# A Hybrid TCN-Transformer Encoder Framework for Gait Classification and Rehabilitation Assessment

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**Abstract.** A rigorous modelling of biomechanical pattern of lower limb fracture patients is required to handle the class imbalance between normal and defective gait, rehabilitation assessment for patients. This work uses vertical ground reaction force (vGRF) data and suggests a novel cost sensitive deep learning framework for gait classification and rehabilitation analysis based on a hybrid temporal convolutional network (TCN) and transformer encoder architecture. The data imbalance is handled using GAN which creates artificial samples during preprocessing. The global temporal context and inter phase gait interactions are recorded by the transformer encoder while the TCN block extracts local temporal gait variables with force magnitude and loading characteristics. A binary classifier is used to classify gait normal or abnormal once the learnt representations from both modules are combined to create a comprehensive gait feature space. Patients with abnormal gait are referred to rehabilitation programs and deep features are extracted from the trained model during rehabilitation sessions to evaluate the gait improvement. The performance metrics like accuracy of 0.9938, precision of 0.9978, recall of 0.9943 and F1 score of 0.9960 are obtained for gait classification. The regression metrics like RMSE of 1.1700, MAE of 0.8536 and R2 of 0.9870 are obtained from the proposed architecture for monitoring gait recovery in lower limb fracture patients.

**Keywords:** GAN, Gound reaction force, Symmetry index, gait classification, rehabilitation

## 1 INTRODUCTION

Gait assessment plays a crucial role in classifying gait as normal or pathological and monitoring functional recovery in lower-limb fracture patients undergoing rehabilitation. Vertical ground reaction force (vGRF) signals provide objective biomechanical information reflecting weight-bearing capacity, force distribution, and gait symmetry. However, gait rehabilitation datasets are often characterized by class imbalance, non-linear temporal dynamics, and gradual recovery patterns, which limit the


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effectiveness of conventional methods based on machine learning and recurrent neural networks. This paper suggests a novel hybrid deep learning framework to address these issues for gait classification and rehabilitation assessment using vGRF data.

In the proposed architecture, Generative Adversarial Network (GAN) [1] is incorporated at the preprocessing stage to generate synthetic gait signals to balance the dataset. Temporal features representing local biomechanical characteristics such as loading response and push-off dynamics are extracted using a Temporal Convolutional Network (TCN) [2], while global gait context and inter-phase dependencies are captured through a Transformer encoder. These complementary representations are fused to form a unified latent gait feature space, which is subsequently used by a binary classifier to distinguish between normal and abnormal gait patterns. Abnormal gait cases are directed toward rehabilitation programs, and the extracted deep features are further utilized to analyse gait improvement across rehabilitation sessions. This integrated framework enables both accurate gait classification and data-driven assessment of rehabilitation progress within a single unified model.

The novel contributions of this architecture are:

1. The architecture incorporates GAN to generate synthetic samples to balance the dataset.
2. The TCN block captures local temporal gait dynamics while the Transformer Encoder models simulates contextual dependencies and global gait phase correlations.
3. This architecture employs feature fusion to combine local and global representations, enabling more robust and discriminative gait classification.
4. Unlike conventional models this proposed framework supports both gait classification [3]-[5] and rehabilitation.
5. Finally, the use of attention-based contextual modelling provides intrinsic interpretability, allowing insight into phase-level gait recovery without relying on post-hoc explainability methods. Together, these contributions establish a unified and novel deep learning framework for both gait classification and rehabilitation monitoring in lower-limb fracture patients.

## 2 LITERATURE SURVEY

The assessment of gait functions constitutes an essential tool that enables medical professionals to both detect motor disorders and create specific rehabilitation treatments and build assistive devices. These assessments performed manually with rating scales pose significant limitations because they suffer from subjective judgments coupled with unreliable results along with poor reproducibility [6]. The vGRF data are used to distinguish the gait as normal or abnormal [7]. The kinetic parameters are extracted from vGRF signal using ML with IMU sensors for the gait analysis [8]-[10]. The clinical gait analysis itself is not reliable for diagnosing neurological impairments and also suggests pathology if the gait pattern differs from normal human gait pattern. The clinical gait analysis is used for diagnosis, assessment, monitoring and prediction [11]. Artificial intelligence developments especially deep learning techniques have brought automatic data-based approaches which improve both accuracy and speed performance in gait evaluation procedures. Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, are particularly well-suited for modelling the temporal dependencies inherent in gait data, and have been successfully applied to tasks like gait recognition and activity classification [12]-[13]. Similarly, Convolutional Neural Networks (CNNs) excel at automatically extracting hierarchical ground truth and spatial features from raw sensor data, demonstrating their effectiveness in identifying gait patterns from sensor signals or images [14]-[15]. The synergistic combination of these architectures into CNN-LSTM hybrid models leverages the strengths of both, with the CNN component extracting features and the LSTM component capturing their temporal context [16]-[18].

Monitoring recovery of lower limb fracture rehabilitation is crucial; however, manual gaits are subjective. A key objective metric for lower limb rehabilitation is the Symmetry Index (SI), which quantifies the functional differences between an affected and an unaffected limb [19]. The SI is a powerful indicator of pathology and is associated with compensatory movements that can lead to long-term issues [20]-[21]. However, most studies using SI have focused on a single point in time rather than tracking its evolution over a patient's entire rehabilitation journey [22].

# 3 PROPOSED METHOD

## 3.1 Experimental Setup with hyperparameters

Python 3.10, CPU of 2.4 GHz, TensorFlow of 2.15 with NumPy, Pandas were used for all computational tests. High level Kera's APIs were used to implement the architecture. The proposed system uses 3 TCN layers with 64 filters, a kernel size of 3 and dilation rates of 1,2, and 4 were employed, each followed by batch normalization, ReLU activation, dropout of 0.2, and L2 regularization (0.0001). The transformer encoder is configured with model dimension of 64, four attention heads, a feed-forward network of size 128, dropout of 0.2 and 0.3 respectively. An additional attention layer and global pooling layer is employed before dense layer with 64 neurons and dropout of 0.4. The model is trained for 20 epochs with a batch size of 64 using Adam optimizer minimizing mean squared error loss.

## 3.2 Dataset

This research work uses a comprehensive and open-source dataset for human gait classification and to predict rehabilitation outcomes in the lower limb fracture patients. The dataset contains 75732 bilateral walking trials of 2084 patients with distinct musculoskeletal impairments. The dataset contains gait records of Healthy control (HC) and the fracture patient's Ankle(A), Hip(H), Knee(K), calcaneus(C) gait records. The data is collected from the patients during the rehabilitation stay varies in terms of months. The noise effect is reduced using 2nd order Butterworth low pass filter with cutoff frequency 20Hz with amplitude and time normalization. The time is normalized to 101 data points. The train-test split is based on the predefined split provided in the

GRF_metadata.csv file. The split is in the ratio 70:30 and is subject wise splitting for our proposed work.

### 3.3 Data Preprocessing

In data preprocessing the patient ID with single session is removed from the processed vGRF datasets for left and right leg separately. The GaitRec dataset is imbalanced. The GAN architecture is used to balance the dataset that synthesizes additional gait samples for the minority class especially for abnormal gait in lower limb fracture patients. A GAN consists of two, generator and discriminator. The generator learns to generate realistic vertical GRF time series and a discriminator distinguishes the real gait cycles from synthetic ones. Both the networks are optimized in an adversarial manner until the generator creates GRF signals that closely resemble real abnormal gait patterns in terms of temporal structure and stance phase characteristics. Once trained the generator is used to produce additional synthetic abnormal gait cycle and are combined with real data to form a balanced training dataset. This process increases the count of minority class samples without throwing away any real data.

### 3.4 Proposed Architecture

The proposed work shown in the Figure 1 uses a deep learning framework for both gait classification and rehabilitation assessment using vertical ground reaction force (vGRF) data. The vertical GRF signal collected from left and right lower limbs and kinetic features are extracted and normalized over a full gait cycle is applied as input to the system. A Generative Adversarial Network (GAN) is used for balancing the dataset. The GAN is trained particularly on minority-class samples with respect to abnormal gait to generate synthetic, biomechanically realistic GRF sequences that preserves temporal structure and pathological characteristics. These generated samples are combined with original data to form a balanced training set, thereby mitigating bias toward the majority class.

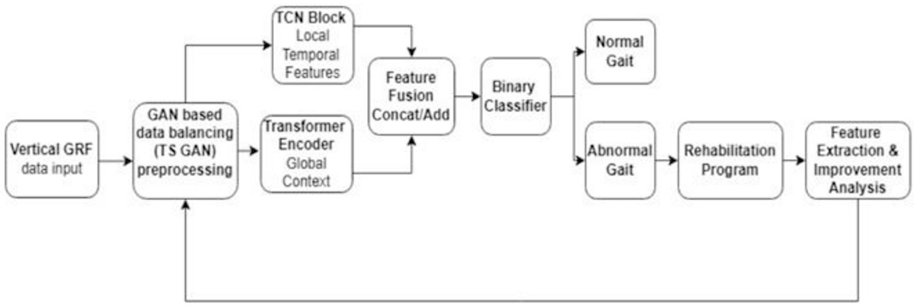



**Fig. 1.** System Architecture of TCN-Transformer Encoder hybrid model

The pre-processed vGRF data are simultaneously fed into two parallel feature extraction pathways. The biomechanical kinetic features like peak force, impulse, time to peak, loading and unloading rate are extracted from the vGRF data. The composite

ASI is computed. The temporal convolutional network (TCN) clock extracts local temporal features from the biomechanical characteristics like loading response, peak force patterns and push-off dynamics through dilated causal convolution and the Transformer Encoder block uses self-attention mechanism to model global temporal context to learn long range dependencies and gait phase interactions across the complete gait cycle.

The TCN and Transformer encoder blocks features are combined in a feature fusion module to form a comprehensive latent gait representation. If composite ASI value is less than 10 then the gait is normal otherwise abnormal. A binary label is added with a value 0 is assigned for normal and 1 for abnormal, and the data is fed to the model. The deep learning (DL) temporal convolutional network and transformer encoder with attention layer hybrid model is used for gait classification. The abnormal gait data is sent to the rehabilitation program with DL model. The initial and final session composite ASI values are extracted from each patient data and the asymmetry reduction percentage from initial to final session is computed. If the percentage of asymmetry is reduced by greater than or equal to 30% then the overall gait of a patient is recovered otherwise not recovered and the patient is suggested rehabilitation again.

The ASI computation is done by mapping affected side from GRF_metadata.csv file for the fractured patients. If only one leg is fractured then the Eq. (1) is used to determine ASI.

$$ASI = \left|\frac{Xu - Xa}{0.5 \times (Xa + Xu)}\right| \times 100 \tag{1}$$

The composite ASI is computed using Eq. (2) by assigning weights to the features, 0.35 for peak force , 0.25 for impulse, 0.15 for time to peak, 0.15 for loading rate, and 0.10 for unloading rate.

$$Composite\ ASI = \sum_{k=1}^{K} w_k \times ASI_k \tag{2}$$

Where $w_k$ is the weight assigned to the k$^{th}$ feature, K represents number of kinetic features, $ASI_k$ is the ASI of k$^{th}$ feature.

The percentage of asymmetry reduction is computed using Eq. (3).

$$ASI\ reduction\ \% = \left(\frac{ASI_{initial} - ASI_{final}}{|ASI_{initial}|}\right) \times 100 \tag{3}$$

The performance metrics for the gait classification are obtained using Eq. (4) to Eq. (7)

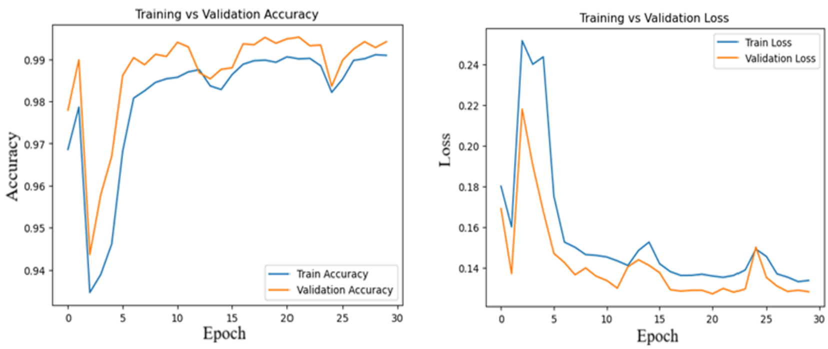
$$Accuracy = \frac{P_{true} + N_{true}}{P_{true} + N_{true} + P_{false} + N_{false}} \tag{4}$$

$$Precision = \frac{P_{true}}{P_{true} + P_{false}} \tag{5}$$

$$Recall = \frac{P_{true}}{P_{true} + N_{false}} \tag{6}$$

$$F1\ score = 2\,\frac{Precision.Recall}{Precision + Recall} \tag{7}$$

The performance metrics accuracy of 0.9938, F1 score of 0.9960, precision of 0.9978, recall of 0.9943 and specificity of 0.9959 are obtained from the proposed system. The learning behaviour of our proposed system for validation versus training accuracy and loss is as shown in Figure 2(a) and 2(b).




(a) (b)

**Fig. 2.** Learning behaviour of the proposed system (a) Accuracy curve and (b) Loss curve

The Table 1 contains actual and model predicted composite ASI values of initial and final session. The asymmetry reduction percentage of actual and model prediction are recorded and overall gait status predicted from initial and final session ASI values are shown. The overall gait is considered as improved after rehabilitation if there is a reduction in the asymmetry index of at least 30% from initial to final session.

**Table 1.** The initial and final session values of Actual and model prediction with overall status

| Sub. ID | Actual Composite ASI | | Model Predicted Composite ASI | | Asymmetry reduction Percentage (%) | | Overall Status |
|---|---|---|---|---|---|---|---|
| | Initial Session | Final Session | Initial Session | Final session | Actual | Model Predicted | |
| S01 | 42.5746 | 24.8374 | 40.2658 | 24.5390 | 41.6613 | 39.0574 | Improved |
| S02 | 20.0535 | 16.3192 | 18.6102 | 15.8375 | 18.6214 | 14.8983 | Not Improved |
| S03 | 10.5187 | 6.9824 | 9.8450 | 6.0166 | 33.6191 | 38.8871 | Improved |
| S04 | 39.8878 | 30.0238 | 38.5005 | 29.6503 | 24.7293 | 22.9872 | Not Improved |

The proposed work regression metrics are computed using the equations (8) to (10).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(z_i - \widehat{z_i})^2} \tag{8}$$

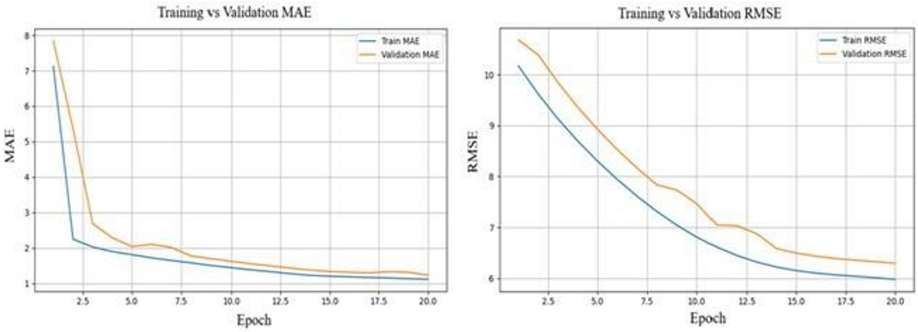
$$MAE = \frac{1}{N}\sum_{i=1}^{N}|z - \widehat{z_i}| \tag{9}$$

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

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(z_i-\widehat{z_i})^2}{\sum_{i=1}^{N}(z_i-\overline{z_i})^2} \tag{10}$$

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

The regression model learning curves, MAE curves and RMSE curves are as shown in the Figure 3(a) and 3(b).




(a) (b)

**Fig. 3.** Regression model learning curves (a) MAE curves and (b) RMSE curves

The Table 2 shows the comparison of performance metrics of gait classification of proposed system with the traditional methods. The gait classification is performed using GaitRec dataset with a data split of 80:20 using GRF data[23].The joint impairments using walkway systems are used for normal and abnormal gait analysis. The Random Forest model is focussing of knee and ankle joint impairments [24].The gait classification is done for human fall risk assessment using force plate open source dataset [25].

**Table 2.** Performance metrics comparison of traditional methods with proposed system

| Model used | Accuracy (%) | Precision (%) | F1 Score (%) | Recall (%) |
|---|---|---|---|---|
| CATBOOST [23] | 0.947 | 0.948 | 0.948 | 0.947 |
| Random Forest [24] | 0.90 | 0.92 | 0.91 | 0.90 |
| CNN [25] | 0.993 | 0.993 | 99.3 | 0.99 |
| Proposed | 0.9938 | 0.9978 | 0.9960 | 0.9943 |

The Table 3 shows the comparison of gait improvement after rehabilitation with regression metrics. The CNN and RNN classifier using CROM and PROM are used to predict the rehabilitation outcomes required for clinical decision. Both regression and classification metrics are extracted from the model. There is an improvement of 9% in F1 score and 12% reduction in MAE compared to traditional ML methods [26]. The data was collected from the GRF curve of 13 tibial fracture patients for the longitudinal study and composite ASI is used as the target for the model. The force plate and motion capture are used to record the data and regression metrics are extracted [27]. The temporal series analysis of lower leg rehabilitation for stroke patients in the limb recovery is performed using xLSTM and Lag-Llama model and regression metrics are extracted for DNS gait and UPS gait [28]. The LSTM model is used to balance the training by incorporating feedback on weight shifting performance in exergames and regression metrics are extracted [29].

**Table 3.** Comparison of gait recovery of Existing Models with proposed work

| Model Type | Target | RMSE | MAE | $R^2$ |
|---|---|---|---|---|
| Proposed | vGRF | 1.17 | 0.8536 | 0.9870 |
| Hybrid CNN+RNN [26] | PROM and CROM | ----- | 4.25 | 0.87 |
| ML(force Plate) [27] | Composite ASI | 4.78 | 3.56 | 0.72 |
| xLSTM and Lag-Lamma [28] | DNS gait | 10.54 | 6.28 | 0.72 |
| | UPS gait | 12.28 | 7.54 | |
| LSTM [29] | vGRF | 4.6 | ------ | 0.97 |

# 4 CONCLUSION

This proposed work used the deep learning framework to classify the gait as normal or abnormal and also to quantify the recovery of the gait of lower limb fracture patients during rehabilitation. This system uses vertical GRF data from GaitRec dataset and biomechanical kinetic features like peak force, impulse, time to peak, loading and unloading rate are computed. The ASI is computed for all features and composite ASI is computed between left and right limb over several sessions. The ASI value is used for gait classification. If ASI value of a patient is less than 10 then it is considered as normal gait otherwise abnormal gait using TCN and transformer encoder hybrid model. The abnormal gait patients will go for rehabilitation. The suggested TCN-Transformer encoder hybrid model provides the gait classification metrics accuracy of 0.9938, F1 score of 0.9960, precision of 0.9978, recall of 0.9943 and regression metrics RMSE of 1.1700, MAE of 0.8536 and $R^2$ of 0.9870. The initial and final session composite ASI values are used to compute the overall gait improvement of a patient. If the asymmetry reduction percentage is greater than or equal to 30% between the limbs then the overall gait of a patient is improved.

**Disclosure of Interests:** The authors have no competing interests.

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