. It illustrates knee adduction moments for three subjects using both powered and passive prostheses, revealing a consistent trend across all participants: powered prostheses generate larger adduction moments compared to passive prostheses throughout the gait cycle, with an observed difference of approximately 300-400 Nm/kg during mid-stance, the phase corresponding to maximum weight-bearing. The peak knee adduction moments for powered prostheses range from 1100 to 1500 Nm/kg, while passive prostheses exhibit lower peaks, generally around 700 to 1000 Nm/kg. The increased inward force associated with powered prostheses contrasts with the minimum adduction moments observed during terminal swing when the prosthetic is not weight-bearing. Additionally, comparisons between prosthetic and contralateral limbs reveal gait asymmetry, with powered prostheses showing adduction moments 800-900 Nm/kg higher than those observed in the intact leg.



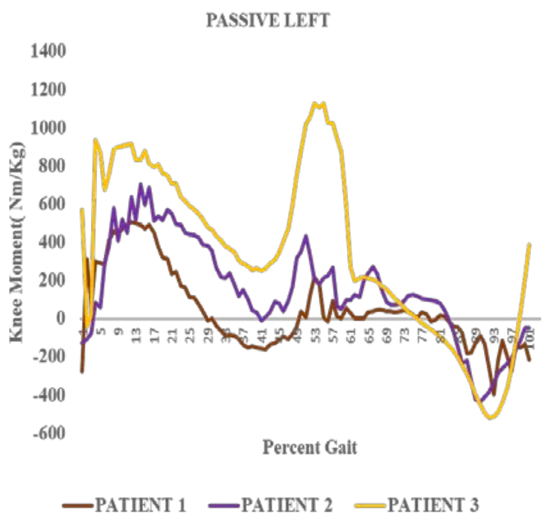
(a)



(b)



(c)



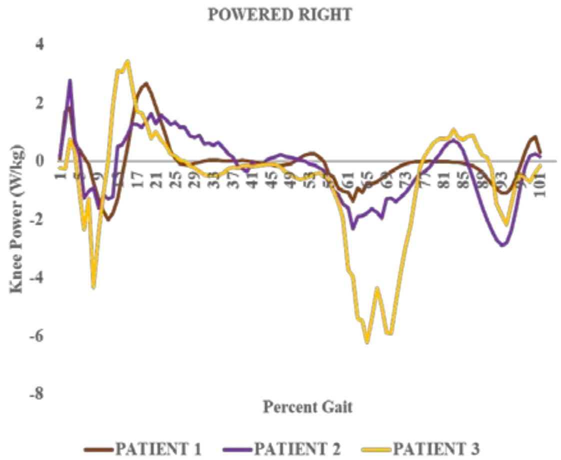
(d)

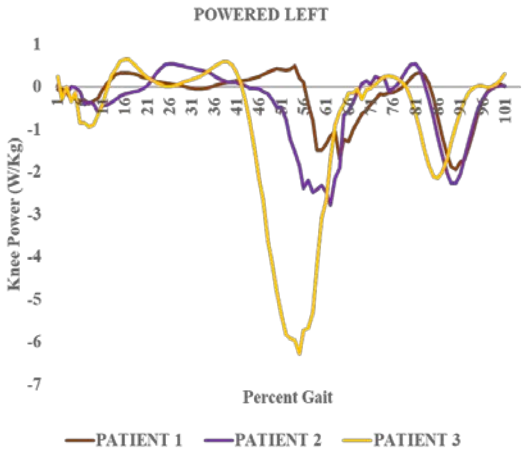
Fig. 1. (a) Knee Adduction Moment for Powered Prosthetic Right Leg, (b) Knee Adduction Moment for Powered Prosthetic Left Leg, (c) Knee Adduction Moment for Passive Prosthetic Right Leg, (d) Knee Adduction Moment for Passive Prosthetic Left Leg

Therefore, the powered prosthetic knee appeared to generate a consistently larger adduction moment compared to the passive prosthetic knee throughout the gait cycle (percent gait). This suggests that the powered prosthesis applies a stronger inward force at the knee joint during walking compared to the passive design. This highlights the effectiveness of powered assistance in reducing the burden on the unaffected leg.

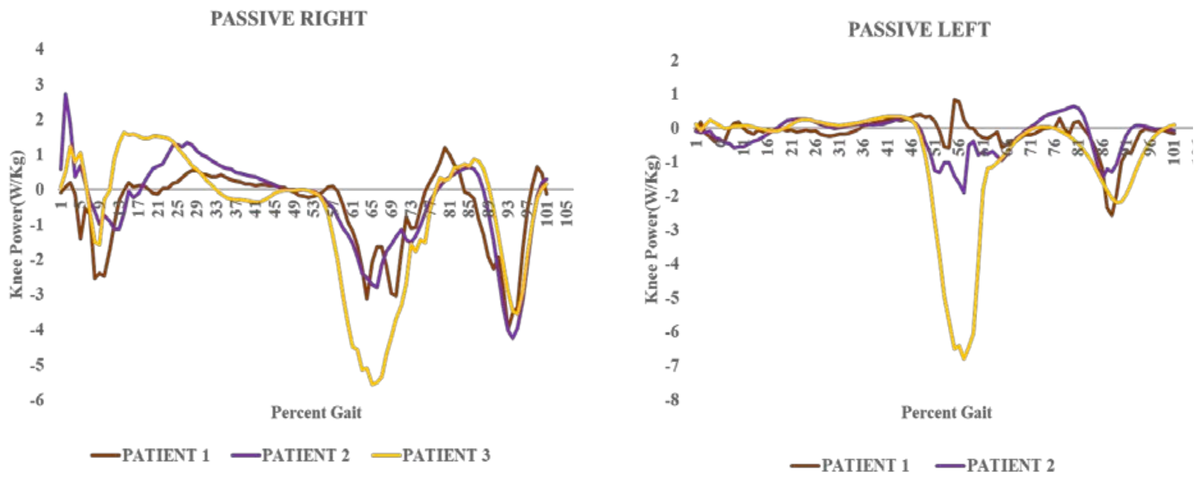
2.2.2. Knee Joint Power:

Figure 2 illustrates knee power for three subjects using both powered and passive prostheses, highlighting a consistent trend where powered prostheses generally require less power than passive prostheses throughout the gait cycle, particularly during the stance phase. The peak power output for powered prostheses ranges from 30 to 35 W/kg, whereas passive prostheses demand peak power outputs between 40 and 45 W/kg. Individual variations in walking speed, stride length, and prosthetic fit can affect the timing of these peak and minimum power phases. Comparing knee power between prosthetics and contralateral limbs reveals that powered prostheses often exhibit a more symmetrical power profile compared to the intact leg. For instance, powered prostheses approach the power consumption of the normal leg more closely, with peak power outputs ranging from 25 to 35 W/kg, while passive prostheses typically show a greater disparity, with peak values ranging from 35 to 45 W/kg.





(a) (b)



(c) (d)

Fig. 2. (a) Knee Joint Power for Powered Prosthetic Right Leg, (b) Knee Power for Powered Prosthetic Left Leg, (c) Knee Power for Passive Prosthetic Right Leg, (d) Knee Power for Passive Prosthetic Left Leg

From the analysis, it is observed that the powered prosthetic knee requires less overall work compared to the passive prosthetic knee across the gait cycle for all three subjects. This is evident from the consistently lower knee joint power output observed with the powered prosthetic knee throughout the stance phase (in all subjects). Lower knee joint power during stance implies reduced metabolic demand on the muscles controlling the knee joint in the powered prosthesis compared to the passive design.

2.2.3. Ground Reaction Force

Ground reaction forces (GRF) for three subjects with powered and passive prostheses is graphically shown in Figure 3. The data shows that powered prostheses generally lead to higher peak GRF in the unaffected leg, indicating compensatory weight-bearing. The GRF curves exhibit an initial peak for weight acceptance and a terminal peak for push-off. For Subject 1, the powered prosthesis results in peak GRF values of 100-105 N during weight acceptance and 90-95 N during push-off, compared to slightly higher values for the passive prosthesis. Subject 2’s powered prosthesis has peaks of 110-115 N during weight acceptance and 85-90 N during push-off, while the passive prosthesis displays a double peak pattern. For Subject 3, the powered prosthesis shows peaks of 120-130 N during weight acceptance and 95-100 N during push-off, compared to the passive prosthesis with similar double peak characteristics.

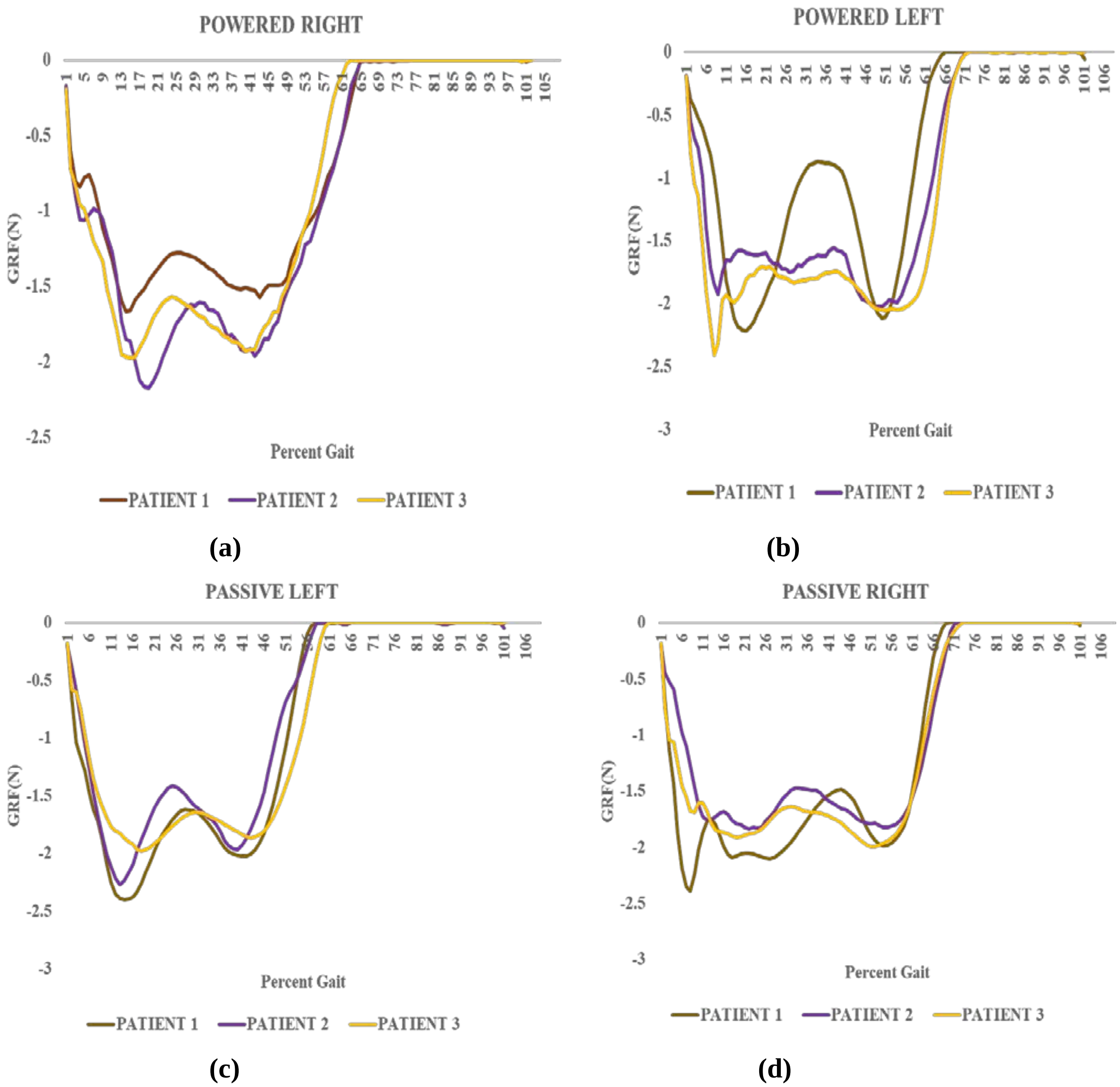


Fig. 3 (a) Ground Reaction Force for Powered Prosthetic Right Leg, (b) Ground Reaction force for Powered Prosthetic Left Leg, (c) Ground Reaction Force for Passive Prosthetic Right Leg, (d) Ground Reaction force for Passive Prosthetic Left Leg

Overall analysis of ground reaction forces (GRF) highlights potential compensatory mechanisms in amputees. The higher GRF in the unaffected leg (powered condition) suggests it bears more weight to maintain stability. Additionally, overall GRF might be higher in the powered condition due to the device's assistance, leading to stronger pushes and improved propulsion. Understanding these adaptations is crucial for optimizing rehabilitation and assistive device design.

2.3 Machine Learning Classification

The human gait cycle is a complex sequence of coordinated muscle activity and joint movements. Analyzing these gait patterns offers valuable insights into human locomotion and can be especially crucial for understanding gait abnormalities in individuals with lower-limb amputations. Machine learning algorithms, particularly adept at handling sequential data, provide powerful tools for gait classification. This study employed three machine learning models—Long Short Term Memory (LSTM), Random Forest (RF), and Support Vector Machines (SVM)—to classify gait patterns in transfemoral amputees based on prosthetic knee type (powered vs. passive) and walking speed (slow, normal, fast).

2.3.1 Long Short Term Memory (LSTM) Network

The proposed work investigates the efficacy of three machine learning algorithms for gait classification based on the dataset. Since LSTMs are a type of recurrent neural network (RNN) that can capture temporal dependencies within data, it is well-suited to analyze sequential data. This makes them ideal for tasks involving gait cycle segmentation, gait pattern analysis and classification.

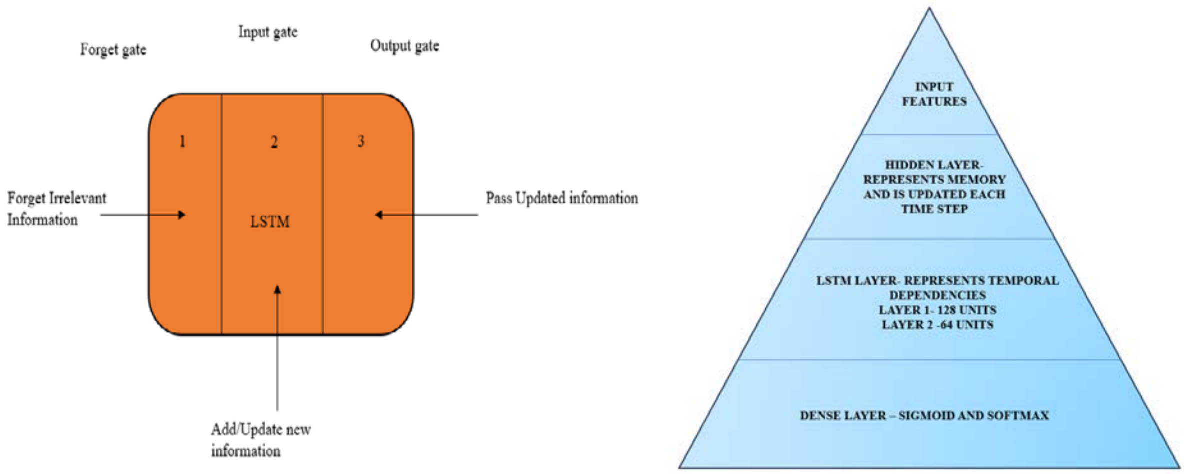


Fig. 4 LSTM Architecture

The model that is developed utilizes an LSTM (Long Short-Term Memory) architecture (Figure 4) by constructing a sequential model. This design is ideal for how LSTMs handle data, processing it one time step (or stride point) at a time. Within the model, LSTM layers are set up with specific numbers of hidden units, which control the model's ability to learn complex patterns from the gait data sequence. An essential part of the model involves defining parameters that indicate the number of data points per gait cycle (stride points) and the number of features extracted from each data point, such as joint angles and power moments. These parameters shape the input structure for the LSTM layer. As the model processes the gait data sequence through the LSTM layers, it learns the temporal relationships between features across different stride points. For example, the model can distinguish between joint movements during the stance phase (when the foot is on the ground) and the swing phase (when the foot is in the air). This capacity to understand temporal dependencies is key to how LSTMs effectively analyze gait patterns. The LSTM architecture is selected for its strength in determining the sequential characteristics of gait data, with the aim of accurately classifying patterns based on variations in prosthetic design and walking speed.

$$\square_{\square} = \square(\square_{\square}[h_{\square-1}, \square_{\square}] + \square_{\square}) \tag{1}$$

$$\square_{\square} = \square(\square_{\square}[h_{\square-1}, \square_{\square}] + \square_{\square}) \tag{2}$$

$$\square_{\square} = \square(\square_{\square}[h_{\square-1}, \square_{\square}] + \square_{\square}) \tag{3}$$

$\square_{\square}$ →represents the input gate.

$\square_{\square}$→represents the forget gate.

$\square_{\square}$→represents output gate.

σ→represents sigmoid function.

$\square_{\square}$→weight for the respective gate(x) neurons.

t-1 →output of the previous LSTM block (at timestamp t-1).

$\square_{\square}$→input at current timestamp.

b →biases for the respective gates(x).

2.3.2 Random Forest Network

Random Forest algorithm, a type of ensemble learning method, excels at tackling classification tasks with diverse features. They operate by combining the predictions of multiple decision trees, creating a robust and accurate classifier. Each decision tree is constructed using a random subset of features and data points from the training data, fostering diversity within the ensemble. This study leverages the capabilities of Random Forests by utilizing functions or libraries specifically designed for this algorithm. These functions handle the creation and training of the ensemble of decision trees. Within the analysis, the number of trees to be included in the Random Forest are defined, that influences the overall accuracy and robustness of the classification. Additionally, the maximum depth of each decision tree, controlling the complexity of the individual trees and preventing overfitting, are set.

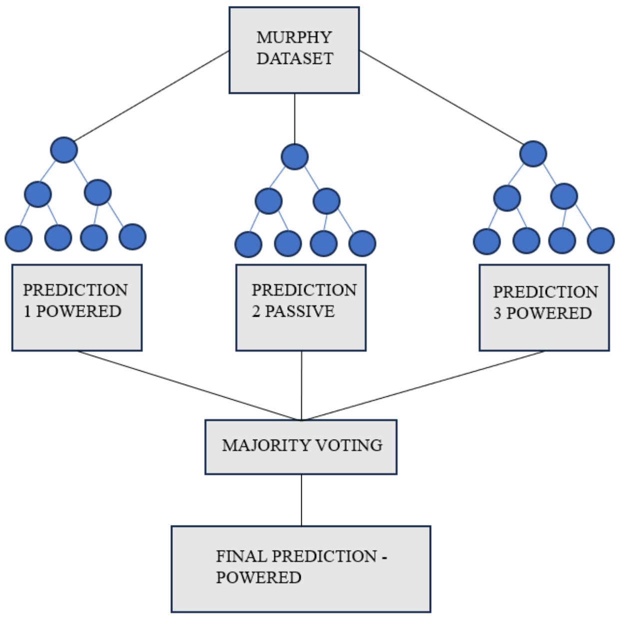


Fig. 5 Random forest Architecture

Figure 5 shows the block diagram of the RF architecture. During the training phase, each decision tree in the Random Forest analyzes a subset of the gait data features. The tree creates a series of branching conditions based on these features, ultimately leading to a classification outcome (e.g., powered knee, passive knee, fast walking). This process is repeated for all trees in the ensemble, using different random subsets of features and data points. Once all decision trees have made their individual predictions, the Random Forest employs a voting mechanism to determine the final classification for a new data point. The class that receives the most votes from the individual trees becomes the predicted class for the new data point. This voting approach reduces the potential biases of any single decision tree and leverages the collective insights of the ensemble to achieve a more accurate classification. This study presents a reliable method for classifying gait patterns in transfemoral amputees.

In the context of a Random Forest classifier, the final prediction for a new data point is determined by aggregating the predictions from each decision tree in the forest. A simplified equation to represent the voting mechanism is given in equation 4:

Each decision tree in the Random Forest classifies the gait data into one of the predefined gait patterns, and the final classification is determined by taking the most common classification result across all trees.

$$\hat{\square} = \square\square\square\square(\{\square_1(\square), \square_2(\square), \ldots \square_{\square}(\square)\}) \quad (4)$$

where:

- y^ is the predicted gait pattern (e.g., powered knee, passive knee, fast walking) for the new gait data point xxx.
- Ti(x) is the gait pattern classification given by the i-th decision tree based on the gait features in xxx.
- T1(x),T2(x),…,Tn(x)} is the set of gait pattern predictions from all n decision trees in the Random Forest.
- mode is the statistical mode function that selects the most frequently predicted gait pattern among all the decision trees.

2.3.3 Support Vector Machine

Support Vector Machines (SVMs) give an alternative approach to classifying gait patterns. Unlike Random Forests, which control an ensemble of decision trees, SVMs aim to identify a hyperplane in the feature space that best separates data points belonging to different classes. During the training phase, the SVM algorithm identifies a specific set of data points, called support vectors. These support vectors lie closest to the hyperplane and essentially define the margins between classes in the feature space.

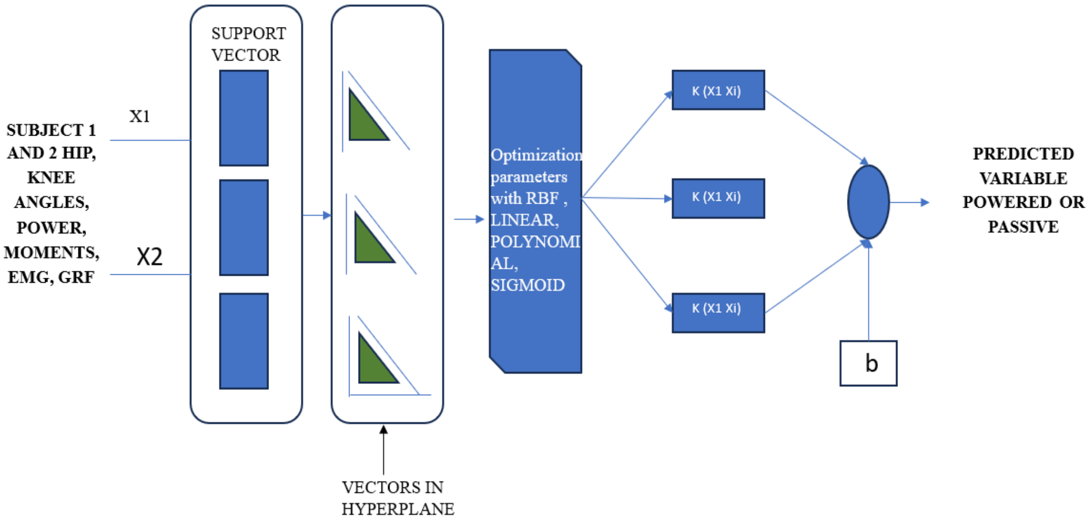


Fig. 6 Support Vector Machine Architecture

The SVM aims to maximize the margin between these hyperplanes, ensuring clear separation of the classes (e.g., powered knee vs. passive knee). Once the SVM is trained and the optimal hyperplane is established, a new stride can be presented for classification. The SVM extracts features from the new stride and maps them onto the same feature space used for training (Figure 6). The SVM then analyzes the position of the new data point relative to the hyperplane, determining its class based on which side of the hyperplane it falls on.

For classifying gait patterns using a Support Vector Machine (SVM), a basic linear SVM equation is used. The equation 5, assumes that the gait data is linearly separable in the feature space. In a linear SVM, the decision boundary (hyperplane) that separates two classes can be represented by:

$$\square . \square + \square = 0 \tag{5}$$

where:

- w is the weight vector perpendicular to the hyperplane.
- x is the feature vector representing the gait pattern.
- b is the bias term.

The decision function for classifying a new gait pattern x is:

$$\square(\square) = \square\square\square(\square . \square + \square) \tag{6}$$

where sgn()is the sign function that outputs +1 or - 1.

3. Results and Discussion

3.1. Predictions using Machine Learning

The developed Long Short-Term Memory (LSTM) models in this study demonstrate robust capabilities in predicting both the type of prosthetic limb and walking speed based on sensor data. As a type of recurrent neural network (RNN), LSTM excels in capturing long-term dependencies in sequential data, making it ideal for analyzing time-series data such as gait sensor readings.This success is attributed to the model's ability to leverage temporal dynamics from sensor data, allowing it to identify characteristic patterns associated with each prosthetic type.

The confusion matrices presented illustrate the LSTM model's performance in classifying prosthetic type and walking speed. The model exhibits high precision, with 91% accuracy in identifying powered prosthetic limbs. Despite its high precision, the model shows moderate recall rates: 27% for fast walking, 32% for normal walking, and 41% for slow walking. The F1-scores, which balance precision and recall, are 0.42 for fast, 0.47 for normal, and 0.56 for slow walking speeds. These metrics suggest that while the model is highly precise, it faces challenges in consistently recalling the correct walking speeds.

In a comparative analysis of classifier performance, the LSTM model outperforms Support Vector Machine (SVM) and Random Forest (RF) classifiers. Specifically, the LSTM model achieved 97% accuracy in prosthetic limb prediction and 98% accuracy in walking speed prediction, underscoring its superior performance in both aspects. The relatively high accuracy of RF (95% for prosthetic limb prediction and 91% for speed prediction) reflects its robustness in handling noisy and high-dimensional data, a common characteristic in gait analysis. SVM offered the least classification accuracy with (94% for prosthetic limb prediction and 88% for speed prediction). However, the slight drop in performance compared to LSTM indicates that the temporal modeling capabilities of

LSTM are particularly beneficial for accurately predicting prosthetic function in real time. Confusion matrix for prosthetic type classification Demonstrated high precision for LSTM models, achieving 91% in identifying "fast" walking and effectively distinguishing between "powered" (91%) and "passive" (86%) prosthetic types. However, the model shows moderate recall rates, with 27% for fast walking, 32% for normal, and 41% for slow instances. The overall F1-scores are 0.42 for fast, 0.47 for normal, and 0.56 for slow categories, indicating a balanced performance between precision and recall across different walking speeds.

TABLE 2: Paired t-test results for powered and passive prosthesis

Parameter	Powered Prosthesis		Passive Prosthesis		Effect size Cohen's d	t-value (df=2)	P Value
	Mean	SD	Mean	SD			
Knee moment* (N*mm/Kg)	212.03	93.29	141.82	23.61	1.03	2.824	.024*
Hip moment (N*mm/Kg)	298.56	173.49	271.4	178.6	0.15	0.154	0.44
Knee angle (deg)	17.31	6.53	19.54	6.49	0.34	-0.34	0.37
Hip angle (deg)	23.89	7.32	22.76	7.31	0.15	0.153	0.44
Knee power (W/Kg)	0.35	0.19	0.22	0.21	0.64	0.608	0.287
Hip power (W/Kg)	0.27	0.03	0.23	0.02	0.39	-0.03	0.487

Knee and hip kinetics and kinematics involving moments, power and angle were observed while using powered and passive prosthesis. A significant increase in knee and hip moment is seen while using powered prosthesis compared to passive prosthesis (refer Table. 2). However, very limited power is observed for both hip and knee joints. The average hip and knee angle during the entire gait cycle is limited to less than 25° for both powered and passive prosthesis.

Independent samples t-test is performed to compare the mean values of the kinetic / kinematic parameters obtained while using powered and passive prosthesis. There is a significant difference in scores of Knee moments for Powered and passive prosthesis t(2)=2.84, p=.024. No significance is seen for all other parameters considered. This observation concludes that the powered prosthesis has a notable impact on the knee moment of the intact leg. Studies suggest that improper alignment of the prosthetics can have a quantitative effect on the biomechanical loading of the intact leg. Significantly higher knee and hip moments can be associated with higher incidence of osteoarthritis. No significant difference in joint angles and power were observed for the two prosthetics.

The effect size is calculated using Cohen's d as a measure of comparison between two means. It calculates the standardized difference between two means in terms of standard deviation units. The larger the effect size the better is the practical significance of the results compared. A small effect size (0-0.3) is observed for hip joint moment and angle, while a nearly moderate effect size (0.3-0.6) is reported for hip power and knee angle. A considerably large effect size(>0.6) is observed for knee joint kinetics namely, Knee power and knee moment, concluding that knee kinetics plays a vital role in understanding the biomechanical loading effects of prosthetics in the intact leg[14]. For more quantitative interpretation of the hip kinetics, more data is required for any conclusive remarks.

TABLE 3: Stance and Swing Phases (in %Gait cycle) for powered and passive prosthesis

Phase	**Prosthetic Type**	**% Gait**	
		Left	**Right**
Stance	**Powered**	60.5±3.2	62.1±2.9
	Passive	58.2±4.1	59.7±3.5
Swing	**Powered**	39.5±3.2	37.9±2.9
	Passive	41.8±4.1	40.3±3.5

Table 3 shows that powered prosthetics result in a stance phase that is approximately 2-3% longer compared to passive prosthetics. This increase in the stance phase indicates enhanced stability, allowing for more secure weight-bearing during walking. The reduction in the swing phase duration reflects greater efficiency in limb movement, contributing to a smoother and quicker gait cycle. Additionally, the lower variability observed with powered prosthetics enhances overall gait stability and reduces the likelihood of compensatory movements that could lead to joint strain or discomfort.

The Long Short-Term Memory (LSTM) models developed in this research demonstrated an overall accuracy of 87.5% in predicting prosthetic type and walking speed based on gait sensor data. This high accuracy underscores the model's ability to capture the temporal dynamics of gait patterns, effectively distinguishing between powered and passive prosthetics and predicting the corresponding walking speeds. Despite the model's strong performance in prosthetic type classification, as indicated by high precision rates (91% for "powered" and 86% for "passive"), it exhibited moderate recall rates for different walking speeds, with F1-scores of 0.42 for fast, 0.47 for normal, and 0.56 for slow categories. These findings suggest that while the LSTM model is proficient in identifying prosthetic types, further refinement is needed to improve recall in speed prediction.

Moreover, the study's analysis of stance and swing phases revealed that powered prosthetics provide more balanced gait mechanics. The mean stance phase duration is slightly longer for powered prosthetics (60.5% on the left and 62.1% on the right) compared to passive prosthetics (58.2% on the left and 59.7% on the right). Conversely, the swing phase is shorter for powered prosthetics (39.5% on the left and 37.9% on the right) compared to passive prosthetics (41.8% on the left and 40.3% on the right). These findings suggest that powered prosthetics offer a more natural and balanced distribution of stance and swing phases, contributing to improved gait symmetry and reduced compensatory movements.

4. Conclusion

A comprehensive analysis of the biomechanical parameters of powered versus passive prosthetics for transfemoral amputees, leveraging advanced machine learning techniques for prediction of optimal walking speed provides enhanced gait stability for long-term usage. Integration of advanced machine learning techniques with biomechanical analysis yields significant insights into the performance and benefits of powered prosthetics. The superior knee stability, reduced hip effort, and improved energy efficiency associated with powered prosthetics highlight their potential to enhance gait efficiency and user comfort.

References

1. Morgenroth DC, Segal AD, Zelik KE, et al. The effect of prosthetic foot push-off on mechanical loading associated with knee osteoarthritis in lower extremity amputees. 2011
2. Elery T, Rezazadeh S, Reznick E, Gray L, Gregg RD. Effects of a Powered Knee-Ankle Prosthesis on Amputee Hip Compensations: A Case Series. IEEE Trans Neural Syst Rehabil Eng.2020
3. Russell Esposito E, Wilken JM. Biomechanical risk factors for knee osteoarthritis when using passive and powered ankle-foot prostheses. Clin Biomech (Bristol, Avon). 2014
4. Toderita D, Favier CD, Henson DP, et al. Hip joint and muscle loading for persons with bilateral transfemoral/through-knee amputations: biomechanical differences between full-length articulated and foreshortened non-articulated prostheses. J Neuroeng Rehabil. 2023
5. Liu Y, An H, Ma H, Wei Q. Online Walking Speed Estimation Based on Gait Phase and Kinematic Model for Intelligent Lower-Limb Prosthesis. 2023
6. J. Lee, W. Hong and P. Hur, "Continuous Gait Phase Estimation Using LSTM for Robotic Transfemoral Prosthesis Across Walking Speeds," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2021
7. Welke B, Jakubowitz E, Seehaus F, et al. The prevalence of osteoarthritis: Higher risk after transfemoral amputation?-A database analysis with 1,569 amputees and matched controls. PLoS One. 2019;14(1):e0210868. 2019
8. I. E. Ghailassi, N. A. B. Hashim, N. A. A. Razak, N. A. Osman, H. Gholizadeh and S. D. Astuti, "Investigation of EMG Parameters for Transtibial Amputees While Treadmill Walking with Different Speeds: A Preliminary Study," in IEEE Access, 2024
9. Teater RH, Wolf DN, McDonald KA, Zelik KE. Unilateral transtibial prosthesis users load their intact limb more than their prosthetic limb during sit-to-stand, squatting, and lifting. Clin Biomech (Bristol, Avon). 2023
10. Mehryar P, Shourijeh M, Rezaeian T, Khandan A, Messenger N, O'Connor R, Farahmand F, Dehghani-Sanij A. The Impact of Different Self-Selected Walking Speeds on Muscle Synergies in Transfemoral Amputees during Transient-State Gait. Biomechanics. 2024

11. Kim M, Hargrove LJ. A gait phase prediction model trained on benchmark datasets for evaluating a controller for prosthetic legs. Front Neurorobot. 2023;16:1064313. Published 2023 Jan 5. doi:10.3389/fnbot.2022.1064313,

12. C. L. Lewis and D. P. Ferris, "Walking with increased ankle push off decreases hip muscle moments," J. Biomechanics, 2008.

13. K. R. Kaufman, S. Frittoli, and C. A. Frigo, "Gait asymmetry of transfemoral amputees using mechanical and microprocessor-controlled prosthetic knees," Clin. Biomechanics, 2012.

14. Zhang T, Bai X, Liu F, Ji R, Fan Y. The effect of prosthetic alignment on hip and knee joint kinetics in individuals with transfemoral amputation. Gait Posture. 2020 Feb;76:85-91. doi: 10.1016/j.gaitpost.2019.11.006. Epub 2019 Nov 7. PMID: 31743872