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Prediction and Detection of Freezing of Gait in Parkinson's Patients using 3D Accelerometer Data

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***Abstract*—— Freezing of Gait (FOG) is a disabling motor syndrome affecting the mobility of individuals suffering from Parkinson's Disease (PD). It increases the risk of falls, thereby impairing the quality of life of PD patients. Wearable 3D lower-back sensors can record and measure time-series data during most of the daily activities of a patient. Such time series data can be used for prediction of Freezing of Gait. This paper focuses on the application of two deep learning models: Transformer encoder and BiLSTM architecture in identifying and predicting the Freezing of Gait (FOG) episodes in patients affected by PD using the dataset provided by Michael J. Fox Foundation for Parkinsons Research. The data considered here has been recorded both in a laboratory setting and in a patient's home, allowing it to capture various scenarios for the training of the detection model. Results obtained, will prove vital support in terms of early detection and differential treatment strategies, thus ultimately reducing the impact of FOG on patients' lives.**

***Index Terms*— Parkinson's Disease (PD), Freezing of Gait (FOG), Machine Learning (ML), Deep Learning (DL)and Recurrent Neural Networks (RNN).**

I. INTRODUCTION

Parkinson's Disease (PD) is a neurodegenerative disorder of the central nervous system that affects both the motor and non-motor systems of the body [1][6]. It is characterized by a sudden and intermittent inability to initiate or maintain movement [2]. It is estimated to affect around 12 million people worldwide by 2040 [7]. Recent advancements in sensor technology and machine learning have helped to analyze FOG and other complex motor characteristics through wearable devices [4]. 3D accelerometer sensors provide continuous time series data that can be used for predictive analytics, identification, and enabling timely intervention. By utilizing the time-series accelerometer data provided by Michael J. Fox Foundation for Parkinsons Research, this paper aims to predict and detect FOG episodes and specify the type of FOG event (start hesitation, turn, or walking). Deep learning models imitate the way a human brain functions to process data and create patterns for decision-making. Key components of deep learning models include neurons, layers (input, hidden, output), weights and biases. This paper discusses the use of Recurrent Neural Networks (RNN) architecture that are designed for sequential and time-series data. By leveraging deep learning models like Bi-LSTM and Transformer Encoder, we aim to overcome the challenge of the onset of FOG to enable real-time operation. The results may help in developing personalized treatments for PD patients.

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II. LITERATURE REVIEW

Paper [1] aimed at the deep learning models as predictors of FOG events in Parkinson's Disease (PD). The signals of the accelerometer and time series taken from a Kaggle dataset were used to design a Trans-BiLSTM model using a transformer encoder and bidirectional LSTM layers that scored a mean average precision of 0.427. Although the performance was found to be strong, but it undergoes the problem of overfitting. Paper [2] examines the brain regions affected by Parkinson's Disease (PD), including the midbrain, subthalamic region, globus pallidus, and frontal lobe. Factors contributing to Freezing of Gait (FOG) involve basal ganglia issues, frontal lobe disorders, and midbrain infarcts. FOG disrupts posture, gait and perceptions and it is challenging to assess due to its episodic nature, often relying on questionnaires and medical history. Despite progress, the mechanisms of FOG and its link to automatic movement control remain unclear, highlighting the need for further research to improve treatment and life quality of patient. The work discussed in paper [3] describes identification and forecasting of Freezing of Gait (FOG) in Parkinson's Disease (PD) patients using plantar pressure and ground reaction force data analysed through LSTM models. Data labelling was performed by the MATLAB application based on the analysis of video at 30 Hz, marking the beginning and end times of FOG. 16 features encompassing centre of pressure coordinates and ground reaction forces, were extracted. A balancing method ensured a 1:1 ratio of FOG to Non-FOG data during training, with the test set being unbalanced. A 2-layer LSTM improved specificity from 89.5% to 93.3%, although sensitivity decreased slightly. A 3-layer LSTM achieved sensitivity of 72.5% and specificity of 81.2%, but with low precision and F1 scores due to imbalanced data. The 2-layer LSTM's efficiency made it suitable for real-time wearable applications.

The authors [4] significantly enhanced the prediction of FOG based on an autoregressive predictive model supported by an SVM classifier. Features were selected based on the Pearson Correlation Coefficient (PCC) and Maximal Information Coefficient filters from the data collected using triaxial accelerometers and gyroscopes attached to 7 body parts. The AR model predicts the feature time series, which the SVM classifies into FOG or normal gait classes. Accuracy was found to be 85.08%, precision was 81.61%, recall was 83.37% and F1-Score was 81.73% with cross-validation using a leave-one-subject-out approach. Limitation with this result was that only 20 patients were included; no one who suffered severely was enrolled; so, the generalizability of the results is limited. In this paper [5], a fine-tuned model of Random Forest (RF) for predicting FOGs in Parkinson's Disease patients was developed. The parameters adopted were window size, a sliding step and pre-FOG duration. An accuracy of 27%, a hit rate of 68%, and the mean time of prediction of 2.99 s was achieved. Patient-dependent F1 scores were 0.89 but inter-patient variability restricted generalizability. An Orthogonal Experimental Design was designed to structure the hyperparameter tuning process and even discovered parameter interactions. In paper [6], authors have investigated Freezing of Gait (FOG) in advanced patients with Parkinson's Disease (PD), clinical correlations and treatment effects. Out of 172 patients, 53% developed FOG, which was correlated with advanced PD (mean Q3 H&Y scores: I=0.28, II=0.38, III=1.19). Long-term exposure to levodopa was associated with higher rates of FOG, whereas long-term use of amantadine lowered the risk of developing FOG. Dyskinesia, morning foot dystonia, and postural instability during the "on" phase were strongly correlated with FOG. The work discussed in paper [7] include development of models based on plantar pressure data to predict FOG episodes in Parkinson's patients. Bilateral model reached 77.3% sensitivity, 82.9% specificity and predicts 94.2% of the FOG episodes with 2.4 false positives. LAS model was highly sensitive at 94.9%, but had more false positives, while MAS model showed high specificity at 88.0% with only minimal false positives but sensitivity was lower. Model selection depends on the type of need from the patient: MAS was particularly useful to reduce false positives for patients resuming mobility; LAS was appreciated for early detection in unstable patients; the bilateral model combines good performance with cost-effectiveness.

In this paper [8], FOG detection in Parkinson's patients is concerned with the impact of L-dopa therapy. Adjusting the false-negative costs increases sensitivity but decreases accuracy and F-scores for SVM and LDA classifiers; the effect seems to be better for SVM in pre-FOG detection. LOSO validation showed better metrics off therapy, which indicates that L-dopa indeed changes the gait pattern and characteristics of FOG. ROC analysis revealed higher sensitivity at higher specificity off therapy. Sensitivity and specificity varied with states of therapy, signifying a need to consider the therapy status during model training. The study shows enormous potential in the detection of FOG using wearable devices and ML and calls for bigger datasets to explore the distinct phenotypes in FOG. This paper [9] has discussed detecting FOG and festination episodes in patients with PD through two comparisons: Freezing Index (FI)and Freezing of Gait Count(FOGC). FOGC developed more episodes of FOG than FI did because FI was not able to capture all the cases that emerged, which indicated the complexity and heterogeneity of FOG. In festination cases, FOGC detected all episodes but FI failed because it is based on the ratios of power frequency bands, making it less sensitive.

This paper [10] describes how a frozen event could be recognized using an ambulatory monitoring system in the diagnosis of FOG in 11 PD patients. They used an ankle-mounted sensor system, which recorded the vertical linear acceleration of the left shank at 100 Hz. The results showed that during FOG events, especially when the patient was initiating walking, on turning or when an obstacle was met, the patients showed definite high-frequency movements within 3-8 Hz. An FI defined as the ratio of power in the 'freeze' frequency to that in the 'locomotor' frequency and subsequently proved sensitive to detecting FOGs. It detected 78% of FOG events, but individual calibration increased detection sensitivity to 89% and decreased the FP rate to 10%. This study [11] says that FOG occurs due to dual cognitive and gait tasks, stress, and environmental factors. Physicians may have to rely on drug therapy or deep brain stimulation. Although these were valid methods at most stages, such advanced treatments may not work for FOG patients. For the sensor-based technology, the analysis of the electrocardiogram, accelerometer, and electromyography signals might be potential solutions for detecting FOG. ML algorithms and ensembles of classifiers can resolve the issue of data imbalance to exceed the preset thresholds for precision and recall metrics. Issues include inter-individual variability between FOG episodes and the restrictions set by the model that require the algorithm to predict real-time FOG with a high level of accuracy.

The paper [13] described a system that could differentiate the normal gait from that of an abnormal one in Parkinson's Disease patients through inertial sensors mounted onto the shank. It detected stride time, distance, and frequency of leg motion, and identified "representative" strides through Pearson's correlation. Then it monitored real-time gait against typical patterns to detect abnormal strides such as knee trembling, motor block known as FOG and short strides. In turn, changes in the longitudinal axis and the angle of the shank may classify FOG. In tests with 12 PD patients, the system achieved 100% accuracy in the detection of FOG episodes and 95% accuracy for normal strides. The system, based on reliability and categorization of gait dysfunction, makes it suitable for wearable integration, aids caregivers, and enhances patient safety during FOG episodes .Abdallah et al. [14] presented CNN-based deep learning method for automatic detection of Freezing of Gait in Parkinson's Disease patients, with no manual preprocessing of catching complex gait patterns directly from raw five sensors of ankle, trunk, thigh, shank, and hip, including foot angle, step rate and inter-foot diameter. The CNN reached over 95% accuracy, sensitivity, and specificity. Khan et al. [15]. identified FOG in patients with Parkinson's Disease by using accelerometer-based wearable sensors on the lower back, shank, and thigh. The data was from random walking and among the features of mean, variance and frequency, they reported that these performed best. Among all the ML classifiers applied, the best results were obtained with Ensemble Bagged Trees at 90.4% accuracy and 96% true positive rate. This study [16]is based on a hybrid approach that combined the use of DWT with a CNN-BiLSTM model for FOG monitoring in Parkinson's patients was proposed by Nguyen and Han in 2021. The DWT transforms sensor data to detect FOG patterns, whereas CNN-BiLSTM extracts spatial and temporal features to enable detection. It showed 90.01% accuracy and 44.92% binary F1 score on the Daphnet dataset. This approach was an improvement toward detection by combining traditional features with deep learning, thus suggesting improved performance in the detection process. This study [17] developed a way to predict FOG events based on patterns of impaired gait that appeared right before the event itself, thus giving warning time for prior posture adjustments. Accelerometer recordings from 12 PD patients with tasks known to induce FOG were used to test stride-related features in addition to cadence symmetry and variability, in addition to standard features extracted using traditional FOG analysis. Personalized labelling ensured the identification of phases preceding the FOG to tailor the predictions. The AdaBoost classifier achieved 82.7% accuracy in patient-dependent tests and 77.9% in patient-independent tests with an average latency of 0.93 seconds.

III. Proposed Model Architecture

Figure 1. indicates the model workflow for application of deep learning models in identifying and predicting the Freezing of Gait (FOG) episodes in patients affected by PD. The dataset used is provided by Michael J. Fox Foundation for Parkinsons Research. The input dataset contains 3D accelerometer data captured using wearable sensors on the lower backs of patients diagnosed with Parkinson's Disease. It includes tdcsfog, defog and daily datasets. The tdcsfog dataset was lab-recorded at 128 Hz, the defog dataset was recorded at 100 Hz and contains experiments that have been undertaken at home; and the daily dataset contains continuous recordings over a week. Data annotations contain FOG events - Start Hesitation, Turn, and Walking. Preprocessing involved integrating multiple CSV files, homogenizing the sampling frequencies to ensure consistency, and using annotated timestamps to label instances as FOG or non-FOG. 16 features are extracted from the acceleration data, which involved temporal metrics like total ground reaction force and its fractions across vertical (AccV), mediolateral (AccML), and anteroposterior axes (AccAP).

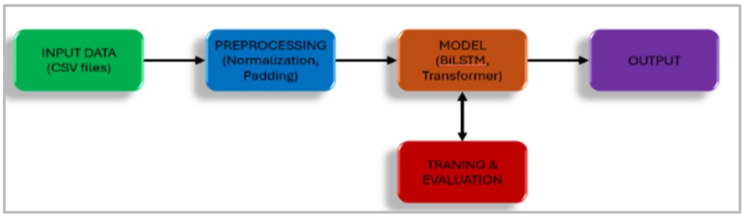

Figure 1. Model Workflow

Figure 2. shows two deep learning models: Transformer encoder and BiLSTM architecture.

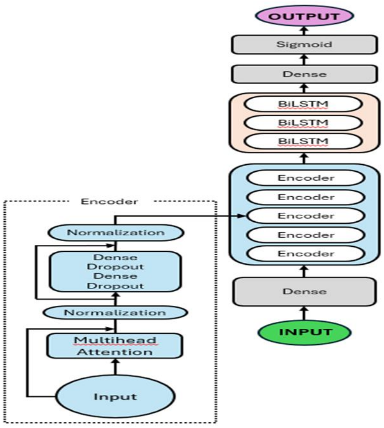

Figure 2. Transformer encoder and BiLSTM architecture

A. Bidirectional Long Short-Term Memory (BiLSTM) Model

The Bidirectional Long Short-Term Memory (BiLSTM) model accepts acceleration features of three axes (AccML, AccV, AccAP) from the tdcsfog dataset. The input data consists of time-series sequences of length 1280-time steps. The training data was divided into an 80:20 ratio for training and validation datasets. The model processes the raw input features through recurrent layers to capture temporal dependencies in the data. In the output layer, the sigmoid activation dense layer was used for binary classification: it predicts FOG or non-FOG events; for multiclass classification event types namely Start Hesitation, Turn, and Walking are classified using dense with softmax activation. The training uses Adam optimizer with a 0.001 learning rate. The model has indicated the occurrence of FOG events, specificity as a measure of correctness of the non-event detection of FOGs, precision, and F1-score. The average latency in the detection of FOG was approximately 0.1 seconds. The proposed BiLSTM architecture was developed with the help of the TensorFlow and Keras libraries in Python. Hyperparameter choices consisted of units in each layer, learning rates, and batch sizes.

B. Transformer Encoder Model:

The Transformer Encoder is an encoder of sequential data, incorporating self-attention techniques to learn the temporal dependencies. Accepted is a sequence of fixed length of 1280 with 3 features, including AccML, AccV and AccAP. Dense layer maps 3D-input features to a high-dimensional space to enable better feature representation. The multi-head self-attention layer models dependencies of time steps across the sequence. Residual connection and layer normalization attach the input of the attention layer at its output to preserve the original information. Feed- Forward Network (FFN) is a two-layer fully coupled network through which the dimension is increased by the ReLU activation. The output layer is a dense layer's with softmax activation that maps the output of the last encoder layer to the number of classes. At each time step, a prediction image is returned for one of the classes. The Adam optimizer adjusts weights to reduce prediction error. The developed Transformer Encoder architecture was realized by using the framework of TensorFlow and Keras libraries in Python.

IV. Results and Discussion

This section discusses the results of application of following two deep learning models to predict and detect Freezing of Gait on 3D accelerometer data of patients diagnosed with Parkinson's Disease:

The Bi-LSTM model was trained over 10 epochs, and its performance on the validation set improved steadily.

- Accuracy: The training accuracy began at 64.07% in the first epoch and steadily increased to 97.23% by the final epoch.
- Loss: The training loss dropped significantly from 0.9455 in the first epoch to 0.1119 by the tenth epoch. Thus, the model successfully learned the underlying patterns in the training data.
- Validation Accuracy: The validation accuracy remained consistently high, starting at 95.28% and reaching 95.53% in the final epoch.
- Validation Loss: The validation loss initially decreased and plateaued, achieving its lowest value of 0.1854 in the final epoch.

The Transformer Encoder model, utilizing self-attention mechanisms, was also trained for ten epochs. Its performance was slightly inferior to the Bi-LSTM model but showed promising results.

- Accuracy: The training accuracy increased from 91.13% in the first epoch to 96.48% by the final epoch.
- Loss: The training loss decreased from 0.4022 in the first epoch to 0.1336 in the tenth epoch, suggesting effective learning during training.
- Validation Accuracy: The validation accuracy hovered around 95%, with a peak of 95.56% during epoch six. However, a slight decline was observed in subsequent epochs, indicating potential overfitting.
- Validation Loss: The validation loss showed fluctuations, achieving its lowest value of 0.1863 during epoch six but increasing to 0.2222 by the final epoch.

Results on time-series tasks shows that the BiLSTM and Transformer encoder models score well, with BiLSTM doing a little better and more stable than the rest when it comes to generalization. The data proves that a BiLSTM model has the best training and validation accuracy rates for several other points improving in metrics via training epochs. It ends with the closest value of 0.1845 loss due to training reduced to 0.1180. There was no overfitting noticed with solid generalization, supported by the ability to explain dependencies both ways in the given sequence. The Transformer encoder model demonstrated 96.08% training accuracy from the total dataset and 95.57% validation accuracy. Validation loss was seen to be stable at t = 310 and corresponded to the highest value seen (0.152 at training loss and 0.208 at validation loss). BiLSTM wins the Transformer in terms of many distinctions, such as having better performance.

FOG can significantly impair patient mobility, independence, and quality of life due to increased fall risks. The challenge demands precision and timely intervention to aid in enhancing the outcomes of patients. So, use of Sensor technology and deep learning might change the face of patient care, as these technologies provides credible insights that can allow clinicians and caregivers to intervene proactively.

REFERENCES

[1] W. T. Mo and J. H. Chan, “Predicting three types of Freezing of Gait events using deep learning models,” Dec. 2023.

[2] J. G. Nutt, B. R. Bloem, N. Giladi, M. Hallett, F. B. Horak, and A. Nieuwboer, “Freezing of Gait: moving forward on a mysterious clinical phenomenon,” The Lancet Neurology, vol. 10, no. 8, pp. 734–744, Jun. 2023.

[3] G. Shalin, S. Pardoel, E. D. Lemaire, J. Nantel, and J. Kofman, “Prediction and detection of Freezing of Gait in Parkinson’s Disease from plantar pressure data using long short-term memory neural networks,” 2021.

[4] S. Ouyang, Z. Chen, S. Chen, and J. Zhao, “Prediction of Freezing of Gait in Parkinson's Disease using time-series data from wearable sensors,” Jul. 2023.

[5] Z. Chen, G. Li, C. Gao, Y. Tan, J. Liu, J. Zhao, Y. Ling, X. Yu, K. Ren, and S. Chen, “Prediction of Freezing of Gait in Parkinson’s Disease using a random forest model based on an orthogonal experimental design: a pilot study,” Mar. 2021.

[6] N. Giladi, T. A. Treves, and A. D. Korczyn, “Freezing of Gait in patients with advanced Parkinson's Disease,” Journal of Neural Transmission, vol. 108, pp. 53–61, Jan. 2001.

[7] S. Pardoel, J. Nantel, J. Kofman, and E. D. Lemaire, “Prediction of Freezing of Gait in Parkinson's Disease using unilateral and bilateral plantar-pressure data,” Frontiers in Neurology, vol. 13, Apr. 2022. [Online]. Available: https://doi.org/10.3389/fneur.2022.831063

[8] L. Borzì, I. Mazzetta, A. Zampogna, A. Suppa, G. Olmo, and F. Irrera, “Prediction of Freezing of Gait in Parkinson’s Disease using wearables and machine learning,” Sensors, vol. 21, no. 2, p. 614, Jan. 2021. [Online]. Available: https://doi.org/10.3390/s21020614

[9] C. A. Coste, B. Sijobert, R. Pissard-Gibollet, M. Pasquier, B. Espiau, and C. Geny, “Detection of Freezing of Gait in Parkinson Disease: preliminary results,” Sensors, vol. 14, no. 4, pp. 6819–6827, Apr. 2014. [Online]. Available: https://doi.org/10.3390/s140406819

[10] S. T. Moore, H. G. MacDougall, and W. G. Ondo, “Ambulatory monitoring of Freezing of Gait in Parkinson's Disease,” Journal of Neuroscience Methods, vol. 167, no. 2, pp. 340–348, Jan. 2008.

[11] S. Mazilu et al., “Prediction of Freezing of Gait in Parkinson's from physiological wearables: An exploratory study,” IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 6, pp. 1844–1852, Nov. 2015.

[12] B. Palakurthi and S. P. Burugupally, “Postural instability in Parkinson’s Disease: A review,” Brain Sciences, vol. 9, no. 9, p. 239, Sep. 2019. [Online]. Available: https://doi.org/10.3390/brainsci9090239
[13] M. D. Djurić-Jovičić, N. S. Jovičić, S. M. Radovanović, I. D. Stanković, M. B. Popović, and V. S. Kostić, “Automatic identification and classification of Freezing of Gait episodes in Parkinson’s Disease patients,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 22, no. 3, pp. 685–693, May 2014.
[14] M. Abdallah, A. Saad, and M. Ayache, “Freezing of Gait detection: Deep learning approach,” in 2019 International Arab Conference on Information Technology (ACIT), Beirut, Lebanon, 2019, pp. 259–264.
[15] Z. Khan, M. U. Khan, F. Aamir, and S. Aziz, “Freezing of Gait detection in Parkinson's Disease from accelerometer readings,” in 2021Mohammad Ali Jinnah University International Conference on Computing(MAJICC), 2021,pp.1–6.