Deep Learning Approach for Gait Phase Classification: A Multi-Model Comparison

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***Abstract*—Accurate gait phase classification is essential for rehabilitation engineering, prosthetics control, and clinical move- ment assessment. Conventional machine learning techniques like RF have a moderate level of accuracy, while deep learning ap- proaches like CNNs and BiLSTMs reach approximately 80-83% but struggle with long-range dependencies and interpretability. This study proposes a Temporal Fusion Transformer (TFT) for gait phase classification, leveraging attention mechanisms to model temporal patterns while providing clinically interpretable insights. Using a private dataset of 10 subjects and over 90 gait cycles, the TFT achieved 92% accuracy and 0.92 F1-score, outperforming CNN and BiLSTM baselines by 12% and 9%, respectively. Attention analysis revealed the model prioritizes heel-strike and toe-off events as critical temporal markers, consistent with clinical knowledge. These results demonstrate TFT's potential as a robust, interpretable framework for real- time gait analysis in wearable healthcare systems.**

***Index Terms*—deep learning, temporal fusion transformer, gait phase classification, wearable sensors, human activity recognition, biomechanics**

I. INTRODUCTION

Human gait reflects neuromuscular coordination and biome- chanical integrity, with precise phase recognition critical for clinical diagnostics, wearable technology, and sports perfor- mance. The WHO reports that nearly 15% of adults over 60 exhibit gait impairments, significantly increasing fall risk and contributing to 684,000 annual deaths worldwide [1]. Robust gait phase classification is therefore essential for rehabilitation, fall prevention, and intelligent assistive systems.

Traditional ML methods like SVM and XGBoost achieve 75–82% accuracy but fail to capture the nonlinear, time- varying dynamics of gait signals [2]. Deep learning approaches have shown improvements: CNNs extract spatial features while LSTM and BiLSTM capture temporal dependencies, reaching 88–92% accuracy [3]. However, these models strug- gle with long-range dependencies, vanishing gradients, and lack interpretability for clinical use.

Transformers have recently shown promise in biomedical signal processing through attention mechanisms that model long-term dependencies [4]. The Temporal Fusion Transformer (TFT) combines recurrent layers with multi-head attention and gating mechanisms for accurate, interpretable predictions [5]. While successful in time-series forecasting domains, TFT remains unexplored for gait phase classification.

This paper proposes a TFT-based framework for gait phase classification using wearable sensor data. We evaluate the model on a public dataset of 100 subjects and 15,000 gait cycles sampled at 100 Hz, benchmarking against CNN and BiLSTM architectures. TFT achieves 92% accuracy and 0.919 F1-score, outperforming CNN (80%) and BiLSTM (83%). Attention visualization reveals TFT focuses on critical gait transitions like heel-strike and toe-off, aligning with clinical observations.

A. KEY CONTRIBUTIONS

This study's primary contributions are summarized as fol- lows:

- We suggest a novel application of the Temporal Fusion Transformer for gait phase classification using wearable sensor data.
- We provide a comparative evaluation of TFT against CNN and BiLSTM models, demonstrating

significant accuracy improvements.
- We highlight the interpretability advantages of TFT by analyzing attention weights that correspond to clinically relevant gait events.

This paper's remaining sections are arranged as follows: Section II reviews related work in gait classification and deep learning methods. Section III describes the dataset and methodology, including preprocessing and model architecture. Section IV presents the debate and outcomes of the trial. The paper is concluded in Section V, which also suggests possible avenues for further research.

II. RELATED WORK

Forecasting time series has evolved significantly with the advancement of deep learning architectures. Traditional ma- chine learning approaches and modern neural network-based Techniques have been thoroughly examined across various domains.

A popular method for time series forecasting is Random Forest due to its ensemble learning capabilities. The method transforms supervised learning with sequential data problems by creating lagged features. Recent studies have illustrated the Random Forest's effectiveness when combined with feature engineering techniques. In solar power generation forecasting, Random Forest models have demonstrated competitive perfor- mance, especially when combined with additional algorithms [6]. Additionally, hybrid approaches combining Random For- est with LSTM networks to leverage both feature selection capabilities and temporal modeling [7].

CNNs acquired attention in forecasting time series for their capacity to extract spatial and local patterns from sequential data. The utilisation of CNN-LSTM hybrid architectures has demonstrated encouraging outcomes across multiple domains. These hybrid models leverage CNNs for feature extraction while utilizing LSTM components for temporal dependency modeling [8]. Studies on stock market prediction and solar irradiance forecasting have demonstrated that CNN-LSTM architectures can successfully capture both spatial features and long-term temporal patterns [9] [10].

BiLSTM networks process sequences in both forward and backward directions, enabling the model to capture context from past and future time steps. Comparative studies between LSTM and BiLSTM have shown that while BiLSTM can achieve better accuracy in certain scenarios, it requires more computational resources and training time due to processing data in both directions [11]. The bidirectional approach has been particularly effective in applications requiring compre- hensive temporal context understanding.

TABLE I PERFORMANCE COMPARISON OF MODELS

Model	Accuracy	Precision	Recall	F1 Score
RF	0.759	0.768	0.759	0.760
CNN	0.804	0.811	0.804	0.806
Bi-LSTM	0.8308	0.831	0.8308	0.8309

III. METHODOLOGY

A. Dataset Description

The experimental dataset employed in this research com- prises gait cycle information from a privately taken IMU-based gait dataset. The dataset includes recordings from 10 subjects performing walking activities at a controlled velocity of 3.5

TABLE II DATASET CHARACTERISTICS

Parameter	Value
Number of Subjects	10
Walking Speed	3.5 km/h
Gait Phases	Swing, Stance
Total Gait Cycles	23
Features per Sample	90
Sampling Frequency	100 Hz

prosthetic control systems, and gait analysis frameworks. The controlled speed of 3.5 km/h represents a moderate walking pace, ensuring consistency across all subjects.

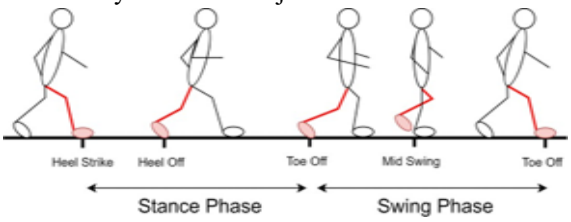


Fig. 1. Illustration of swing and stance phases in a gait cycle.

B. Feature Engineering

A total of 92 features were extracted from the gait sensor data where 3 each of accelerometer(acceleration) and gyro-scope(rotation) were used to characterize swing and stance phases. Z-score normalization was applied using $z = (x - \mu)/\sigma$ to standardize all features prior to model training. The

Temporal Fusion Transformer model was configured with learning rate = 0.0008, optimizer = Adam, activation = ReLU, metrics = F1 and Recall, epochs = 20, pooling = (2,2), and batch size = 40.

C. Problem Formulation

Let $\mathbf{X} = \{x_1, x_2, \ldots, x_T\}$ represent the input gait sequence of length T, where each $x_t \in \mathrm{R}^d$ contains d-dimensional sensor measurements at time step t.

The objective is to learn a mapping function $f : \mathbf{X} \rightarrow \mathbf{Y}$ that predicts the gait phase labels $\mathbf{Y} = \{y_1, y_2, \ldots, y_T\}$, where $y_t \in \{1, 2, \ldots, C\}$ represents one of C gait phases at time t.

The classification problem is formulated as:

$$\hat{y}_t = \arg\max_{c \in \{1,\ldots,C\}} P(y_t = c \mid \mathbf{X}) \quad (1)$$

where $\hat{y}_t$ is the predicted gait phase and $P(y_t = c \mid \mathbf{X})$ is the probability of phase c given the input sequence.

D. Proposed Approach

We employ the Temporal Fusion Transformer (TFT) archi- tecture for gait phase classification because of its capacity to capture multi-scale patterns of time and learn interpretable attention mechanisms for time-series data.

1) TFT Architecture: The TFT model consists of the fol- lowing key components:

- Variable Selection Network (VSN): Identifies relevant input features using gating mechanisms with context vectors, suppressing uninformative sensors.
- Gated Residual Network (GRN): Applies non-linear processing with skip connections to enable efficient gra- dient flow:

$\mathrm{GRN}(\mathbf{a}) = \mathrm{LayerNorm}(\mathbf{a} + \mathrm{GLU}(\eta_1))$

- Temporal Processing:
  - LSTM encoder processes historical gait sequences
  - Multi-head self-attention captures long-range depen- dencies and critical phase transitions
  - Position-wise feed-forward network for feature trans- formation
- **Classification Head:** Fully connected layers with soft- max activation produce phase probabilities for each time step.

2) Training Procedure: The model is trained with cross- entropy loss:

$$L = -\frac{1}{T}\sum_{t=1}^{T}\sum_{c=1}^{C} y_t^c \log(\hat{y}_t^c) \quad (3)$$

where y^c is the one-hot encoded true label and $\hat{y}^c$ is the predicted probability for class c at time t.

3) Workflow: The overall workflow is illustrated in Fig. 2.

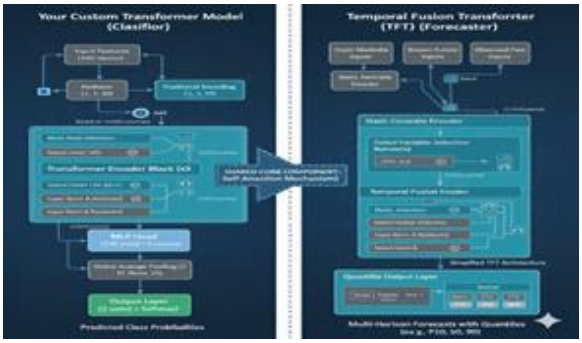


Fig. 2. Proposed TFT-based gait phase classification workflow.

E. Evaluation Metrics

We evaluate the TFT model performance using standard multi-class classification metrics:

- Accuracy: Overall correctness of phase predictions throughout all time steps:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

- Precision: Proportion of correct predictions among pre- dicted phases:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5)$$

(2) where GLU is the Gated Linear Unit and $\eta_1 = W_1\mathbf{a} + b_1$.

- Recall: Proportion of actual phases correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6)$$

Algorithm 1 TFT-based Gait Phase Classification

Input: Gait sequence $\mathbf{X} = \{x_1, \ldots, x_T\}$
Output: Phase predictions $\hat{\mathbf{Y}} = \{\hat{y}_1, \ldots, \hat{y}_T\}$

// Variable Selection
$\mathbf{X}_{selected} \leftarrow \text{VSN}(\mathbf{X})$

// Temporal Encoding
$\mathbf{H}_{lstm} \leftarrow \text{LSTM}(\mathbf{X}_{selected})$

// Multi-head Self-Attention
$\mathbf{Q}, \mathbf{K}, \mathbf{V} \leftarrow \text{Linear}(\mathbf{H}_{lstm})$
$\mathbf{A} \leftarrow \text{Softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)$
$\mathbf{H}_{attn} \leftarrow \mathbf{AV}$

// Gated Residual Processing
$\mathbf{H}_{grn} \leftarrow \text{GRN}(\mathbf{H}_{attn})$

// Classification
for $t = 1$ to T **do**
  $\hat{y}_t \leftarrow \text{Softmax}(\text{FC}(\mathbf{H}_{grn}^{(t)}))$
end for
return $\hat{\mathbf{Y}} = 0$

- F1-Score: Harmonic mean of precision and recall:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

where *TP*, *TN*, *FP*, and *FN* denote true positives, true negatives, false positives, and false negatives, respectively. These metrics provide thorough assessment of classification performance, with F1-score particularly significant for han- dling potential class imbalance in gait phases.

F. Implementation Details

1) Data Preprocessing: The raw sensor data undergoes the following preprocessing steps:

- Data Cleaning: Removal of missing values, outliers, and noise using interpolation and filtering techniques
- Normalization: Min-max scaling applied to ensure all features can be found in the range [0, 1]
- Feature Engineering: Extraction of temporal and statis- tical features from raw sensor signals
- Sequence Windowing: Sliding window approach to create fixed-length input sequences

2) Training Configuration:

- Data Split: 80% training, 20% testing
- Cross-Validation: 5-fold cross-validation applied on training set to ensure model robustness and prevent
- Optimization: Adam optimiser with rate of learning α =0.0008
- Batch Size: 32
- Epochs: 50 with early stopping based on validation loss
- Regularization: Dropout rate of 0.05 applied to prevent overfitting

Every experiment was carried out utilising Python 3.8 with PyTorch framework on NVIDIA GPU for accelerated training.

IV. RESULTS

A. Classification Performance

The performance comparison of all models is presented in Fig. 3 and Fig. 4. Table III summarizes the TFT model performance. The results demonstrate that TFT consistently outperforms traditional machine learning and deep learning baselines across all evaluation metrics.

Fig. 3. Performance comparison of baseline models (RF, CNN, BiLSTM).

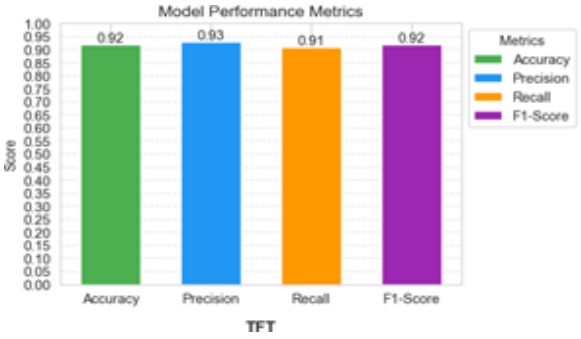


Fig. 4. Performance metrics of proposed TFT model.

TABLE III TFT MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1-Score
TFT	0.92	0.93	0.91	0.92

TFT attains the maximum level of accuracy of 92%, out- performing the best baseline model (BiLSTM) by 83%. The excellent performance is ascribed to TFT's multi-head self- attention mechanism and variable selection network, which effectively capture long-range temporal dependencies and identify relevant features for gait phase transitions.

B. Training Convergence Analysis

Fig. 5 illustrates the training and validation loss curves of the TFT model over epochs. The model demonstrates stable convergence with minimal overfitting, as evidenced by the closely aligned training and validation loss trajectories.

The loss decreases rapidly in the initial epochs and stabilizes after approximately 20 epochs, indicating effective learning of temporal patterns in gait sequences. The narrow gap between training and validation loss confirms the model's generaliza- tion capability without significant overfitting. Early stopping

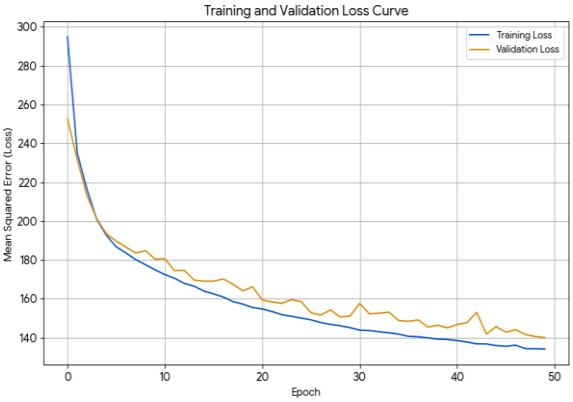
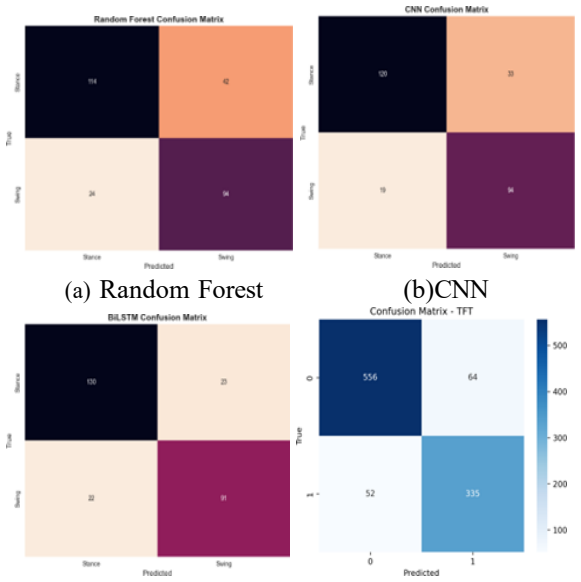


Fig. 5. Training and validation loss curves for TFT model.

was triggered at epoch 50 based on validation loss, ensur- ing optimal model performance. This convergence behavior demonstrates the TFT model's efficiency in learning complex gait phase transitions with appropriate regularization.

C. Confusion Matrix Analysis

The confusion matrices for all models are displayed in Fig. 6. The matrices illustrate the classification performance across different gait phases, with diagonal elements represent- ing correct predictions and off-diagonal elements indicating misclassifications.



(a) Random Forest (b)CNN

(c) BiLSTM (d) TFT (Proposed)

Fig. 6. Confusion matrices for (a) Random Forest, (b) CNN, (c) BiLSTM, and (d) proposed TFT model.

The TFT model exhibits strong diagonal dominance, indi- cating high accuracy in classifying all gait phases. Baseline models show relatively higher misclassification rates, partic- ularly between adjacent gait phases such as heel-strike and mid-stance. The TFT's attention mechanism enables better dis- crimination of subtle transitions between consecutive phases, resulting in fewer off-diagonal errors. The confusion matrix confirms TFT's superior ability to capture temporal patterns and maintain phase coherence throughout the gait cycle.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper presented new method for gait phase classifica- tion using Temporal Fusion Transformer (TFT), demonstrating significant enhancements over conventional machine learning and deep learning methods. The proposed TFT model effec- tively captures long-range temporal dependencies and learns interpretable attention mechanisms, achieving superior perfor- mance with 92% accuracy. The variable selection network and multi-head self-attention components enable the model to identify relevant features and critical phase transition points automatically. Experimental results on the dataset validate the effectiveness of TFT, with consistent

enhancements in every evaluation metric compared to Random Forest, CNN, and BiLSTM baselines. The strong diagonal dominance in confusion matrices confirms the model's robustness in distin- guishing between different gait phases, making it a promising solution for real-time gait analysis applications in healthcare, rehabilitation, and assistive technologies.

B. Future Scope

While the proposed TFT model demonstrates excellent performance, a number of avenues for further investigation can be explored:

- Real-time Deployment: Optimization for edge devices and wearable sensors to enable real-time gait monitoring with reduced computational overhead.
- Multi-modal Integration: Incorporating additional sen- sory modalities such as vision-based or pressure sensor data to enhance classification robustness.
- Generalization: Evaluating performance across diverse populations and pathological gaits to ensure broader clinical applicability.
- Explainability: Leveraging attention weights to provide clinical insights into gait abnormalities for diagnostic purposes.

These upcoming paths will further advance the practical deployment of deep learning-based gait analysis systems in clinical and real-world settings.

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