Symmetry index-based gait improvement prediction using a CNN-LSTM-attention framework

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ABSTRACT

The shortcomings of existing clinical assessments are addressed by using a deep learning (DL) framework. This study will assess the gait improvement of lower limb fractured patients using the publicly available GaitRec dataset. The dataset contains the vertical ground reaction force (GRF) data used to compute biomechanical kinetic features. This framework considers hip, knee, ankle, and calcaneus fractures as lower limb fracture class, and the symmetry indices computation is done between affected and unaffected limbs, and their temporal changes were examined to analyze and track the rehabilitation progress of individual subject. The framework successfully identifies the reduction in the asymmetry between left and right leg features. The overall gait improvement in patients is computed using initial and final session composite asymmetry index (ASI) values and if it is at least 30% then overall gait is improved, demonstrating its robustness and clinical relevance. The suggested convolutional neural network (CNN)-long short-term memory (LSTM)-attention hybrid model outperformed with regression metrics of root mean square error (RMSE) of 1.09, mean absolute error (MAE) by 0.64, and R^2 score of 0.98 and classification metrics of accuracy 97.1%, precision of 97.6%, recall of 96%, and F1-score of 96.8% by capturing both the local patterns and temporal dynamics of the gait data.

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1. INTRODUCTION

Rehabilitation plays a critical role in restoring mobility, functional independence, and overall quality of life after a lower limb fracture. Traditional clinical assessment relies on observational gait analysis, which is subjective and often unable to detect subtle biomechanical improvements. With the advancements in wearable sensors and force platforms, clinicians can now obtain quantitative gait measures such as peak force (PF), impulse, and symmetry. However, a significant challenge remains in effectively interpreting these complex, large-scale datasets to accurately track a patient's functional recovery. This study designs and validates a deep learning (DL) rehabilitation framework that combines a convolutional neural network (CNN)-long short-term memory (LSTM) modelling with an attention layer and symmetry index analysis to objectively monitor gait recovery in lower limb fracture patients. The framework aims to compute key biomechanical features from vertical ground reaction force (GRF) signals, calculate symmetry indices across multiple rehabilitation sessions, and use a CNN-LSTM hybrid architecture to classify a patient's progress as either improved or not improved.

The assessment of gait and balance in the aged people with mild impairment is done using a gait and balance smartphone app. The gait parameters were measured using the app. This method is not generalized for different age groups [1]. The gait analysis and motion score tool is used only for 10 observational and five other gait parameters are used to divide the pathological and physiological gait and is used for clinical practice [2]. Technologies like wearable sensors and machine learning (ML) methods are used for modern gait analysis. The ML methods improve the accuracy of the system [3]. Many ML classifiers are used, and post-injury recovery of gait variables is computed for different patients for the gait analysis [4]. The knee and ankle biomechanics were influenced by the heel-first strike gait in the healthy person athlete. The gait pattern is modified to reduce the lower knee stress with the potential application in rehabilitation [5]. The gait improvement is monitored by using vertical GRF as marker after lower limb injury, with the spatio-temporal, joint kinematics, and kinetic measures improved after some months. The walking speed is examined during rehabilitation [6]. The force plate is used to get the GRF data for patients. The intra-inter leg weight bearing and stability are estimated using the gathered data with all fracture types [7]. The patients are watched on the Anterior cruciate ligament for 6 to 12 months after operation and explored that by changing the vertical GRF with biofeedback, that impact the knee during walking [8]. The gait symmetry evaluation of post-stroke patients is done using 3D accelerometer [9]. The lower limb optimization is done using ML data-driven approaches [10]. Real-time gait and position monitoring in enabled by using the sensFloor smart carpet with an inertial measurement unit (IMU). The cloud-based dashboards are provided to the therapist and patients by analyzing the data using ML algorithms, supporting training ideas and improvements in the rehabilitation outcomes [11]. The wearable IMU provide reliable gait parameters to track the long-term rehabilitation outcomes of tibial fracture and lower extremity trauma patients [12]–[14].

The research gaps identified from the existing work are that the gait analysis is improved by the DL and the majority of DL applications have been limited to discrete classification tasks such as identifying healthy and disorder gaits. While these diagnostic tools are valuable, they do not address the continuous, fine-grained monitoring required for rehabilitation. Conventional models often consider each gait session as a discrete event, instead as part of a progressive time series. For lower limb fractures, a framework is required to quantify the functional progress over time.

The novel contribution of the proposed framework directly addresses this gap. The CNN-LSTM architecture is integrated with symmetry index analysis, provides a quantitative approach to track the rehabilitation progress. From the vertical GRF data the model derives the kinetic metrics PF, time to peak (TTP), impulse, loading rate **(**LR), and unloading rate **(**UR) for both the legs to characterize gait improvement. The convolution 1D layer transforms each feature independently means the point wise convolution is performed. The LSTM layer captures the temporal dependencies and models the progression of gait features across time. The attention layer improves the predictive performance and also interpretability and allowing clinicians to understand which part of the gait cycle contributes most to the model decision. The longitudinal tracking of gait improvement is done from session to session with the reduction of 3% in asymmetry and finally, the model predicts gait improvement if there is a reduction in asymmetry greater than or equal to 30% with the change in composite asymmetry index (ASI) value from initial to final session. The model introduces a regression to classification bridge, allowing continuous prediction and binary decision-making within the same framework. The publicly available GaitRec dataset to can be used to track the long-term recovery of lower limb fracture patients.

2. PROPOSED METHOD

2.1. Biomechanical feature extraction

Key biomechanical features were computed for each recorded session and trial for both the affected and unaffected limbs. The (1) to (5) represent the mathematical formulas used to compute features.

- PF: the maximum vertical force vertical value recorded during the stance phase of a gait cycle.

$$PF = \max\left(Fvertical(t)\right) \tag{1}$$

- TTP: the time elapsed from initial foot contact to the occurrence of the PF.

$$TTP = tPF - tinitial \tag{2}$$

- Impulse: the integral of the vertical force over the duration of the stance phase of gait, representing the total load applied over time.

$$Impulse = \int_{tinitial}^{tfinal} Fvertical(t)dt \tag{3}$$

– LR: the rate of force increases during the weight acceptance phase.

$$LR = \frac{Fvertical(t_{10\%}) - Fvertical(t_{0\%})}{t_{10\%} - t_{0\%}} \tag{4}$$

– UR: the rate of force decreases during the push-off phase. The unit of PF is %BW, TTP is instance phase, impulse in (%BW/s), LR and UR in (%BW/s).

$$UR = \frac{Fvertical(t_{100\%}) - Fvertical(t_{90\%})}{t_{100\%} - t_{90\%}} \tag{5}$$

2.2. Symmetry index modelling

The biomechanical kinetic features are computed for both the left and right leg. The affected and unaffected legs are identified by mapping values from the GRF_metadata.csv file. To provide a quantifiable measure of gait symmetry, the absolute symmetry index was computed using (6) for each biomechanical feature (X). The gait improvement is checked using the symmetry index after rehabilitation. The gait symmetry is captured only at single point [15]. where Xaffected and Xunaffected are the feature values for the affected and unaffected limbs, respectively.

$$ASI = \left| \frac{Xunaffected - Xaffected}{0.5 \times (Xaffected + Xunaffected)} \right| \times 100 \tag{6}$$

For bilateral fracture patients, the ASI is computed using (7). This data translates the bilateral biomechanical differences into a quantifiable metric of asymmetry, which is essential for rehabilitation assessment. The data serves as a representative example of the analysis performed for all subjects in the study.

$$ASI = \left| \frac{Xleft - Xright}{0.5 \times (Xleft + Xright)} \right| \times 100 \tag{7}$$

2.3. Longitudinal gait progress analysis

The longitudinal tracking over time is conducted to evaluate functional recovery of knee replacement surgery by collecting gait data and patient-reported outcome measures (PROM) of 20 patients [16]. In the proposed work to monitor the temporal progression of gait rehabilitation, a weighted composite ASI is computed by combining different kinetic features. Since each feature contributes differently to overall gait symmetry, evidence-based weights were assigned to reflect their relative biomechanical importance: 0.35 for PF, 0.25 for impulse, 0.15 for TTP, 0.15 for LR, and 0.10 for UR. The weighted composite score is computed using (8) by taking the sum of product of ASI value of feature by its corresponding weight. The improvement in the symmetry is quantified by computing session to session change from the consecutive sessions using a sliding window approach using (9). The (10) is used to compute the overall improvement in the gait from the composite ASI values of the initial and final session.

$$Composite\ ASI_i = \sum_{j=1}^{n} w_j \times ASI_{ij} \tag{8}$$

$$\triangle\, ASI_f^{(p)} = ASI_f^{(p_{t+1})} - ASI_f^{(p_t)} \tag{9}$$

$$ASI\ reduction\ percentage = \left(\frac{ASI_{initial\ session} - ASI_{final\ session}}{|ASI_{initial\ session}|} \right) \times 100 \tag{10}$$

In (8), ASI_i is the composite ASI for the i[th] sample, ASI_{ij} represents the ASI value of j[th] feature for the i[th] sample, w_j is the weight assigned to the j[th] sample, and the summation runs over all features. In (9), $\triangle\, ASI_f^{(p)}$ represents the change in ASI for the feature f between consecutive sessions $ASI_f^{(p_{t+1})}, ASI_f^{(p_t)}$ at sessions p_{t+1} and p_t respectively. In (10), $ASI_{initial\ session}, ASI_{final\ session}$ denote the first and last session composite ASI values of each patient. It measures the percentage decrease in the asymmetry over time.

2.4. Deep learning classification model

The local sequential patterns are captured using DL methods like CNN, CNN-LSTM, and other hybrid models based on GRF time series data for gait classification, and to predict the improvement after rehabilitation. The results are explained using the layer-wise relevance propagation tool. In recent studies, the vertical GRF is estimated from IMUs, 2D video using ML for the assessment of the gait outside the lab and to track the longitudinal rehabilitation [17]–[19]. This study used the CNN-LSTM-attention hybrid classifiers and evaluated to automate the classification of rehabilitation of outcomes based on their capacity to analyze the temporal ASI sequences. The mathematical underpinnings for these models are as follows.

2.4.1. The CNN-LSTM-attention hybrid model

This hybrid approach enables the model to recognize complex gait patterns over time, a capability that distinguishes its performance. Algorithm: forward propagation for the CNN-LSTM hybrid DL model.

i) Model input: in (11) where n is the batch size, d is the number of time steps (e.g., rehabilitation sessions), and 1 represents the number of channels (univariate ASI time series).

$$X \in R^{n\times d\times 1} \tag{11}$$

ii) The processing of input X of (11) into prediction ŷ is defined by the following sequence of mathematical operations.
   - Step 1: feature extraction via 1D convolution. In (12) and (13) $W^{(k)} \in R^{1\times f}$ is the k^th convolution filter, b_k is the bias for filter k, k=1,2, 3…...,32 filters, and C =1 means it reduces to a linear transform with rectified linear unit (ReLU). This extracts the local feature representation for each time step.

$$Z_{i,t,k} = \sum_{j=1}^{C}\sum_{s=0}^{f-1} W_{j,s}^{(k)} X_{i,t+s,j} + b_k \tag{12}$$

$$Z \in R^{n\times d\times 32} \tag{13}$$

   - Step 2: dimensionality reduction via max pooling, max pooling 1D with pooling size =2 scans the temporal feature map two-time steps at a time and keeps only the strongest activation for each channel, and this reduces the sequence length is shown in (14). Where T=d/2.

$$M_{i,l,k} = \max(Z_{i,2l,k}, Z_{i,2l+1,k}) \in R^{n\times T\times 32} \tag{14}$$

   - Step 3: LSTM feature extraction. The LSTM is used to extract long-term dependencies and temporal evolution of rehabilitation outcomes under multiple sessions using (15) to (21). Where $h_t \in R^{32}$ is the hidden state, $C_t \in R^{32}$ is the cell state, ⊙ represents elementwise multiplication, and σ denote the sigmoid activation.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}; m_t] + b_f\right) \tag{15}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}; m_t] + b_i) \tag{16}$$

$$\widetilde{C_t} = \tanh(W_c[h_{t-1}; m_t] + b_c \tag{17}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \tag{18}$$

$$O_t = \sigma(W_o[h_{t-1}; m_t] + b_o) \tag{19}$$

$$h_t = O_t \odot \tanh(C_t) \tag{20}$$

$$H = [h_1, h_2, \dots\dots . h_T] \in R^{n\times T\times 32} \tag{21}$$

   - Step 4: attention, linear projections are $E = HW_E, B = HW_B, D = HW_D$. Where $W_E, W_B, W_D \in R^{32\times 32}$. The similarity score between query at timestep i and key at step j is given by $e_{ij} = \frac{E_i B_j}{\sqrt{32}}$. For each timestep i the scores $e_{i1}, e_{i2}, \dots\dots . e_{iT}$ into probabilities that sum to 1. In (22) $\alpha_{i,j}$ represents how much timestep j contributes to the timestep i.

$$\alpha_{i,j} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T}\exp(e_{ik})} \tag{22}$$

   - Finally, the timestep I become the weighted sum of all D vectors using attention weights α and is shown in (23).

$$A_i = \sum_{j=1}^{D} \alpha_{ij} D_j \in R^{n\times T\times 32} \tag{23}$$

– Step 5: transition to fully connected layers (Flatten), in (24) is used to reshape the multidimensional feature map generated by previous layer into a one long vector for each sample.

$$U = Reshape(A, (n, T \times 32)) \in R^{n\times 1600} \tag{24}$$

– Step 6: dropout, in this layer a regularization technique is applied to reduce overfitting by disabling a portion of neurons during training using (25), dropout =0.4 and keep probability =0.6.

$$G = U \odot \frac{J}{0.6}, \qquad J \sim Bernoulli(0.6) \tag{25}$$

– Step 7: high-level reasoning via fully connected (Dense) layers, the nonlinear composition of extracted features is learnt by processing the flattened vector using one or more dense layers. The (26) represents flattened input from the previous step. Where $W^{(1)} \in R^{32\times(T\cdot 32)}$ is the weight matrix and $b^{(1)} \in R^{n\times 32}$ is the bias vector.

$$S = ReLU\left(W^{(1)}U + b^{(1)}\right) \tag{26}$$

– Step 8: output regression layer, the output layer predicts the ASI using (27).

$$\hat{y} = \left(W^{(out)}\, S + b^{(out)}\right) \in R^{n\times 1} \tag{27}$$

3. METHOD

3.1. Proposed model architecture

The model synergistically combines the strengths of CNNs for local temporal pattern extraction and fully connected networks for non-linear classification, enabling robust analysis of temporal gait symmetry patterns for predicting rehabilitation outcomes. Figure 1 describes the suggested CNN-LSTM-attention model to be used in feature extraction and sequential learning. The workflow starts with ASI input data which is passed into the convolutional layers where local sequential patterns are extracted. The extracted characteristics are conveyed to LSTM layers that allow learning dependencies and sequence models across time. The attention layer assigns weights to the features for better model prediction. For classification or prediction, the output layer comes after the fully connected layers, which aggregate the previously obtained representations.

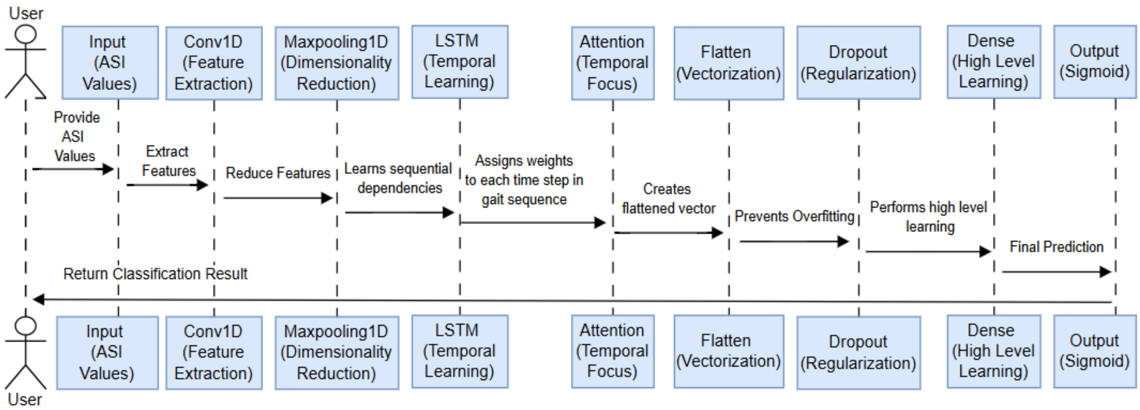


Figure 1. CNN-LSTM model architecture

3.2. System workflow: overview and system workflow

The Figure 2 shows the gait analysis during rehabilitation. Here the processed GRF data is collected and the unwanted noise was filtered and is standardized the measurements in the GaitRec dataset. The healthy control related data and the patient with single session are removed from the dataset. The affected and unaffected side is mapped from the GRF metadata dataset. Then the biomechanical kinetic features like PF, TTP, impulse, LR, UR are computed for both the limbs. The ASI is computed from these features between two limbs. The composite ASI is determined by assigning weights to the features. The model performs longitudinal tracking from session to session and if the asymmetry is reduced by at least 30% from initial to final session values, then the gait is recovered and that is the end of rehabilitation. If not, the patient will be suggested for next session.

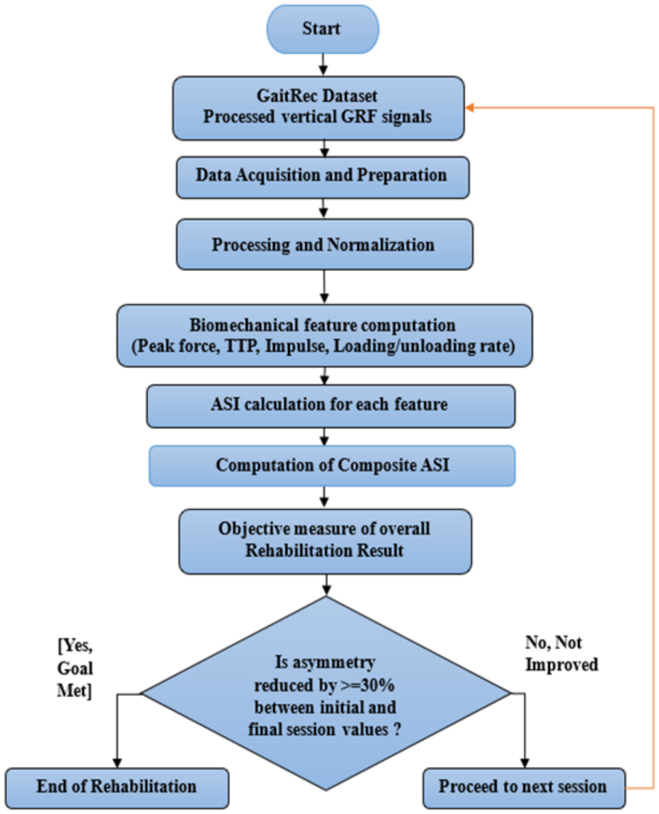


Figure 2. Workflow of gait analysis during rehabilitation using the processed GaitRec dataset

3.3. Experimental setup
3.3.1. Dataset description

This research work leverages the GaitRec dataset, a comprehensive and open source for human gait analysis, to investigate objective rehabilitation outcomes in patients with lower limb fractures. As a large-scale dataset, it contains 75,732 bilateral walking trials of 2,084 patients with different musculoskeletal impairments. The affected limb was identified for each patient using the GRF_metadata.csv file, where a value of '0' indicates a left affected leg, '1' indicates a right affected leg, and '2' signifies a bilateral fracture. The dataset comprises gait records from patients with fractures classified into four groups: calcaneus, ankle, hip, and knee. This record uses the data collected during the complete rehabilitation stay of patients varies from weeks to months. The effect of noise is reduced by using 2nd order Butterworth LPF with cutoff frequency 20 Hz is used with amplitude and time normalization. The time is normalized to 101 data points, which reduces temporal differences and allows comparative analysis of diverse steps. This robust dataset is well-suited for ML mining applications aimed at categorizing specific gait patterns and tracking functional recovery over time. The train-test split follows the predefined split provided in the GRF_metadata.csv file. It is in the ratio 70:30 for work. The subject-wise splitting is used in the proposed work.

3.3.2. Data preprocessing

The proposed work utilized the processed vertical GRF data files from the GaitRec dataset, which had already undergone denoising, segmentation, and normalization as part of the dataset's official protocol. The dataset contains 101 samples of vertical GRF values for each patient, exclusively representing the stance phase of the gait cycle [20]. It was observed that the class distribution of the dataset was unbalanced. To address this, a data balancing procedure was performed, which involved removing healthy control data and subjects with only a single recorded session.

The Borderline synthetic minority oversampling technique (SMOTE) is an oversampling technique focusses the instances near the decision boundaries and generates the synthetic samples for minority classes to balance the class distribution of the dataset. The minority class samples that are surrounded by the majority class neighbors that are likely to be misclassified are identified by the Borderline SMOTE algorithm. It synthesizes the new samples by incorporating between the minority samples and neighbors and enriches the decision boundary. The synthetic samples a_{new} are generated using the minority sample $a_i$and one of the k-nearest neighbors a_j is selected from the minority class and is given by (28). Where λ∈ [0, 1] represents random scale. So, the local structure of the minority class is saved and the new samples resides along the line segment between a_i and a_j.

$$a_{new} = a_i + \lambda.\left(a_j - a_i\right) \quad (28)$$

3.3.3. Implementation details

All computational experiments conducted using Python 3.10, CPU of 2.4 GHz, TensorFlow of 2.15 with NumPy, Pandas. The architecture was implemented using Keras high level APIs. The proposed architecture used 1D convolutional layer (32 filters, kernel size =1, ReLU activation) and LSTM layer with 32 unit. The attention mechanism is used to assign adaptive weights to various time steps and allows the model to concentrate more the sessions that contributes towards improvement. The output of attention layer is flattened and passed through dense layer of 32 units with ReLU activation. A dropout layer of rate 0.4 is used to enhance the generalization. The output layer sigmoid is used for binary prediction whether the patient gait is improved or not. An Adam optimizer with the learning rate of 0.0001 and binary cross entropy loss is used to train the model ensures stable convergence. The training was performed with a batch size of 32 for 25 epochs using Early stopping with patience of 10 to avoid overfitting. The z-score normalization is used standardize all the features and the data splitting is done subject wise to avoid data leakage across sessions.

4. RESULTS AND DISCUSSION

In the proposed system, the kinetic features are extracted from the GRF data for both left and right limb for multiple sessions and the composite ASI is computed for each session. The patients with at least two sessions are considered for analysis. The ASI data of the kinetic features are fed to the proposed system. The model performs longitudinal tracking of 3% reduction in asymmetry from session to session. If the percentage of reduction in the asymmetry is greater than or equal to 30% from initial to final session, then the overall status of gait is considered as improved or not improved. Table 1 shows the initial and final session composite ASI values, the percentage of reduction in the asymmetry, and the overall status of the gait whether it is improved or not improved.

Table 1. The initial session and final session ASI values with overall status

Subject_ID	Initial session composite ASI	Final session composite ASI	Asymmetry reduction percentage	Overall_status
S01	19.82	8.98	54.69%	Improved
S02	38.43	22.39	41.72%	Improved
S03	35.23	28.09	20.28	Not improved
S04	20.78	13.56	34.74	Improved
S05	33.02	22.57	31.63	Improved

Figure 3 illustrates the relationship between the actual ASI improvement computed from patient gait data and the proposed model-predicted ASI improvement between the initial and final session of rehabilitation. Each point in the plot represents one rehabilitation subject. A linear trend is observed along the diagonal direction, indicating the model predictions closely match the actual improvement values, demonstrating strong model accuracy and generalizability.

Figure 4 illustrates the model's predictive improvement across the first 20 patients with the actual improvement percentages with the predicted values derived from GRF-based features. The ground truth improvement is shown by the blue line, and the model's output is shown by the orange line. The close alignment of two curves shows strong predictive fidelity, with minimal deviation in the case of moderate improvement. This visual comparison supports the model's clinical applicability for individualized gait recovery assessment.

Figure 5 shows the confusion matrix that illustrates the model's classification performance in predicting the status of the rehabilitation improvement among lower limb fracture patients. The model correctly identifies 242 patients as improved and 294 patients as not improved. The misclassification rate is very low; 10 patients are identified as false negatives and 6 patients as false positives. The model captures gait recovery patterns with high accuracy and maintains balanced sensitivity and specificity.

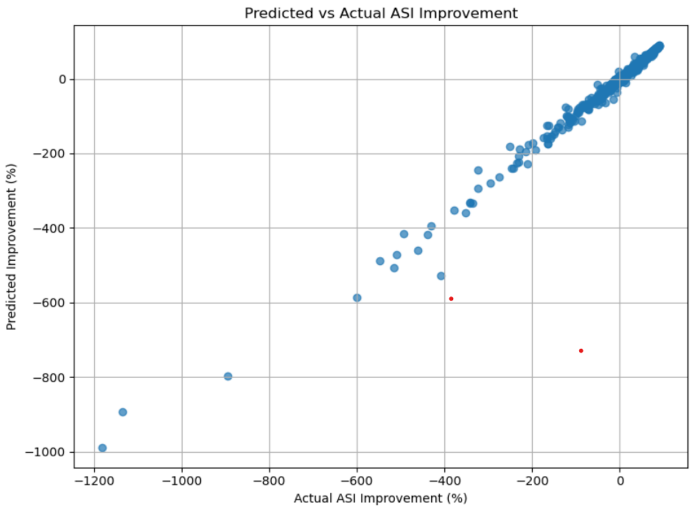


Figure 3. Predicted ASI improvement versus actual ASI improvement

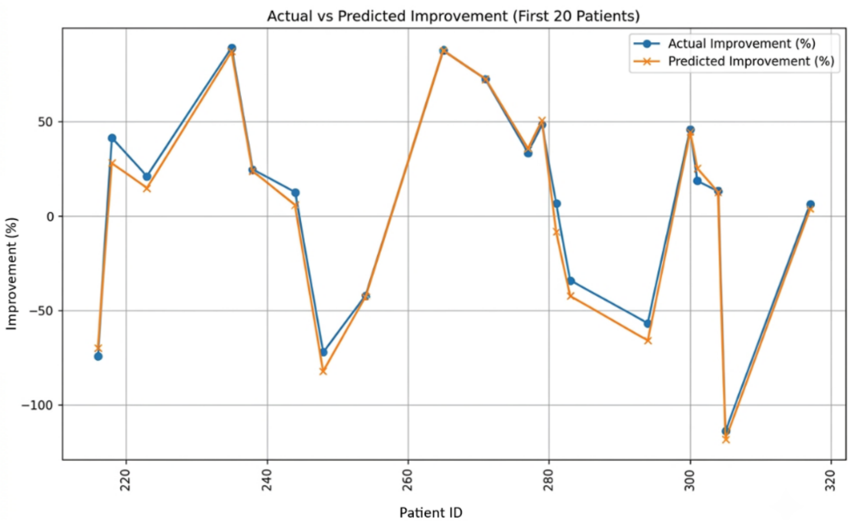


Figure 4. Model predictive improvement across the first 20 patients

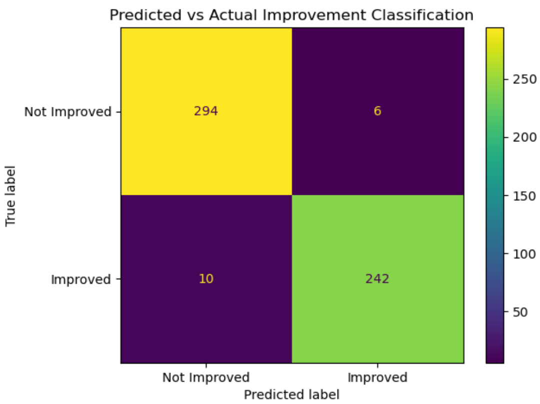


Figure 5. Confusion matrix showing model classification performance

The model's classification metrics of the proposed system are computed using (29) to (32).

$$Accuracy = \frac{P_{true}+N_{true}}{P_{true}+N_{true}+P_{false}+N_{false}} \quad (29)$$

$$Precision = \frac{P_{true}}{P_{true}+P_{false}} \quad (30)$$

$$Recall = \frac{P_{true}}{P_{true}+N_{false}} \quad (31)$$

$$F1-score = 2\frac{Precision \times Recall}{Precision+Recall} \quad (32)$$

The proposed system regression metrics are computed using the (33) to (35).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2} \quad (33)$$

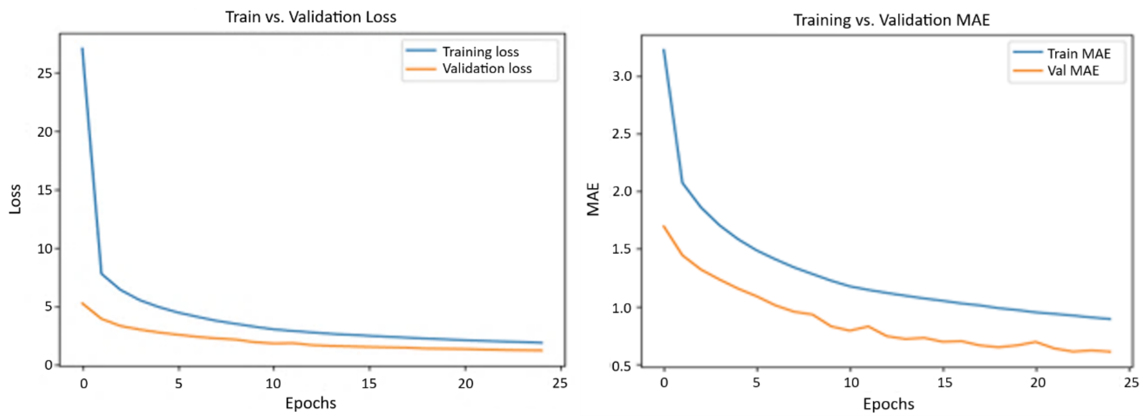
$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \widehat{y_i}| \quad (34)$$

Where y_i is the actual target value, $\widehat{y_i}$ is the model predicted value, and N is the number of test samples.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i-\widehat{y_i})^2}{\sum_{i=1}^{N}(y_i-\overline{y_i})^2} \quad (35)$$

Where $\sum_{i=1}^{N}(y_i - \widehat{y_i})^2$ is the residual sum of squares, $\sum_{i=1}^{N}(y_i - \overline{y_i})^2$ is the total variance and $\overline{y_i}$ is the mean of the total actual values. The $R^2 = 1$ represents perfect prediction, $R^2 = 0$ indicates the model is no better than predicting the mean and $R^2 < 0$ represents is worse than predicting the mean.

Figure 6 shows the regression model learning behaviors of training and validation loss in Figure 6(a) and mean absolute error (MAE) curves in Figure 6(b) across 25 epochs. Here, both the loss and MAE plots are decreasing monotonically with the increasing epochs, indicating stable and effective learning. The validation curves closely follow and remain below the training curves, demonstrating good generalization and absence of overfitting. The smooth convergence of both metrics confirms that the model learns discriminative patterns from the data and achieves reliable predictive performance. The regression metrics like root mean square error (RMSE) of 1.09, MAE of 0.64, and R^2 score of 0.98 are obtained from the proposed model. The classification metrics of the proposed system, like accuracy of 97.1%, recall of 0.960, precision of 0.976, and F1-score of 0.968, are obtained.



(a) (b)

Figure 6. Learning curves of the regression model of (a) loss and (b) MAE

Figure 7 illustrates the longitudinal progression of the composite ASI for subject S04 across multiple gait sessions. The blue markers show session-wise ASI changes, indicating the patient's recovery trajectory over time. The green points highlight sessions where a ≥3% reduction in ASI from the previous session reflects a measurable improvement in gait symmetry, whereas the red dashed line represents the 3% clinical threshold used to identify meaningful progress. Overall, the downward trend in ASI values demonstrates a consistent reduction in asymmetry, signifying functional recovery and enhanced gait symmetry throughout the rehabilitation period.

The wearable sensors are integrated with the ML to predict fracture healing. The continuous underfoot data was processed, and the features are extracted using logic regression classifier. The classification metrics are obtained from the model [21]. The depth videos and pressure data are used from the online dataset that comprises 30 healthy subjects performing seven rehabilitation exercises using a 3D CNN classifier and achieved a classification accuracy of 95.71%. Only the classification metrics are extracted from the model [22]. The rehabilitation outcomes that are essential for the clinical decision are predicted using CNN and an RNN classifier using clinician-reported outcome measures (CROM) and PROM. The regression metrics and classification metrics are both extracted from the model. The F1-score is improved by 9% and 12% reduction is MAE compared to traditional ML methods [23]. In the longitudinal study, the data were collected from the GRF curve of 13 tibial fracture patients. The composite ASI is used as a target for the model. The motion capture and force plate are used to record the data and the regression metrics such as RMSE, MAE and R^2 are extracted [24]. A xLSTM and Lag-Llama model architecture is used to temporal series analysis of lower limb rehabilitation for the post stroke patients in the limb recovery, and extracted the RMSE and MAE for dynamic neuromuscular stabilization (DNS) gait and upper-limb supported (UPS) gait. The R^2 of 0.72 is achieved from this model [25]. Table 2 compares the performance metrics of CNN-LSTM-attention hybrid model with the existing traditional architectures. Table 3 shows the 5-fold cross-validation result of our model. The means of RMSE, MAE, and R^2 obtained from this 5-fold cross-validation are 1.4393, 0.8819, and 0.9773 and are very close to the single-time execution result.

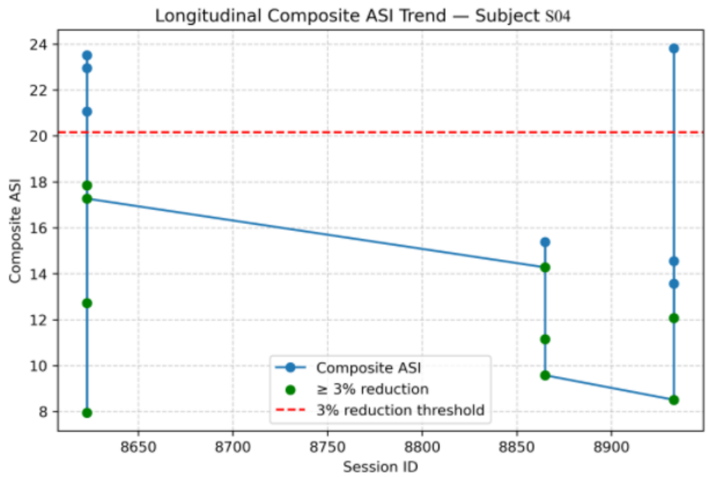


Figure 7. Longitudinal trends of composite ASI for subject S04

Table 2. Comparison of proposed work with existing models

Reference	Model type	Target	RMSE	MAE	R^2	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
Proposed work	CNN+LSTM+attention	vGRF	1.09	0.64	0.98	97.1	96.8	97.6	96
[21]	Logistic regression	GRF features	-	-	-	75.6	75.4	76.1	75.6
[22]	3D CNN	Pressure data	-	-	-	95.71	95.74	95.83	95.71
[23]	Hybrid CNN+RNN	PROM and CROM	-	4.25	0.87	84.2	86	88	85
[24]	ML (force Plate)	Composite ASI	4.78	3.56	0.72	-	-	-	-
[25]	xLSTM and Lag-Lamma	DNS gait	10.54	6.28	0.72	-	-	-	-
		UPS gait	12.28	7.54		-	-	-	-

Table 3. Five-fold cross-validation result

Fold	RMSE	MAE	R^2
1	1.360355	0.831097	0.976229
2	1.447679	0.864313	0.980148
3	1.458943	0.927904	0.978906
4	1.359335	0.849553	0.97805
5	1.570665	0.93704	0.973599

5. CONCLUSION

This proposed work used the DL framework to quantify the gait recovery of the lower limb fracture patients during rehabilitation. This model uses vertical GRF data from GaitRec dataset, and the biomechanical features like PF, TTP, impulse, LR, and UR are computed. The ASI is determined to measure gait asymmetry between the left and right legs over several sessions. The suggested CNN-LSTM-attention hybrid model provides regression metrics RMSE as 1.09, MAE as 0.64, and R^2 as 0.98, and classification metrics accuracy of 97.1%, recall of 96%, precision of 97.6%, and F1-score of 96.8% compared to other traditional methods. The overall gait improvement of a patient is computed by taking the initial session and final session composite ASI values, and if there is at least 30% reduction in asymmetry between the limbs, the overall gait of a patient is improved. Overall, this work lays a strong basis for an automated gait rehabilitation evaluation. This research has the potential to greatly improve the results for the people recovering from lower limb injuries by developing individual treatment.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Pushpalatha Obanna	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓			
Premkumar Ramesh		✓		✓		✓		✓		✓		✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in figshare at https://doi.org/10.6084/m9.figshare.c.4788012.

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