

PathoGaitNet: A Deep Temporal Model for Predicting Pathological Gait Trajectories in Pediatric Patients

Jyotindra Narayan¹, Abhijeet Mishra², and Hassène Gritli³

Abstract—Predicting future gait movements in children can provide crucial input for controlling lower limb robotic exoskeletons. Unlike previous research that primarily focused on predicting gait patterns of typically developing individuals, this study targets pathological gait forecasting, which is more complex due to high intra- and inter-subject variability. In this study, a deep temporal model, named as *PathoGaitNet*, is developed by combining a Convolutional Neural Network (CNN) with a Long Short-Term Memory (LSTM) network to predict joint angle trajectories at the hip, knee, and ankle in pitch and roll directions. The open-access dataset consists of motion capture recordings of children aged 4–19 years with various neurological disorders, primarily cerebral palsy, collected using a VICON system at 120 Hz. Three different input window sizes (200 ms, 400 ms, and 600 ms, corresponding to 24, 48, and 72 timesteps) were tested while keeping the output window size fixed at 8.33 ms (single timestep). Results show that the CNN-LSTM consistently outperformed the standalone CNN and LSTM models in terms of Mean Absolute Error (MAE), Mean Squared Error (MSE), and Pearson Correlation Coefficient (PCC), achieving the best performance with a 72-timestep input window (MAE = 0.631, PCC = 0.996). Joint-wise analysis revealed that the model achieved higher prediction accuracy for knee and hip joints than the ankle, likely due to the lower variability and smoother dynamics in proximal joints. These findings suggest the feasibility of deploying deep learning-based single-step gait forecasting in real-time control systems for rehabilitation robotics.

Index Terms—pathological gait prediction, pediatric cerebral palsy, CNN, LSTM, input window size, joint angle forecasting

I. INTRODUCTION

Cerebral Palsy (CP) is a prevalent motor disability that affects approximately 2.11 per 1,000 live births globally, making it the most common motor disorder in children [1]. CP is a lifelong, non-progressive condition caused by a lesion in the brain, which can occur before, during, or after birth, or due to abnormalities during fetal development. The disorder is characterized by motor impairments, varying severity depending on the affected body regions, such as hemiplegia, diplegia,

or quadriplegia. While CP is incurable, interventions like physical therapy, orthotic devices, and robotic exoskeletons can help manage symptoms and improve the quality of life [2]. These technological innovations, particularly exoskeletons, have shown promise in enhancing gait rehabilitation by reducing the metabolic cost of movement and improving gait parameters [3]. However, the success of such interventions heavily relies on accurately predicting gait trajectories, motivating the use of deep learning models [4].

Machine learning (ML) and deep learning (DL) models have been extensively employed for gait prediction, offering significant improvements in capturing complex gait patterns [5]. Traditional ML approaches, including Support Vector Machines (SVMs) and Random Forests, have been used to classify and predict gait anomalies [6]–[8]. In contrast, DL models, such as Convolutional Neural Networks (CNNs) [9], Long Short-Term Memory (LSTM) networks [10], and Transformers [11], [12], have demonstrated superior performance in modeling the intricate temporal and spatial features of gait. These models have been particularly effective in predicting joint kinematics, which are crucial for the control strategies of exoskeletons designed for children with CP. Despite their potential, most of these models have been validated on gait data from typically developing individuals, leaving a gap in their application to pathological gait seen in CP.

Time series forecasting is integral to gait trajectory prediction, where the sequential nature of joint movements is modeled to predict future gait patterns accurately. Techniques such as Dynamic Time Warping (DTW) [13], Recursive Neural Networks (RNNs) [14], and autoregressive models [15] have been widely used to capture the temporal dependencies in gait data. Advanced DL models have further enhanced prediction stability by incorporating recursive forecasting and noise-resilient methods, making them suitable for applications in CP, where gait patterns are often asymmetric and variable. These models are essential for predicting and correcting gait trajectories, offering potential improvements in the stability and effectiveness of exoskeleton-assisted rehabilitation for children with CP.

Despite significant advancements in gait prediction models, several gaps remain, particularly concerning the specific challenges posed by CP gait. Current models often overlook stride-to-stride variability and the asymmetry inherent in CP gait, leading to suboptimal rehabilitation outcomes when using exoskeletons. Additionally, pathological gait, especially in

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children with spastic cerebral palsy, exhibits even greater within-day and between-day variability due to spasticity [16], [17] as compared to typically developed children. Motivated by these gaps, the present work aims to develop a stable deep temporal model that predicts one-step-ahead kinematic trajectories of the hip, knee, and ankle joints. The major contributions of the work are:

- (i) Designed a deep temporal model (*PathoGaitNet*) by integrating CNN and LSTM to address the complex problem of pathological gait prediction in pediatric patients.
- (ii) Introduced a structured approach using variable input window lengths (24, 48, and 72 timesteps) to evaluate temporal dependencies in joint angle forecasting.
- (iii) Conducted a joint-wise analysis framework to assess model performance across different lower-limb joints, facilitating rehabilitation improvements.

The organization of the work is as follows. Section II presents the related data and processing information. The proposed *PathoGaitNet* model is detailed in Section III followed by results and discussions in Section IV. Finally, Section IV provides the concluding remarks.

II. RELATED DATA AND PROCESSING

This study considers publicly available data collected by Gillette Children’s Specialty Healthcare between 1994 and 2017 [34]. This dataset was previously utilized for automated gait event detection, specifically identifying foot contact and foot-off events [35]. It includes motion capture recordings (VICON, 120 Hz) of children aged 4 to 19 walking a 15-meter path. Most participants (73%) had cerebral palsy, while the remaining 27% had various neurological, developmental, orthopedic, or genetic conditions. The dataset comprises a 99-dimensional vector containing kinematic and marker position data, which was split into training and testing sets. In the training set, the children’s average age was 11.4 ± 6.2 years, weight 35.7 ± 17.7 kg, height 135.7 ± 21.6 cm, and walking speed 0.84 ± 0.28 m/s. The testing set had similar distributions: age 11.0 ± 4.5 years, weight 35.9 ± 16.7 kg, height 135.6 ± 21.4 cm, and walking speed 0.85 ± 0.29 m/s [35]. This study focused exclusively on kinematic data for trajectory forecasting, utilizing hip, knee, and ankle joint angles in yaw and pitch directions for the right leg. Out of the total observations (.csv files) for the right leg, 1500 and 150 random observations were considered from the training and testing datasets, respectively, as per the availability of computational resources. For validation, 20% observations from the training dataset are considered.

Preprocessing involved removing leading and trailing zeros and discarding trials with values exceeding ± 90 . To ensure fixed-length sequences for the proposed and contrast deep learning models, input and target trajectories were generated using a sliding window approach (Fig. 1, where each input sequence of length k corresponded to an output sequence of length z , with a stride of single time-step. Deep learning models were trained with three input windows of 200, 400, and 600 ms (24, 48, and 72 time-steps at 120 Hz) and

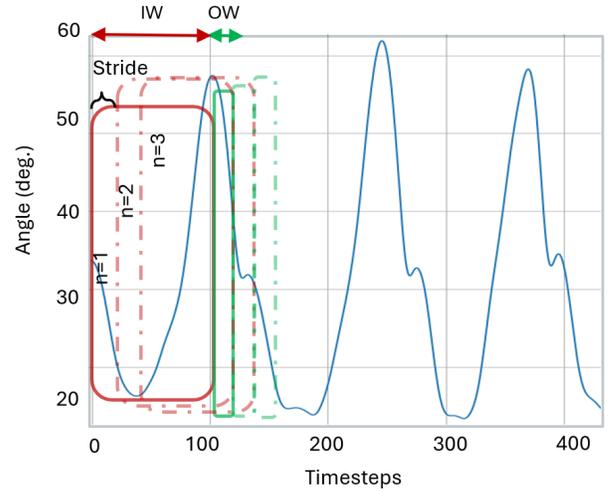


Fig. 1. Schematic of sliding window approach. Continuous gait data is fed into input-output pairs by shifting fixed-size windows along the gait trajectory. Each shift, defined by the stride, creates a new training sample (n) from the sequence.

output windows of 8.33 ms (1 time-step), forming three input-output combinations. Longer input windows may improve accuracy but increase computational load and latency. A trade-off exists—shorter windows offer faster predictions, making them more suitable for real-time control in assistive devices where low latency is essential. Moreover, these time ranges align with previous research on gait forecasting, where input windows varied from 5 to 40 steps, predicting a single step in the future [18]. The dataset was structured into an input matrix $X \in \mathbb{R}^{n \times l_{in} \times f}$ and an output matrix $Y \in \mathbb{R}^{n \times l_{out} \times f}$, where f represents joint angles in yaw and pitch. Both matrices were normalized between 0 and 1, aiming to develop a model $g()$ that maps X to predicted outputs \hat{Y} , approximating actual values Y .

III. PROPOSED PATHOGAITNET MODEL

In this section, CNN and LSTM models are described briefly followed with the details of the proposed hybrid CNN-LSTM-based *PathoGaitNet* model.

A. Convolutional Neural Network

In this study, a Convolutional Neural Network (CNN) is used to map input trajectories X to forecasted predictions \hat{Y} for lower limb joint angles in time series forecasting. The convolution operation is applied between a sequence and a kernel, whose weights are optimized during the learning process. The output of the convolution operation S , adapted from Goodfellow et al. [19] for 1D time-series I_T forecasting with kernel \mathcal{K} , is calculated using:

$$C(i) = (I_T * \mathcal{K})(i) = \sum_m I_T(m) \mathcal{K}(i - m). \quad (1)$$

The CNN architecture consists of multiple 1D convolutional layers that extract spatial-temporal features from the input sequences of lower limb joint angles, capturing relationships

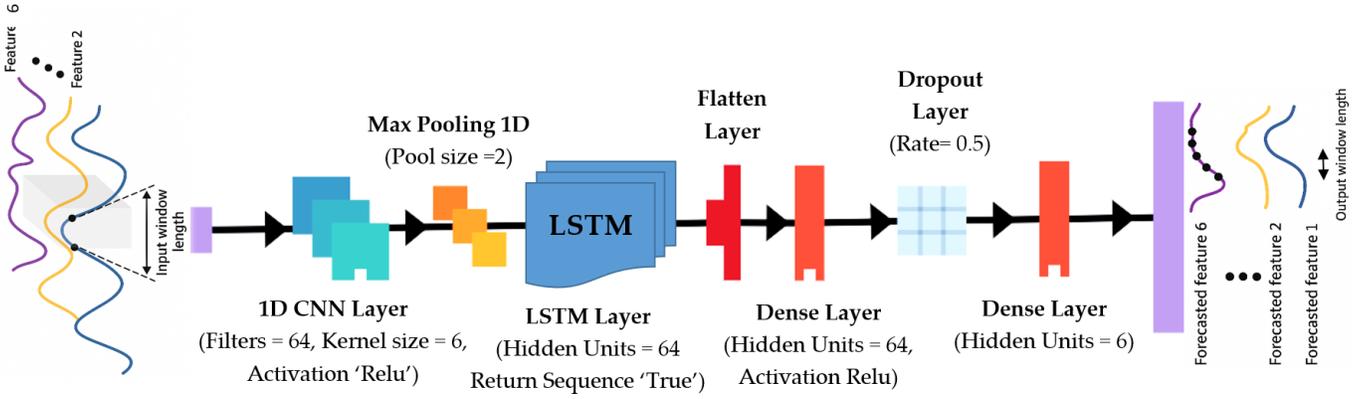


Fig. 2. Proposed Hybrid CNN-LSTM-based *PathoGaitNet* architecture

between past motion patterns and future states. Pooling layers, such as MaxPooling1D, are used to downsample the feature maps, reducing computational complexity while retaining key temporal dependencies. Dropout layers are included to prevent overfitting by randomly deactivating a subset of neurons during training, ensuring the model generalizes well to unseen gait patterns. The Rectified Linear Unit (ReLU) activation function introduces non-linearity, enhancing the model's ability to learn complex movement variations by preserving only positive activations. Key hyperparameters in the 1D-CNN architecture include the number of convolution layers, the number of filters per layer, the filter size (kernel size), and the pooling size, all of which influence the model's ability to capture both local and global motion trends.

While 1D-CNNs excel in extracting spatial dependencies from joint angle sequences, they are limited in capturing long-term temporal dependencies critical for lower limb motion prediction. To address this, a hybrid approach combining CNN with Long Short-Term Memory (LSTM) networks integrates short-term spatial dependencies with long-range temporal correlations, enabling more accurate and robust joint angle forecasting.

B. Long Short-Term Memory (LSTM) Network

While 1D-CNNs excel at spatial feature extraction by capturing local dependencies within input sequences, they are limited in modeling long-term temporal relationships. On the other hand, Long Short-Term Memory (LSTM) networks enable learning both short-term and long-range interactions within sequential data. LSTMs introduce memory cells and gating mechanisms—input, output, and forget gates—that selectively retain and discard information over time, overcoming the vanishing and exploding gradient issues of traditional RNNs. The equations governing LSTM's gating mechanisms, as described in Goodfellow et al. [19], ensure efficient information flow and retention across time steps, making it well-suited for forecasting lower limb kinematics.

The forget gate activation $f_i^{(t)}$ at time step t for unit i , given the input vector $v^{(t)}$, hidden state $r^{(t)}$, biases β^f , input weight matrix M^f , and recurrent weight matrix N^f , is computed as:

$$f_i^{(t)} = \sigma \left(\beta_i^f + \sum_j M_{i,j}^f v_j^{(t)} + \sum_j N_{i,j}^f r_j^{(t-1)} \right) \quad (2)$$

The internal memory state $d_i^{(t)}$ is updated using the forget gate $f_i^{(t)}$ and the candidate state contribution, defined as:

$$d_i^{(t)} = f_i^{(t)} d_i^{(t-1)} + p_i^{(t)} \sigma \left(\beta_i + \sum_j M_{i,j} v_j^{(t)} + \sum_j N_{i,j} r_j^{(t-1)} \right) \quad (3)$$

The external input gate activation $p_i^{(t)}$ is given by:

$$p_i^{(t)} = \sigma \left(\beta_i^p + \sum_j M_{i,j}^p v_j^{(t)} + \sum_j N_{i,j}^p r_j^{(t-1)} \right) \quad (4)$$

The output $r_i^{(t)}$ of the unit is then computed as:

$$r_i^{(t)} = \tanh \left(d_i^{(t)} \right) q_i^{(t)} \quad (5)$$

where the output gate activation $q_i^{(t)}$ is calculated as:

$$q_i^{(t)} = \sigma \left(\beta_i^q + \sum_j M_{i,j}^q v_j^{(t)} + \sum_j N_{i,j}^q r_j^{(t-1)} \right) \quad (6)$$

C. PathoGaitNet: Hybrid CNN-LSTM Network

To harness the advantages of both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, we introduce a hybrid CNN-LSTM framework, named *PathoGaitNet*, to forecast joint angles. By iteratively adjusting learning rates and utilizing 30 training epochs, the model achieves an optimal balance between convergence speed and performance enhancement, ensuring reliable classification. As shown in Fig. 2, the fusion of CNN and LSTM enables effective joint angle forecasting by capturing both spatial and temporal dependencies in motion data. First, CNN layers

extract spatial features from the input joint angle sequences by applying filters that detect movement patterns. These extracted features are then processed by LSTM layers, which analyze the data to capture both past and future dependencies in limb movements. The enriched temporal features are subsequently passed through dense layers that learn high-level motion representations, ultimately predicting future joint angles. While such hybrid frameworks are well-known, their application over recent transformer-based models is becoming increasingly popular as they require smaller datasets with reduced computational resources.

The model architecture in this study was carefully optimized through a detailed ablation study to determine the most effective configurations and hyperparameters for accurate joint angle forecasting. A comprehensive grid search was conducted, systematically evaluating all possible combinations of selected hyperparameter values. This process involved adjusting key parameters, including the number of Conv1D filters, kernel sizes, LSTM units, and dense layer sizes. By systematically testing different configurations and analyzing their influence on forecasting performance, the model was fine-tuned to effectively learn the temporal dynamics of joint movements, ultimately enhancing prediction accuracy. Finally, the study employs Conv1D filters of size 64, kernel sizes of 6, LSTM units of 64, dense units of 64, another dense unit of 8, and dropout rates of 0.5, as illustrated in Fig. 2.

D. Performance Metrics

To determine how closely the predicted trajectories \hat{Y} align with the actual trajectories Y , we computed various metrics such as the mean squared error (MSE), mean absolute error (MAE), and Pearson correlation coefficient (P). These metrics were calculated after reversing the normalization process (i.e., rescaling predictions to their original values). Given that n represents the number of test samples, f denotes the number of features, and l_{out} is the output window size, the following equations were used:

$$MSE = \frac{1}{n \times f \times l_{\text{out}}} \sum_{i=1}^n \sum_{j=1}^f \sum_{k=1}^{I_{\text{out}}} (y_{i,j,k} - \hat{y}_{i,j,k})^2 \quad (7)$$

$$MAE = \frac{1}{n \times f \times l_{\text{out}}} \sum_{i=1}^n \sum_{j=1}^f \sum_{k=1}^{I_{\text{out}}} |y_{i,j,k} - \hat{y}_{i,j,k}| \quad (8)$$

$$PCC = \frac{1}{f} \sum_{j=1}^f \frac{\text{cov}(y_j, \hat{y}_j)}{\text{std}(y_j) \times \text{std}(\hat{y}_j)} \quad (9)$$

These metrics are used to evaluate and compare the performance of the networks in the next section.

IV. RESULTS AND DISCUSSIONS

A. Performance for Varying Input Window Sizes

In this section, the performance of the proposed *PathoGait-Net* model (CNN-LSTM) and the contrast models (CNN and LSTM) is investigated for three input window sizes (24, 48,

and 72 timesteps). Fig. 3 compares the Mean Absolute Error (MAE) along with standard deviation for CNN, LSTM, and CNN-LSTM models across three input window (IW) sizes: 24, 48, and 72 timesteps. In Fig. 3(a), for IW: 24 timesteps, CNN shows the highest MAE of $0.915^\circ \pm 0.131^\circ$, while LSTM improves upon it with $0.711^\circ \pm 0.180^\circ$, and CNN-LSTM achieves the lowest error of $0.676^\circ \pm 0.157^\circ$. In Fig. 3(b), with IW: 48 timesteps, the MAE increases for CNN to $1.119^\circ \pm 0.509^\circ$, while LSTM records $0.914^\circ \pm 0.391^\circ$, and CNN-LSTM performs slightly better with $0.853^\circ \pm 0.354^\circ$. In Fig. 3(c), for IW: 72 timesteps, CNN again yields the highest error at $1.198^\circ \pm 0.720^\circ$, LSTM performs better with $0.853^\circ \pm 0.388^\circ$, and CNN-LSTM remains most accurate with $0.631^\circ \pm 0.194^\circ$. These results highlight that CNN-LSTM consistently outperforms both CNN and LSTM individually regarding prediction accuracy for single-timestep joint angle forecasting. Moreover, although CNN shows increasing MAE and higher variance with longer input windows, LSTM and CNN-LSTM demonstrate improved consistency, especially the CNN-LSTM model at 72 timesteps. This suggests that longer temporal windows allow the hybrid model better to capture the underlying temporal dynamics of joint motion, leading to more precise and stable forecasts.

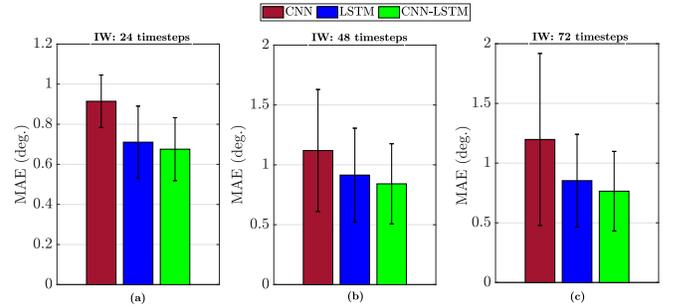


Fig. 3. MAE over testing dataset with an input window size of (a) 24 timesteps, (b) 48 timesteps, and (c) 72 timesteps

Unlike MAE, which treats all errors linearly, MSE emphasizes larger discrepancies due to its squaring effect, making it valuable for identifying significant deviations in joint angle forecasting. Table I shows that for CNN, LSTM, and CNN-LSTM models, MSE generally increases with longer input windows (24 to 72 timesteps). For example, CNN's MSE rises from 1.840 to 2.216, with increasing standard deviation, indicating higher and less stable errors. LSTM shows a rise from 1.537 to 1.715, though its standard deviation decreases, suggesting more consistent but larger errors. CNN-LSTM, while more stable, still shows a slight MSE increase from 1.393 to 1.462 between 48 and 72 timesteps, reflecting occasional deviations with longer inputs. It suggests a trade-off where increasing context can help up to a point (e.g., 48 timesteps); however, beyond that, the models—particularly CNN and LSTM—may struggle with information overload or overfitting, leading to increased squared error. Still, the CNN-LSTM's ability to maintain a relatively low and stable MSE highlights its strength in managing temporal depth.

TABLE I
PERFORMANCE METRICS (MSE, MAE, PCC) FOR CNN, LSTM, AND CNN-LSTM MODELS ACROSS DIFFERENT INPUT WINDOW SIZES

| Input Window Size (ms) | Input Window (timesteps) | MSE (deg. ²) | MSE SD (deg. ²) | MAE (deg.) | MAE SD (deg.) | Mean PCC |
|------------------------|--------------------------|--------------------------|-----------------------------|------------|---------------|----------|
| CNN | | | | | | |
| 200 | 24 | 1.840 | 0.492 | 0.915 | 0.131 | 0.985 |
| 400 | 48 | 1.397 | 0.926 | 1.119 | 0.509 | 0.983 |
| 600 | 72 | 2.216 | 1.632 | 1.198 | 0.720 | 0.972 |
| LSTM | | | | | | |
| 200 | 24 | 1.537 | 0.824 | 0.711 | 0.180 | 0.993 |
| 400 | 48 | 1.291 | 0.625 | 0.914 | 0.391 | 0.994 |
| 600 | 72 | 1.715 | 0.720 | 0.853 | 0.388 | 0.989 |
| CNN-LSTM | | | | | | |
| 200 | 24 | 1.551 | 0.383 | 0.676 | 0.157 | 0.994 |
| 400 | 48 | 1.393 | 0.425 | 0.853 | 0.354 | 0.996 |
| 600 | 72 | 1.462 | 0.673 | 0.631 | 0.194 | 0.996 |

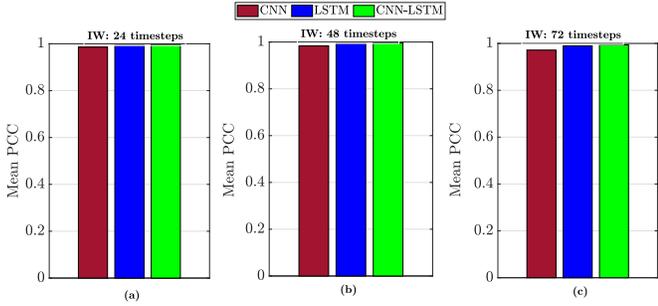


Fig. 4. PCC over testing dataset with an input window size of (a) 24 timesteps, (b) 48 timesteps, and (c) 72 timesteps

PCC measures how well predicted trajectories follow actual motion trends. High PCC values across models confirm effective temporal pattern capture. Observed from Fig. 4 and Table I, CNN’s PCC drops slightly from 0.985 (24 timesteps) to 0.972 (72 timesteps), suggesting reduced coherence with longer windows. In contrast, CNN-LSTM maintains excellent PCC—up to 0.996 at both 48 and 72 timesteps—indicating highly accurate trend tracking, highlighting its superior capability in minimizing errors and preserving joint angle patterns.

B. Performance for the CNN-LSTM model for each joint

Figure 5 presents the MSE with standard deviation (top row) and mean Hip Yaw and Pitch joint trajectories (bottom rows) for input window sizes of 24, 48, and 72 timesteps. The CNN-LSTM model outperforms at 48 timesteps, achieving the lowest MSE of 1.13 with minimal variation (cyan bar), while MSE increases to 1.75 at 24 timesteps (magenta) and 2.35 at 72 timesteps (orange), indicating declining stability with longer inputs. For Yaw angle prediction in Fig. 5(b), the input window size of 48-timestep shows high accuracy (27.34° predicted vs. 27.34° actual), whereas the 24- and 72-timestep inputs exhibit underestimations as illustrated in Figs. 5(a) and 5(c). For Pitch in Figs. 5(a)-5(c), all cases show underpredictions, with the most significant error at 48 timesteps (-0.19° predicted vs. +0.32° actual), indicating challenges in forecasting low-magnitude signals. These observations suggest that while the 48-timestep input provides the best balance between prediction

accuracy and consistency for both yaw and pitch, the model can still produce notable errors in low-magnitude signals.

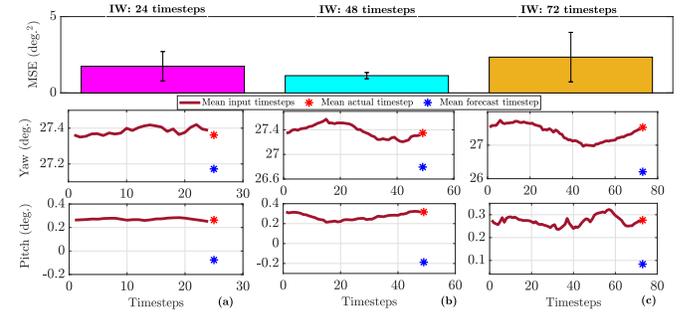


Fig. 5. MSE for overall hip angle along with the mean forecasted hip yaw and hip pitch angles, evaluated on the testing dataset for input window sizes of (a) 24 timesteps, (b) 48 timesteps, and (c) 72 timesteps

Figure 6 shows MSE with standard deviation (top row) for knee yaw and pitch angles using input windows of 24, 48, and 72 timesteps. The 48-timestep window achieves the lowest MSE (1.05) with minimal variation, indicating the most accurate and stable predictions. The 24-timestep window yields a higher MSE of 1.85, while the 72-timestep input shows an MSE of 1.29, suggesting reduced precision at short or long sequences. Referring to Figs. 6(a) and 6(b) in the bottom row, yaw and pitch are underpredicted (30.08° vs. 30.39° and 2.69° vs. 2.92°) at 24 timesteps, whereas the closest match observed at 48 timesteps. Fig. 6(c), with 72 timesteps, again shows slight underprediction (yaw: 30.44° vs 30.46°, pitch: 2.58° vs 2.96°). These trends indicate that the 48-timestep input window strikes the best balance between capturing sufficient temporal context and maintaining accurate joint angle prediction.

Figure 7 shows the MSE with standard deviation and joint angle trajectories for ankle yaw and pitch using input windows of 24, 48, and 72 timesteps. The 72-timestep input achieves the lowest MSE (0.71) with minimal variation, indicating the most stable predictions. The 24-timestep input yields a slightly higher MSE (1.1), while the 48-timestep input performs worst with an MSE close to 2.0 and the highest variability. As shown in Fig. 7(a) for 24 timesteps, yaw is underestimated (0.46° vs. 0.71° actual), and pitch is predicted marginally below the

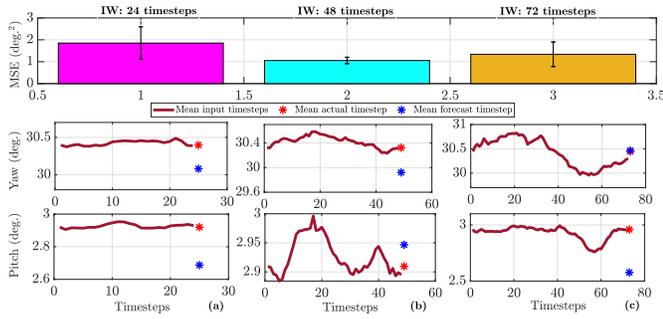


Fig. 6. MSE for overall knee angle along with the mean forecasted knee yaw and knee pitch angles, evaluated on the testing dataset for input window sizes of (a) 24 timesteps, (b) 48 timesteps, and (c) 72 timesteps

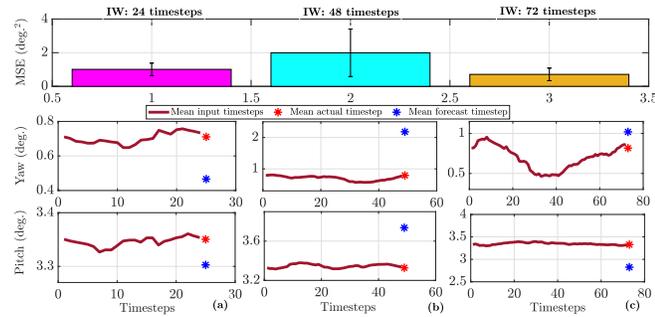


Fig. 7. MSE for overall ankle angle along with the mean forecasted ankle yaw and ankle pitch angles, evaluated on the testing dataset for input window sizes of (a) 24 timesteps, (b) 48 timesteps, and (c) 72 timesteps

actual value (3.30° vs. 3.35°). With 48 timesteps in Fig. 7(b), both yaw (2.18° vs. 0.79°) and pitch (3.73° vs. 3.32°) are overestimated. Fig. 7(c) shows the predictions closely match actual values at 72 timesteps—yaw (0.81° vs. 1.01°) and pitch (2.82° vs. 3.33°)—confirming that the model performs best with the longest input window.

V. CONCLUSIONS

In this study, a hybrid CNN-LSTM model, named as *PathoGaitNet*, has been developed and evaluated to predict one-step-ahead joint angle trajectories in children with pathological gait, particularly those with cerebral palsy. The model has consistently outperformed standalone CNN and LSTM architectures across multiple evaluation metrics, including MAE, MSE, and PCC, with the best performance observed at a 72-timestep input window. Joint-wise analysis has shown that the model achieves higher accuracy for knee and hip joints compared to the ankle, due to smoother kinematic patterns in proximal joints. Notably, the model is trained on a heterogeneous dataset including severe CP cases, enabling it to generalize well across irregular and unpredictable gait patterns. One of the model’s limitations is its sensitivity to low-magnitude joint motions and potential overfitting with long input windows. Future work will focus on real-time integration, generalization across subgroups and comorbidities, and improving low-magnitude prediction using attention or weighted loss functions.

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