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DEEP CHANNEL AND TEMPORAL ATTENTION TO DETECT PARKINSON'S DISEASE USING GAIT SIGNALS

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Abstract
Parkinson's disease (PD) is a neurodegenerative disorder that changes constantly. A general and clinically relevant gait impairment is a significant symptom, emerging as a non-invasive method to support early diagnosis and monitoring of PD. In this paper, an enhanced deep learning (DL) framework that combines convolutional neural networks (CNNs) and bidirectional long short-term memory (BiLSTM) with dual attention (DA) fusion consisting of channel-temporal attention (CNN-BiLSTM-CTA) is implemented to classify PD versus healthy controls (HC) using the signals' vertical ground reaction force (VGRF). The model was trained on gait recordings, in which VGRF signals were segmented into 300-sample windows with 50% overlap using basic augmentation and focal loss. Unlike prior studies that relied on pooled cross-validation, we adopted a rigorous protocol by training and validating on the Ga and Ju cohorts while holding back the Si cohort for independent testing. The results demonstrate that CNN–BiLSTM-CTA enhances subject-level performance across accuracy, sensitivity, specificity, and F1-score compared to the baseline CNN, BiLSTM, and CNN–BiLSTM models, as well as prior reported transformer-based approaches that achieve accurate gait signal-based PD identification.
Keywords: cross-cohort, Gait, VGRF signals, deep channel, temporal.

1. INTRODUCTION

PD is a neurodegenerative disease that primarily damages dopaminergic neurons in the substantia nigra, which governs balance and movement [1]. Tremors, postural instability, muscle rigidity, and slow movement are the core symptoms of PD, which impact gait [2]. According to previous studies, tremor and uneven gait are early signs of PD. Therefore, the key indicators of PD are the gait patterns, including periodic and rhythmic foot motions [3]. Hence, analysing gait movement serves as an effective method for identifying PD at an initial stage [4]. Evaluating gait is time time-consuming and expensive technique [5]. However, with the advancement of wearable sensor technology, it has become familiar [6]. To diagnose PD, various gait parameters are utilized, including wrist sensors, signal turn counts, stride fluctuations, gait rhythm signals, and time-stamped data. A kind of gait variable, VGRFs, which vary from person to person across time, is monitored non-invasively using force-sensitive resistors on the foot [7].

Compared to HCs, PDs typically walk with an altered flat-foot strike, slower gait cycle, and smaller steps due to their rhythmic irregularities. several studies developed automatic approaches for PD diagnosis, implementing these gait alterations [4]. Advanced learning techniques such as machine learning (ML) and DL have a significant impact on healthcare. These methods, which utilize speech patterns, writing, electroencephalography (EEG), sensory data, and magnetic resonance imaging (MRI), were recently developed for the intuitive diagnosis and categorization of PD. Despite the fact that several techniques are being studied for the use of DL and the possible identification of PD, the present method of clinical evaluation is still the observation of anomalies in the motor system [8].

Biomedical models provide a powerful approach to identifying PD. In recent years, biomechanical data, such as VGRF, have gained attention for their potential to predict PD [9]. Traditional approaches extract the hand-crafted gait features, such as temporal-spatial gait parameters, VGRFs, and joint kinematics, manually, and feed them into ML classifiers. These approaches displayed significant accuracy, specifically when combined with feature selection or dimensionality reduction methods. However, they frequently required extensive handcrafting of features and were unable to fully capture the complex patterns present in gait data [10], [11]. Later DL approaches have been explored to automatically learn discriminative features from raw gait data. CNNs can extract local spatial patterns from gait signals. In contrast, temporal dependencies across sequential gait cycles are captured by recurrent neural networks (RNNs) or long short-term memory networks (LSTMs). Hybrid architectures combining CNN and LSTM layers have shown improved performance by jointly modeling spatial and temporal information, enabling more accurate and robust PD detection without extensive manual feature engineering [12]. More recently, DL has enabled the end-to-end classification of multi-sensor gait signals, enhancing the detection of PD. Attention mechanisms have also been introduced, focusing either on temporal dynamics, spatio-temporal representations, or CNN-Bidirectional LSTM (BiLSTM) fusion frameworks [13], [14], [15]. However, these works are typically evaluated within a single cohort and lack channel (sensor)-level attention. To address these gaps, a deep CNN-BiLSTM-CTA fusion framework is adopted in this work, enabling adaptive emphasis on discriminative gait regions and transient time intervals associated with PD.

The main highlights of this paper are:

• To the best of our knowledge, this is the first study to propose a CTA fusion framework, integrates channel and temporal attention for multisensor gait signals.

• The class imbalance and false positives are reduced with the implementation of time-series augmentation techniques and focal loss.

• Operated on 300-step continuous segments, enabling the capture of long-term gait dynamics beyond single-stride analysis.

• The cross-cohort evaluation is done to demonstrate robust generalization to independent subjects.

• The proposed approach is compared with strong baseline models (CNN, BiLSTM, and CNN-BiLSTM) under the same evaluation strategy.

The structure of this work is organized as follows: Section 2 discusses several methods and techniques related to the same domain. The complete methodology of the proposed model is illustrated in Section 3. Finally, sections 4 and 5 discuss the results obtained after implementing the suggested model, the conclusion, and future work.

2. RELATED WORKS

In this section, various ML and DL-related methods utilized for detecting PD using gait sensor signals are discussed.

Balaji et al. [10] employed temporal and spatio-temporal gait features with correlation-based selection and examined by various supervised ML algorithms for PD detection, demonstrating the applicability of ML to conventional supervised approaches. By applying multi-stage feature selection and evaluation, Trabassi et al. [16] developed a PD detection model using IMU-based gait data with multiple ML classifiers. Maachi et al. [17] introduced an automatic feature learning approach with multiple parallel 1-D CNNs to distinguish PD from HC. This method is effective in identifying PD, but it has high computational costs and limited interpretability of gait characteristics. Seitwan et al. [18] proposed a VGRF-based PD detection model that utilizes time- and frequency-domain feature transformations, combined with PCA and CNN classification. Nair et al. [19] applied DWT and K-means-based feature extraction on VGRF data, followed by logistic regression for PD classification. The model effectively distinguished PD from HCs. A successful tremor-based PD detection hybrid CNN-LSTM model to classify PD tremor was proposed by Oktay and Kocer [20] using a Leap Motion controller.

Veeraragavan et al. [21] framed an ANN-based gait analysis model, which also supports PD severity assessment, oversampling, cross-validation to address class imbalance, and adequate validation. Although focused on severity, it highlights the broader use of ML in PD detection. It underscores the limitations of hand-crafted features, motivating DL approaches for automatic feature extraction. GaitFormer in Jiao et al. [15] developed a transformer-inspired architecture, which removes the softmax operation to enhance interpretability. However, this approach is limited to intra-dataset evaluation and also has a higher computational cost. Pei et al. [13] proposed a temporal pyramid attention model (PAST), which emphasizes multi-scale temporal patterns in gait sequences and does not incorporate channel-level attention across foot sensors. A CNN–BiLSTM fusion network for multi-sensor gait signals was used in Jing et al. [14] which effectively captured spatial and temporal dependencies and lacked explicit attention mechanisms. Xia et al. [22] adapted a dual-modal attention-enhanced DL network for PD recognition. Nguyen et al. [23] presented a Transformer network to extract relevant gait parameters, and a traditional feed-forward network uses these extracted features to provide the classification outcome.

Overall, existing studies either emphasize temporal or spatio–temporal attention or fuse CNN and BiLSTM features without selective weighting. Moreover, most rely on intra-dataset cross-validation, which may inflate accuracy by mixing subjects across training and testing sets. In contrast, our proposed DA fusion integrates channel attention to highlight discriminative foot sensors and temporal attention to capture disease-relevant gait intervals, while validating performance in a cross-cohort setting for robust generalization.

3. PROPOSED METHODOLOGY

In Figure 1, the overview of the entire workflow for the proposed model is illustrated. The raw input signals were pre-processed and trained on the CNN-BiLSTM-CTA model.

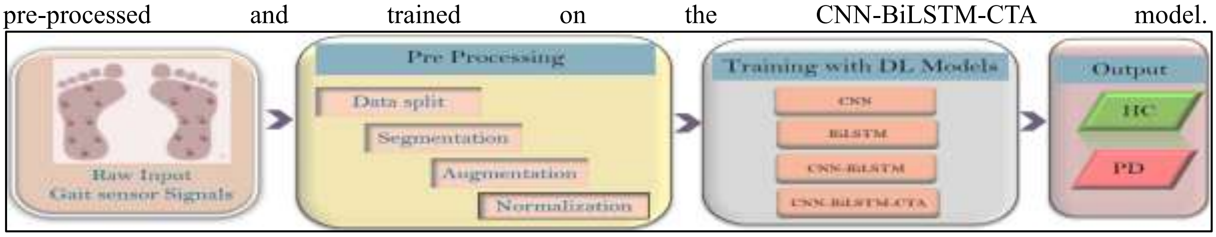

Figure 1: Process of the proposed model

The proposed model enables the robust extraction of channel (sensor) and temporal (gait cycle) patterns, thereby improving the performance and accuracy of PD detection.

3.1 Dataset

The dataset used in this work is employed from [24] and it is publicly available on [25]. It includes contributions from three research groups, namely Ga [26], Ju [27], and Si [28]. In this, PD and HCs walked with sensors attached to their shoes for two minutes at their normal, self-selected speed (based on [27] and [28]). The collection includes measures ([26]) from people performing a second task while walking. A total of 306 walks were recorded from 166 persons, including 93 PD and 73 HC, with 214 recorded PD and 92 HC walks.

3.2 Preprocessing

The raw VGRF signals were systematically pre-processed to optimize the dataset for training the proposed architecture. This pipeline includes data splitting, segmentation, augmentation, and normalization. Figure 2 displays the resulting data distribution before and after pre-processing.

Data split:

. The raw gait recordings were first divided at the subject level to avoid data leakage. A cohort-based split was adopted for the proposed approach in which the Ga and Ju cohorts were used for training and validation, while the Si cohort was held out as an independent test set. This approach provides a stronger assessment of generalization compared to random cross-validation commonly used in existing studies.

Segmentation:

Each walking trial was segmented into fixed-length overlapping segments to enlarge the effective training set and capture local gait dynamics. Here, the signals were segmented into windows of 300 time steps with 50% overlap, resulting in 21,608 segments. The Ga, Ju has 4,304 HC and 12,548 PD (16,552 segments), and Si has 2,291 HC and 2,765 PD (5,056 segments). This balances temporal resolution with the ability to capture gait cycles.

Augmentation:

The basic data augmentation techniques (jittering, scaling, and temporal shifting) mentioned in [29], [30] are applied only on HC samples to address the class imbalance in the training and validation sets. This effectively doubles the count of HC alone and produces a more balanced data distribution of 20,856 overall (8,608 HC and 12,248 PD). The test sets remained unchanged.

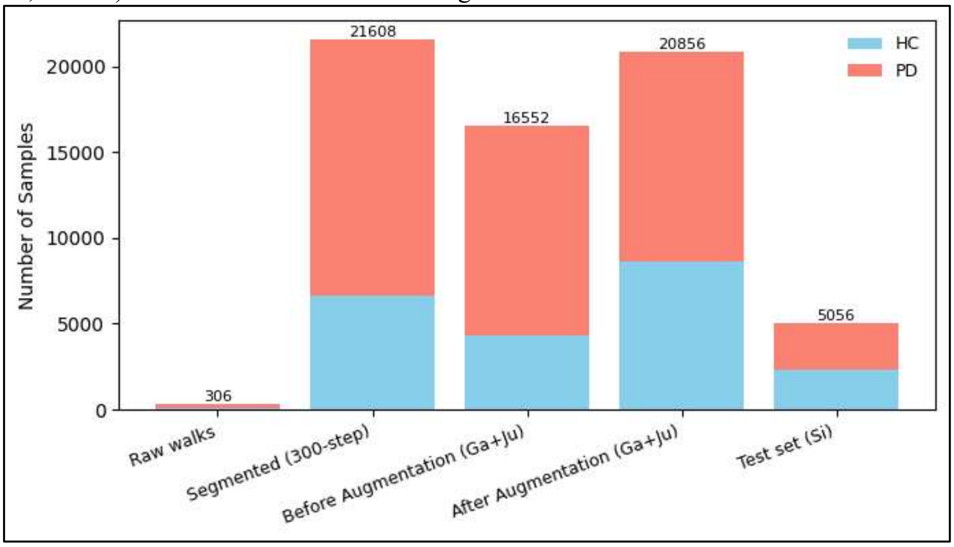

Figure 2: Data Distribution Before and After Preprocessing

Normalization:

Finally, all signals were standardized channel-wise using Z-score normalization on a per-window basis, ensuring that each segment had zero mean and unit variance before being fed into the model. This reduces inter-subject variability and stabilizes the optimization.

3.3 Proposed CNN-BiLSTM-CTA

The proposed hybrid CNN-BiLSTM-CTA is developed to enable accurate PD detection using gait signals, as represented in Figure 3. The suggested network captures discriminative sensor channels and the critical time interval in the gait sensor signal to improve PD detection accuracy.

It comprises two stacked 1D convolutional blocks, each of which is followed by batch normalization and max pooling for local temporal feature extraction, followed by a BiLSTM to capture sequential dependencies. Next, an attention block (channel and temporal) was emphasized. Finally, the attended characteristics were normalized,

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processed through fully connected layers with dropout, and classified as PD or HC.

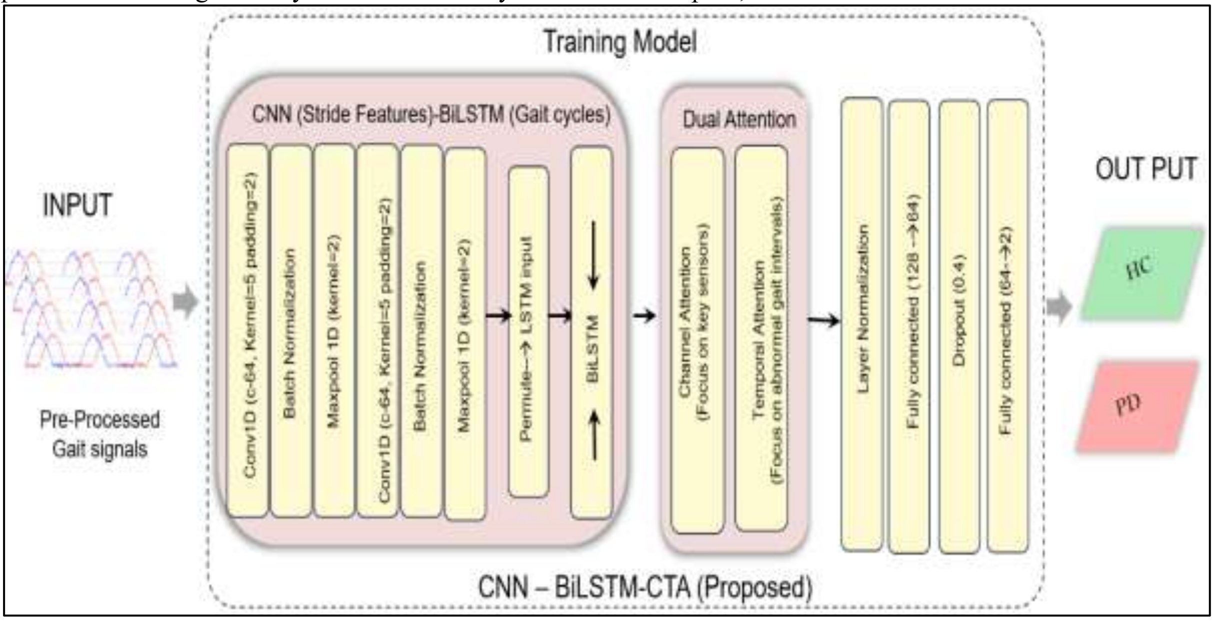

Figure 3: Architecture of the CNN-BiLSTM-CTA (proposed) Model

Let a segmented gait window be:

$$X \in \mathcal{R}^{L \times C} \tag{1}$$

where, L and C = number of time steps, and gait channels.

Feature Extraction:

Local stride Features (CNN):

CNN layers are employed as the first stage of the model to extract local stride features from the multi-sensor VGRF input. By applying filters across the time-series windows, CNN captures short-term variations and inter-sensor correlations, such as abnormal foot-strike force distributions in PD. This reduces noise and provides compact representations of sensor-level patterns before passing them to the temporal module. In this, changes in step dynamics, stride variability, and acceleration are extracted. Batch normalization and ReLU activations stabilize and add nonlinearity. However, max-pooling reduces temporal resolution to concentrate on the most critical movement aspects.

The extracted gait dynamics are given by:

$$H^{(k)} = \mathrm{ReLU}\left(\mathrm{BN}\left(X * W^{(k)} + b^{(k)}\right)\right) \tag{2}$$

where, $*$ denotes 1D convolution with kernel $W^{(k)}$

The output of these layers is permuted to (Batch, Timesteps, Channels), then processed by BiLSTM.

Sequential gait cycles (BiLSTM):

The BiLSTM models sequential dependencies in both forward and backward directions. Since gait is inherently rhythmic and sequential, BiLSTM effectively captures stride-to-stride irregularities, prolonged stance phases, and other time-dependent abnormal characteristics of PD. The bidirectional nature ensures that both past and future context within the gait cycle contribute to the representation. This layer captures long-range temporal dependencies (forward and backward) in gait cycles. The final hidden state is mentioned as:

$$h_t = \left[\overrightarrow{h_t}\,;\overleftarrow{h_t}\right] \in \mathcal{R}^{2H} \tag{3}$$

Dual Attention Fusion:

The DA fusion mechanism combines channel and temporal attention to enhance discriminative feature learning. The Channel Squeeze-and-Excitation (SE) and temporal attention were introduced by [31], [32] adaptively recalibrating channel-wise feature responses by modelling interdependencies between channels, strengthening the representational capacity of CNNs, and allowing the models to focus on specific time intervals in sequential data, improving performance in tasks like machine translation.

Channel Attention (SE Block):

The most informative sensor signals are emphasized in this block, highlighting the key gait signal features (ankle or foot accelerations) that indicate PD movement. Here, the weights are computed as:

$$s = \sigma\left(W_2 . \delta\left(W_1 . \frac{1}{L}\sum_{t=1}^{L} h_t\right)\right) \tag{4}$$

where, σ and δ are ReLU, sigmoid function. Then the reweighted features are given by:

$$h_t' = h_t \odot s \tag{5}$$

Temporal Attention:

The temporal attention module lets the network focus on the critical time intervals within each gait window, where PD-specific abnormalities occur. The attention scores for gait time steps are obtained by:

$$e_{t=v^T}\tanh(Wh'_t) \quad (6)$$
$$\alpha_{t=\frac{\exp(e_t)}{\sum_{k=1}^{L}\exp(e_k)}}$$

The final attended gait features are obtained by combining channel and temporal contexts. The fused representation is computed as:

$$F^*_{c,t} = s_c.\propto_t.F_{c,t} \quad (7)$$

where $F_{c,t}$ is the feature map at channel c and time t, s_c and $\propto_t$ denotes the channel and temporal attention weights.

Classification Head:

The outcome of the attention modules is normalized and passed through the fully connected layers. Its final representation is given below:

$$z = \mathrm{ReLU}(w_f c + b_f)\ ,\ \hat{y} = \mathrm{Softmax}(w_\circ z + b_\circ) \quad (8)$$

where, $\hat{y}$ denotes the probability of PD vs. HC.

Loss Function and Class Imbalance:

The focal loss is integrated to handle class imbalance and focus training on hard-to-classify samples. It is defined as

$$\mathcal{L}_{focal} = \alpha_t(1-p_t)^{\gamma}\log(p_t) \quad (9)$$

where, p_t is the predicted probability for the actual class (PD), α_t is a balancing factor between classes, and γ is a focusing parameter that reduces the relative loss for well-classified samples. By down-weighting easy samples and emphasizing difficult ones, focal loss optimizes the proposed model to complex gait abnormalities that distinguish PD from HC.

3.4 Training Strategy

The proposed model was trained using the Adam optimizer with an initial learning rate, and the ReduceLROnPlateau scheduler was employed. This makes the model adaptively reduce the learning rate when the validation loss plateaus. Training was done with a batch size of 16 for a maximum of 40 epochs. Early stopping with a patience of 10 epochs was applied to avoid overfitting, and the model checkpoint corresponding to the lowest validation loss was restored for final evaluation. Table 1 lists the hyperparameters used for training.

Table 1. List of Hyperparameters (training)

Hyperparameter	Value
Batch size	16
CNN Channels	64
Conv1D Kernel Size	5
LSTM Hidden State	64
BiLSTM	Yes
Dropout	0.4
Channel Attention (SE) Reduction	8
Learning Rate	le^{-3}
Weight Decay	le^{-4}
Focal Loss Gamma	2.0
Epochs	40
Early Stopping Patience	7

3.5 Evaluation Protocol

The performance of the proposed CNN-BiLSTM-CTA was first computed at the segment gait window. However, subject-level performance was reported for each test subject's predictions, and the final class label (PD or HC) was determined using majority voting. This strategy ensures robustness to occasional misclassified segments and aligns with prior studies [33]. The final performance was reported using the following metrics:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (10)$$
$$\text{Specificity} = \frac{TN}{TN+FP} \quad (11)$$
$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

where

TP, FP, TN, and FN are the total number of true and false positives/negatives.

4. RESULTS AND DISCUSSIONS

The proposed framework was first evaluated on baseline architectures (CNN, BiLSTM, and CNN-BiLSTM) in the dataset [34], using the same preprocessing and evaluation protocol to establish a fair comparison with our proposed framework. The experimental analysis demonstrates the progressive benefits of combining channel and temporal modeling with attention mechanisms. Table 2 illustrates that the CNN and BiLSTM baseline achieved reasonable performance by extracting local gait features, sequential dynamics across gait cycles, although it underutilized spatial information from multiple foot sensors. By integrating the two approaches, the CNN–BiLSTM hybrid provided a more balanced representation of both channel and temporal characteristics, resulting in further performance gains. Building upon this foundation, our proposed CNN-BiLSTM-CTA model incorporates channel/temporal attention, as well as focal loss, enabling it to selectively emphasize the most informative sensors, focus on discriminative stride intervals, and address class imbalance simultaneously. As a result, the proposed architecture achieved the best performance across all metrics. This shows the effectiveness of the DA strategy in capturing clinically relevant gait patterns. Figure 4 illustrates the training/validation accuracy and loss curves, showing smooth convergence with minimal fluctuations, which represents constant optimization and indicates that the proposed model does not overfit. Using focal loss and augmentation, the generalization gap is reduced, and validation performance is enhanced.

Table2. Comparison of the CNN-BiLSTM-CTA with baseline on the external Si

Architecture	Accuracy	Sensitivity	Specificity	F1-score
CNN	89.7%	90.3%	88.8%	89.0%
BiLSTM	91.2%	92.0%	90.1%	91.1%
CNN-BiLSTM	92.4%	92.9%	91.8%	92.0%
CNN-BiLSTM-CTA (Proposed)	**95.8%**	**95.2%**	**94.1%**	**95.0%**

Earlier studies on the [34] The dataset primarily used pooled cross-validation, without strict subject separation, and reported accuracies of 89–92%. In contrast, we adopted a stricter protocol by training on Ga and Ju cohorts and testing on the independent Si cohort, thereby avoiding data leakage and providing a more realistic assessment of generalization. Under this setup, our suggested CNN-BiLSTM-CTA achieved 95.8% accuracy, surpassing both internal baselines and prior transformer-based approaches. The explicit use of an external test (Si) cohort represents a methodological advance, thereby strengthening the clinical relevance compared to works that rely solely on pooled validation.

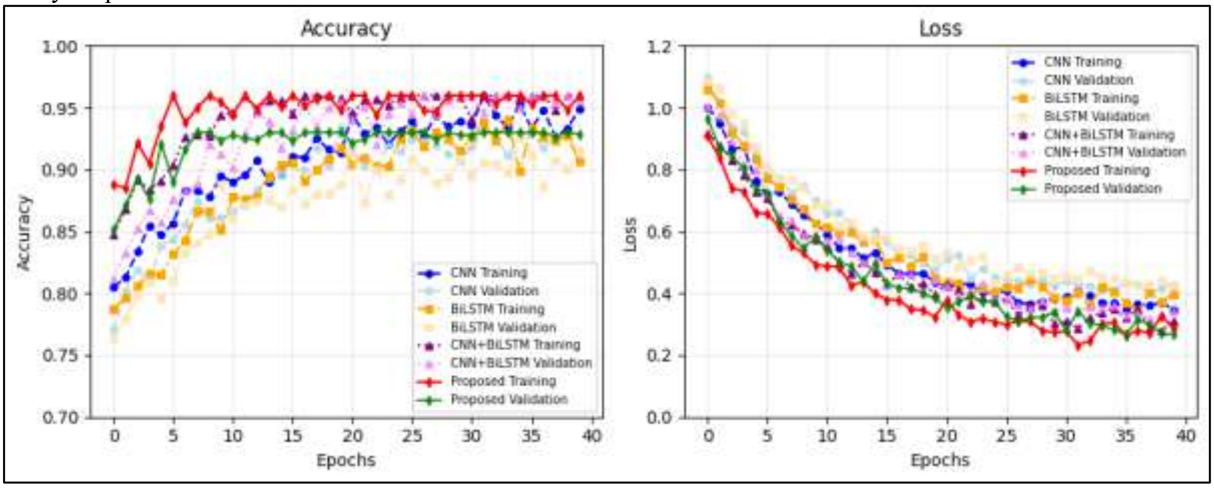

Figure 4: Accuracy and Loss graphs

5. Conclusions and Future Work

This paper presented a CNN-BiLSTM-CTA framework for PD detection using gait signals. By employing basic data augmentation and focal loss, the proposed model achieved robust performance, outperforming the baseline architectures. Unlike prior works that relied solely on pooled cross-validation, this study adopts a data split evaluation by reserving the Si cohort as an independent test set, thereby providing stronger generalization. Future work will focus on validating the model across additional cohorts, integrating multimodal sensor data, and enhancing interpretability through attention analysis linked to clinical gait markers. Another significant development is the building of a real-time PD detection system, where the trained model can be deployed in portable devices for continuous gait monitoring in natural environments. Such real-time analysis could support the early diagnosis of PD.

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