Dynamic Modeling of Parkinsonian Gait Using Latent Biomarkers

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Abstract- *Parkinson's disease (PD) affects gait dynamics, and hence, objective analysis is required for accurate diagnosis. In this regard, this manuscript proposes a deep learning framework for modeling Parkinsonian gait using Vertical Ground Reaction Force (VGRF) signals. A hybrid CNN-LSTM network is used to effectively capture spatial and temporal features of the gait, and a 16-dimensional latent space is used to effectively capture discriminative gait features. An accuracy of 99%, along with high precision and recall, is achieved by the network, and a high AUC of 0.999 indicates effective separability of classes. Furthermore, using Principal Component Analysis on the learned 16D space, distinct clusters of healthy and Parkinsonian gait patterns are observed. It is thus concluded that the proposed framework is effective for accurate detection of PD using gait analysis.*

Keywords: Parkinson's Disease, Gait Analysis, Vertical Ground Reaction Force, Deep Learning, CNN–LSTM, Latent Biomarkers

I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor impairments arising from dopaminergic neuron degeneration. Gait disturbance represents one of the most prominent and clinically relevant manifestations, directly affecting mobility, balance, and fall risk. Parkinsonian gait typically exhibits reduced stride length, impaired rhythmicity, and instability during weight transfer, reflecting disruption in motor coordination mechanisms [1].

Clinical assessment of gait abnormalities primarily relies on observational scales, which are limited by subjectivity and temporal sparsity. These evaluations fail to capture the continuous and dynamic nature of locomotion, particularly in real-world conditions. Sensor-based gait analysis provides an objective alternative by enabling continuous measurement of biomechanical signals during walking [2].

Vertical Ground Reaction Force (VGRF) signals offer a direct representation of foot–ground interaction and encode key characteristics of locomotion, including force distribution and propulsion. The availability of publicly accessible datasets, such as the PhysioNet Parkinson's gait database, enables systematic analysis of VGRF signals for distinguishing healthy and pathological gait patterns [3]. However, the complexity of these signals poses challenges for conventional analysis methods.

Traditional computational approaches rely on handcrafted features derived from VGRF signals. These features often simplify the underlying dynamics and may fail to capture nonlinear temporal relationships present in continuous gait sequences. As a result, such methods exhibit limited robustness when applied to heterogeneous datasets.

Deep learning models provide a data-driven alternative by learning feature representations directly from raw signals. Convolutional neural networks extract localized spatial patterns, while recurrent architectures model temporal dependencies. However, many existing approaches do not explicitly enforce compact representations that capture the essential structure of gait dynamics.

The present study develops a hybrid CNN–LSTM framework for dynamic modeling of Parkinsonian gait using VGRF signals. The model integrates spatial feature extraction and temporal sequence modeling, while incorporating a low-dimensional latent representation that encodes discriminative biomechanical characteristics. This latent space enables both accurate classification and interpretable analysis of gait patterns, providing a foundation for objective and continuous assessment of PD.

II. LITERATURE REVIEW

PD impacts locomotion in a significant manner, making gait analysis a reliable indicator of the disease. Wearable sensor-based gait analysis has gained considerable attention in recent years due to its ability to offer a precise and continuous assessment of motor impairment. Among the available databases, the PhysioNet Parkinson's gait database is popularly used for conducting research activities [4]. It consists of VGRF signals from both healthy and PD patients.

These signals are recorded using multiple force sensors placed at the feet.

Traditional methods of PD detection were based on handcrafted features of the gait signal. Statistical features such as stride interval, variability, and force distribution were extracted from the gait signal and used with traditional machine learning techniques. Although these techniques were able to prove the feasibility of PD detection using machine learning techniques, the performance of the traditional machine learning approach was largely dependent on the expertise of the researcher.

With the availability of large-scale gait datasets, data-driven methods have become prominent in recent times. Machine learning algorithms such as Support Vector Machines and Random Forest Classifiers have been employed for classification of VGRF signals, differentiating between healthy and Parkinsonian gait patterns. Despite the success of machine learning algorithms, it has been seen that these methods are limited in learning complex nonlinear relationships in the data, which might be present in the raw signals [5].

Recent trends in classification of VGRF signals for PD diagnosis have been seen in the context of deep learning algorithms, which allow for the learning of features from the raw data itself, eliminating the need for any manual feature engineering process. One-dimensional CNNs have shown promising results in classifying PD by learning spatial features from the multi-channel VGRF signals.

Although CNN-based approaches have achieved good results, they are mostly used for local information and are unable to fully capture temporal information for gait sequences. The gait sequence is a sequential activity, and there are transitions between different states, including both stance and swing. Recurrent neural networks, specifically the Long Short-Term Memory (LSTM) network, have gained popularity for gait analysis. The main reason for their popularity is their ability to capture temporal information through their memory cells. The ability of LSTM to capture long-range temporal dependencies in physiological signals makes it a popular choice for gait analysis [6].

Hybrid approaches have also gained popularity for gait analysis. The hybrid approach combines CNN with Recurrent Neural Networks. The combination of CNN and RNN has achieved better results compared to CNN and GRU on VGRF datasets. The CNN-RNN approach has achieved better accuracy compared to CNN-GRU on gait analysis [7].

In addition to classification accuracy, recent studies on deep learning models have focused on their interpretability in clinical applications. The feature representations learned by deep models can provide insights into the underlying data structure. Using dimensionality reduction methods such as Principal Component Analysis, previous studies have successfully demonstrated the separation between healthy and pathological gait patterns.

Although previous studies have successfully demonstrated the effectiveness of deep learning models in PD gait analysis, some limitations are identified in the existing literature. First, most of the existing models are either focused on spatial feature extraction or temporal feature extraction, but not both. In addition, the importance of extracting a compact feature representation, which can provide insights into PD characterization, is not well explored in the existing literature.

III. METHODOLOGY

The overall processing pipeline of the proposed framework is illustrated in Fig. 1, where raw VGRF signals are segmented, normalized, and processed through a CNN–LSTM architecture to obtain a latent representation for classification.

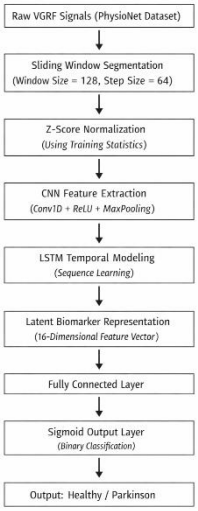

Fig. 1.Block diagram of the proposed framework

A.Dataset Description and Segmentation

In this work, a publicly available PD gait dataset is used, which is available on the PhysioNet platform [4]. This dataset consists of VGRF signals collected using force sensors placed under the feet of the patients. Both healthy controls and patients suffering from PD are included in this dataset. These signals are continuous time signals, which are divided into segments of a fixed length to perform supervised learning on

the data. A sliding window approach is used to segment the signals, with a window size of$W$=128 samples, along with a step size of S=64. This ensures that each window is a complete signal, i.e., a complete walking cycle, while the overlapping windows avoid edge effects.

B.Data Normalization

To evaluate the model without bias, the dataset is divided into training and test sets using stratified sampling. Normalization is carried out using statistics computed only from the training set. This technique avoids information leakages and ensures the model generalizes well on new, unseen data. Normalization stabilizes the gradient updates and improves the convergence of the model.

$$X_{norm} = \frac{X - \mu_{train}}{\sigma_{train}}$$

C. Spatiotemporal Feature Extraction

The proposed architecture consists of convolutional layers that extract spatial features from the multichannel VGRF signal. The convolutional layer is defined as:

$$y_i(t) = \sum_{k=1}^{K} w_i(k)x(t-k) + b_i$$

Two one-dimensional convolutional layers with 32 and 64 filters are used to extract features from the VGRF signal [8]. These features represent local patterns in the signal that correspond to changes in force and pressure distribution on the foot. Convolutional neural networks have been successfully used in the analysis of time-series data with the advantage of automatically extracting features without the need to define them. This allows the model to learn directly from the raw data.

D.Temporal Modeling Using LSTM

The sequential nature of the gait signal is captured by a LSTMnetwork, which processes the sequence of features learned by the convolutional layers and captures the temporal dependencies in the gait cycle [9]. The internal state of the LSTM is updated by gated mechanisms, which allow it to retain relevant information and filter out noise in the sequence. LSTM architectures are appropriate for modeling physiological signals, as they are capable of learning long-range dependencies in sequential data.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_{f)}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_{i)}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh(W_c x_t + U_c h_{t-1} + b_c)$$

E.Latent Biomarker Representation

The final state of the LSTM is projected into a 16-dimensional latent space:

$$z = W_z h_n + b_z$$

This latent vector is a compact representation of the gait sequence. The constraint on the dimensionality of the latent space imposes an information bottleneck, which forces the model to retain only the most discriminative information in the sequence. Latent representations have been shown to be useful for the visualization of learned features and have been applied successfully in modeling biomedical signals.

F. Classification and Optimization

The latent representation is fed into a fully connected layer, which generates a binary classification output:

$$y = \sigma(W_y z + b_y)$$

The model is trained using the Binary Cross-Entropy with Logits loss function, which is defined as:

$$L = -[y\ log(\hat{y}) + (1-y)\ log(1-\hat{y})]$$

The model is trained using the Adam optimizer, which has a learning rate of 10-3 and is run for 15 epochs, with a batch size of 32. Adam is a popular choice for its ability to optimize parameters by dynamically updating the learning rates of each parameter [10]. This architecture allows for the joint learning of spatial force distributions and temporal gait dynamics, as it has the ability to incorporate localized biomechanical features, sequential dependencies, and a latent representation of the data.

IV. RESULTS AND DISCUSSION

The training process indicates a consistent rate of convergence, as shown in the figure, with a reduction in loss from 0.4028 to 0.0292 over 15 epochs. The smooth reduction of loss indicates an efficient optimization of network parameters, along with the refinement of feature representations. The lack of fluctuations in training indicates that the learning rate used, along with the capacity of the network, is appropriate for the complexity of the VGRF data. The rate of convergence indicates that the network effectively learns generalizable patterns, avoiding any overfitting to noise,

which is verified through the good performance of the network on the test set.

Moreover, the biomechanical features of the VGRF signals give a direct indication of abnormalities in gait. As shown in Fig. 2, the total VGRF signal of healthy gait has a consistent quasi-periodic pattern, which means that the gait has a regular pattern of heel strike and toe-off in the gait cycle. The peaks of the signal indicate the points of force application in the stance phases, and the transitions between peaks indicate smooth weight transfer.

On the other hand, the Parkinsonian gait signal has irregularly spaced peaks and inconsistent peak heights, which indicate abnormalities in motor coordination. The reduction in peak sharpness and the occurrence of sudden changes indicate a lack of propulsion and instability in the stance phases of gait. This is consistent with the characteristics of Parkinsonian gait, which include reduced stride length, shuffling, and lack of rhythmicity. The VGRF signal not only measures the force applied in gait but also the timing of gait, which is useful in dynamic modeling of the gait cycle.

The classification performance of the proposed model is shown in Table I. The overall accuracy of the model is 99%. The precision and recall of the model are consistently higher for both classes, with a recall of 0.99 for the Parkinson class, which implies that the model effectively classifies the pathological gait sequences with a very low number of false negatives.

The uniform performance of the model across the classes suggests that the model does not bias towards the majority class, even though the database might be slightly imbalanced towards the Parkinsonian class. The weighted and macro averages are consistent, which further confirms that the classifier performs uniformly across various evaluation criteria.

The confusion matrix, as shown in Figure 3, presents a detailed summary of the classification results. The model classifies 3080 healthy samples and 7090 Parkinsonian samples correctly, whereas 59 healthy samples are misclassified as Parkinsonian, and 52 Parkinsonian samples are misclassified as healthy. The total number of misclassifications, i.e., 111 samples out of 10,281, accounts for an error rate of merely 1.08%, which is extremely low for a real-world biomedical classification problem.

It can be noted that the distribution of false positives and false negatives is almost symmetric, which indicates that the decision boundary is well calibrated and does not introduce any bias in the classification results. False negatives, which refer to the missed classification of Parkinsonian patients, are very low, which indicates the effectiveness of the proposed model in diagnostic support tool development.

Moreover, the Receiver Operating Characteristic (ROC) curve in Fig. 4 also shows the robustness of the classifier. From the figure, it can be noted that the Area Under the Curve (AUC) is 0.999, which indicates that the classification results are almost perfect. In addition, the curve is very close to the top-left path, which indicates that the classifier is not sensitive to the choice of threshold. In other words, the classification results are not sensitive to the choice of threshold, which indicates the effectiveness of the proposed classifier in terms of discriminative ability.

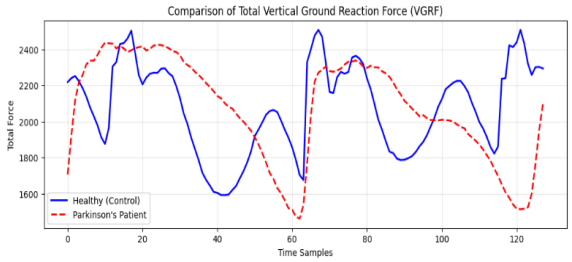

Fig. 2. Comparison of total VGRF signals

This behavior again validates our observation that the performance of the classification is not dependent on the choice of the threshold and also ensures that our model retains high discriminative ability. The high AUC also validates our observation that there is a good separation between healthy and pathological gait patterns in the feature space learned by our algorithm.

More information can be gathered regarding the feature space by performing an analysis on the latent space. From Fig. 5, it can be seen that by performing a PCA on the 16-dimensional latent vectors, two distinct and linearly separable classes are formed for healthy and Parkinsonian samples. The distinction is mostly along the first principal component, validating our observation that the most significant variance in the data is with regards to pathological gait patterns.

Table I. Classification Performance of the Proposed CNN–LSTM Model

Class	Precision	Recall	F1-Score	Support
Healthy	0.98	0.98	0.98	3139
Parkinson	0.99	0.99	0.99	7142
Accurac			0.99	10281

y				
Macro Avg	0.99	0.99	0.99	10281
Weighted Avg	0.99	0.99	0.99	10281

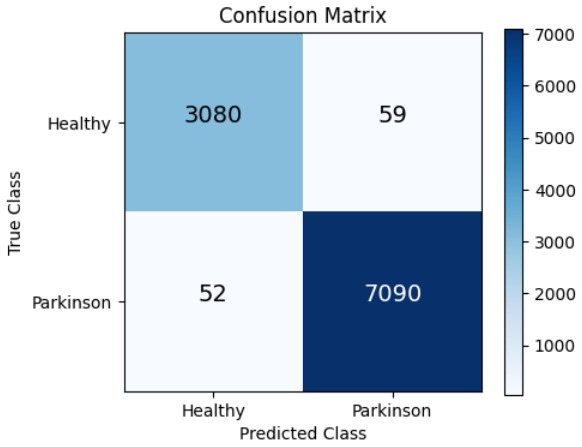

Fig. 3. Confusion matrix

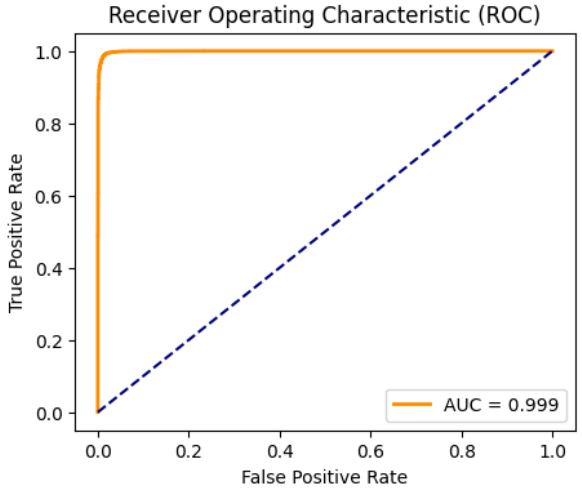

Fig. 4. ROC curve of the proposed model

The Parkinsonian cluster seems to be more compact, indicating less variability in the pathological gait patterns, while the healthy cluster seems to be more dispersed, indicating the normal variability in gait patterns among healthy individuals. The lack of overlap between the clusters indicates that the latent space effectively represents discriminative information rather than noise.

From a modeling point of view, the results confirm that the CNN effectively extracts local features based on force, which are related to specific events in the gait cycle, while the LSTM effectively extracts temporal relationships during the gait cycle. The latent layer effectively maps the features to a lower-dimensional space that retains class-specific information.

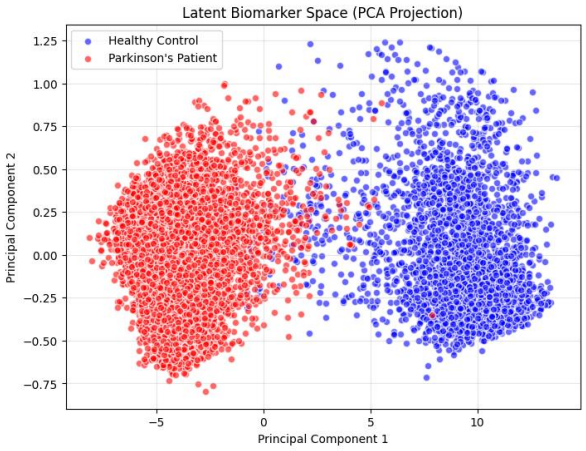

Fig. 5. PCA projection of the latent biomarker space

The consistency of the results from training convergence, classification performance, confusion matrix, ROC curve, and latent space configuration indicates that the proposed framework effectively models the spatiotemporal dynamics of the Parkinsonian gait. The results indicate that the latent space effectively represents a discriminative feature space, which can reliably distinguish the pathological gait patterns. The results confirm the potential of the proposed method for objective detection of PD based on wearable sensors.

V. CONCLUSION AND FUTURE WORK

The results of this study show that the VGRF signals can successfully classify between healthy and Parkinsonian gait patterns, using a hybrid CNN-LSTM approach. This is evident by the high accuracy obtained, which is 99%, along with high precision and recall values. It is also evident that the latent space is providing a compact yet discriminative representation of the characteristics, which are well-separated between the two classes, indicating that the features are related to the underlying biomechanics of the two types of gaits.

Future work will concentrate on the extension of this work to larger datasets, incorporating more sensor modalities to enrich the representation of the gait, and exploring the latent space to provide a way to predict disease severity.

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